Empirical investigation of risk factors at the Oslo Stock Exchange

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Abstract

In this thesis an empirical investigation of the Oslo Stock exchange is conducted. The main objective with the investigation is to increase our understanding of how different factors explain returns in a Norwegian context. The thesis uses data from 1996-2016 and is limiting the tested factors to the most prevalent and researched ones in recent decades. This includes market risk, size, book-to-market ratio, momentum and liquidity. Relying on sorting, and statistical tests using ordinary least square time series and Fama & MacBeth regressions, results are presented for estimation of CAPM, descriptive statistics of each factor, factor risk premium estimations and multifactor model estimations.

The investigation reveals that momentum and a negative liquidity risk premium, proxied by turnover ratio, is priced on the Norwegian stock market. Less evidence is found for market risk, size and book-to-market ratio which where all negative in the test period. Based on these results different multifactor models are tested. A three factor model including market risk, momentum and turnover ratio, and a two factor model with only momentum and turnover ratio can equally well explain asset returns on the Norwegian stock market.

Based on recent research and the thesis' empirical findings it is reasonable to assume that the size factor does not exist. The evidence for a book-to-market effect is ambiguous. The HML factor had a slight negative return for the full test period, but this is mainly because of the large negative HML factor in recent crises in the Norwegian stock market. Research from Næs, Skjeltorp & Ødegaard (2009) show a positive HML effect for the Norwegian market in the period 1980-2006 and similar results have been found in several developed markets (Fama & French, 2015).

The three remaining factors are explained by behavioral phenomena. The negative market risk premium is explained by high demand for high beta stocks due to investor biases and mutual fund manager's incentives. Momentum occurs mainly because of under- and overreaction from the investors and it shows how these effects reverse themselves after a given period. The negative liquidity premium is explained by the fact that the measure used, turnover ratio, captures a return premium related to volume shocks which improves the visibility of a stock. Gervais, Kaniel & Mingelgrin (2001) finds similar results where these volume shocks in fact leads to higher return for a period of time.

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1 Introduction

The risk-return relationship is one of the most studied fields within finance. For several decades models have been suggested with the purpose of explaining asset returns. The main model has since its inception been the capital asset pricing model, hereafter CAPM (Sharpe 1964, Lintner 1965a, Mossin 1966). Based on numerous assumptions, the model shows how the return should only be affected by the risk free rate and the exposure to systematic market risk. As an educational tool the model is great for explaining systematic and idiosyncratic risk, and how it relates to return. However, the underlying assumptions of the model is not realistic. This have led to the development of a large research field testing the empirical relationship between risk and return. Such research has made several different discoveries that are characterized as anomalies and deviations from the CAPM predictions. Banz (1981) found that small firms have a tendency to experience higher returns than large firms. Stattman (1980) found the same tendency for firms with a low book-to-market ratio compared with high book-to-market ratio. Later similar anomalies were discovered for momentum, liquidity, volatility and various other factors (Jegadeesh & Titman 1993, Amihud & Mendelson 1986 and Bodie, Kane & Marcus, 2011; 425)

These anomalies have been intensely investigated for the US stock market and later for markets across the world. Throughout the studies similar results have been found which can indicate that there are risk factors investors need compensation for besides the market risk. It is therefore a big surprise that only a single study has been done on the Norwegian market testing these anomalies. Næs, Skjeltorp and Ødegaard (2009) conducted such an empirical investigation for the period 1980-2006. This means there is no test for the Norwegian market after important financial events such as the global financial crisis and the drop in the price of crude oil in recent years. Their empirical investigation found similar results for size, B/M and liquidity, but no momentum effect. We would like to test if this is still the case when updating the test period from 1980-2006 to 1996-2016. It would be interesting to test if the factors have remained similar. Especially because of the aforementioned macro events which have impacted the Norwegian stock market tremendously after the test period of Næs et al. (2009) ended. Some evidence has shown that the market risk premium has flattened and the size effect has disappeared in the recent decades (Brealey, Meyers & Allen, 2011; 197). Our investigation could reveal if this also occurs on the Norwegian stock market by comparing our results with the ones of Næs et al (2009).

Næs et al. (2009) made no effort in explaining their findings in a theoretical perspective. They only presented the most common explanations without attempting to connect them to their findings. An important part of this thesis will therefore be to connect our findings with theories and hypothesis proposed from researchers in order to explain these effects. By investigating the underlying factors set forth by the theories it is possible to determine if they can explain the anomalies found on the Oslo Stock Exchange, hereafter OSE. We have therefore chosen to formulate the following research questions:

1) *How can risk factors, empirically found elsewhere, explain the returns of stocks present at the OSE in the period 1996-2016?*

    a. *How can additional risk factors improve on explaining returns compared to the CAPM?*

    b. *How have the factor risk premiums developed over time, and is this consistent with other markets?*

The analyses conducted to answer the research questions are based on all stocks listed on the OSE in the period 1996-2016. Both stocks that are currently on the stock exchange and all stocks that have been delisted in the period are included. By limiting our research to the OSE the results are most relevant for investors on the Norwegian market. However, the research could further enhance the understanding of anomalies related to CAPM by supplementing previous findings and theoretical explanations.

Only anomalies proved to be consistent across different financial markets and through time are tested. This include size, book-to-market ratio, momentum and liquidity. These factors are well documented internationally which make them more likely to explain asset returns in our test period. Another benefit of restricting the test to well documented anomalies is the comprehensive research. A range of explanations are often hypothesized which makes it possible to connect these with our findings on the Norwegian market to determine which fit the best. By choosing similar factors as Næs et al. (2009) it is possible to track the development of the factors through time.

Two methods for investigating asset pricing models and risk premiums is applied. To test the validity of the CAPM and multifactor models the time series regression is used. Black, Jensen and Scholes (1972) showed how the CAPM is only true if the intercepts from a time series regression are zero. To estimate risk premiums, the method constructed by Fama & MacBeth (1973) is used. The Fama Macbeth, hereafter FM, regression is a cross sectional regression performed in every time period which mitigates the problem of cross sectional correlation between assets. Although some research use general method of moments which do not rely on the assumption of normal distribution and homoscedasticity, we chose to stick with FM regression. The reason for choosing these methods is their simplicity and intuitiveness, which is why they are still widespread methods in the academic field of empirical finance.

Based on the two methods described above, the CAPM and multifactor models are tested on portfolios sorted on different empirically documented risk factors. Furthermore, sorting is used to provide descriptive statistics on each factor before estimating risk premiums for all risk factors. The results show compelling evidence for no size effect and a market risk premium that is nonexistent in Norway. Moreover, the B/M risk factor has been heavily influenced by the recent crises affecting the Norwegian stock market. The momentum effect is strongest when using a six-month formation period with rebalancing every sixth months, but is found in symmetric formation and rebalancing intervals for 3 and 12 months as well. For liquidity, the results show a significant negative risk premium. This is directly contradicts the liquidity research suggesting the measure used is not an adequate measure of liquidity. However, it is argued that it can fit well with a high volume risk premium found by Gervais, Kaniel and Mingelgrin (2001).

The CAPM had varying results depending on whether the portfolios were value weighted or equally weighted. The CAPM was rejected for all equally weighted portfolios, whilst only rejected for the value weighted momentum portfolios. By constructing multifactor models, the results improved compared to the CAPM and it turned out that a multifactor model including market risk, momentum and turnover did a good job explaining asset returns. However, the market risk factor was almost redundant since the two factor model with only momentum and turnover had similar results.

The remainder of the master thesis is organized in the following way. Section 2 will contain an overview of necessary theories to provide a general understanding of asset pricing models. Section 3 contains a brief overview of the empirical research used to determine which factors to test. In section 4 the methodology is presented and in section 5 data and some general information about the OSE is presented. Section 6 describes in detail the portfolio and factor creation, while section 7 contains results from our extensive empirical investigation. This will include a CAPM estimations, returns from sorted portfolios, risk premium estimations and testing of different multifactor models. The section also includes analysis and interpretations of the results. However, it will not be covering the theoretical reasons for why these results occur as this will be covered in section 8. Finally, everything is summarized with a conclusion in section 9 with perspectives and further research suggestions in section 10.

2 Asset pricing theory

Asset pricing theory tries to understand prices in relations to values of claims to uncertain payments (Cochrane, 2001, xiii). A low price in comparison to expected future payments will imply a high rate of return. Using that line of thought, asset pricing can be thought of as why some assets pay higher average return than others. The return of an asset can be divided into the time delay and risk associated with the asset's pay off. The time delay effect can easily be calculated using the risk free rate as a discount factor where there is zero expected risk. The more complicated part of asset pricing theory is to determine the riskiness of a cash flow and what types of risks that need compensation.

In order to have an in depth discussion about our empirical results, the reader first needs an understanding of asset pricing theory. The following section will therefore present the necessary models of asset pricing and empirical tests of these models, in addition to anomalies the model cannot explain. Although the models are good intuitive tools to understand the relationship between risk and return they do not always capture the reality. This is because the models are based on simplified assumptions about the real world to make them comprehensible. Empirical testing is therefore complementary to asset pricing models to get a clearer picture of the relationship between risk and return.

2.1 Modern portfolio theory

Insights in how risk is determined and what kinds of risk investors need compensation for have evolved over time. The modern way to think about risk was presented by Harry Markowitz in his seminal paper in 1952. His motivation was to explain which portfolios would be the best to hold in a mean-variance perspective. He only used expected return and variance of the portfolios to determine the pay off and risk associated with any given portfolio (Markowitz, 1952). If w_i is the weight of an asset and $E(r_i)$ that asset's expected return, the portfolio's expected return and risk can be expressed mathematically in the following way:

$$E\left(r_p\right) = \sum_{i=1}^{n} w_i E(r_i)$$

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Cov(r_i r_j)$$

The expected return of the portfolio p is calculated as the weighted average of the individual assets i. The variance of the portfolio σ_p^2 is calculated as the weight of assets i and j multiplied by the covariance between them. By adjusting the portfolio weights, it is possible to find the portfolio that maximizes the expected return at any given level of risk. Markowitz (1952) called these efficient portfolios. Constructing efficient portfolios for every level of risk will create a graph in a mean-variance diagram called the efficient frontier (Elton & Gruber, 1997). Now investors can choose the level of risk they want to be exposed to, given their level of risk aversion.

Later, Tobin (1958) added an extension of the efficient frontier by introducing lending and borrowing at a risk free rate. He argued that the portfolio selection should not be based on risk aversion because borrowing and lending could adjust the level of risk. Formulated in the Separation Theorem, the optimization problem was divided into two separate stages (Hebner, 2013). First, the investor constructs the optimal portfolio of risky assets which is the one with the highest ratio of expected return to standard deviation, called Sharpe ratio. Then adjustments to risk can be made by leveraging or deleveraging the portfolio by lending or borrowing at the risk free rate (Elton & Gruber, 1997). The best possible portfolio would therefore be a combination of a portfolio of the optimal risky assets and risk free asset. This portfolio has a linear relationship between expected return and standard deviation called the capital market line. Based on this research, Sharpe (1964), Lintner (1965a) and Mossin (1966) independently introduced the CAPM which have been the center of asset pricing for several decades. This model will be presented later in the theory section.

Beside the introduction of the mean-variance concept to investigate portfolios, Markowitz made a contribution of even greater importance. Before his paper in 1952, asset pricing theory focused on individual asset's risk and return. Markowitz was the first to understand that the return of assets was not perfectly correlated with each other, and the variance could therefore not be calculated using a simple weighted average of the assets variances (Marling and Emanuelsson, 2012). The covariance of the securities must be accounted for in order to get the correct portfolio variance. Furthermore, by taking the covariance between securities into account, Markowitz was able to construct portfolios that had the same expected return but less variance than portfolios that did not consider the covariation (Elton & Gruber, 1997). His discovery laid the foundation on how risk is interpreted today. Due to the covariance of securities, firm specific risk can be diversified away by the construction of portfolios. This risk is uncorrelated with other securities, implying that only risk correlated between securities affect the portfolio's variance. This is showed mathematically below by rewriting the formula for variance where the portfolio is equally weighted and where i=j is in a separate sum:

$$\sigma_p^2 = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{n}\sigma_i^2 + \sum_{\substack{i=1 \\ i\neq j}}^{n}\sum_{j=1}^{n}\frac{1}{n^2}\, Cov(r_i r_j)$$

Using the equation above the average variance ($\bar{\sigma}^2$) and average covariance ($\overline{Cov}$) can be defined as:

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

$$\overline{Cov} = \frac{1}{n(n-1)}\sum_{\substack{i=1 \\ i\neq j}}^{n}\sum_{j=1}^{n} Cov(\, r_i r_j)$$

By inserting $\bar{\sigma}^2$ and $\overline{Cov}$ into the previous equation for σ_p^2 the portfolio variance is expressed as:

$$\sigma_p^2 = \frac{1}{n}\bar{\sigma}^2 + \frac{n-1}{n}\overline{Cov}$$

The result demonstrate that when n → ∞, σ_p^2 converges to $\overline{Cov}$. Therefore, when n increases, the effect of the individual asset's variance decreases and the portfolio variance moves towards the covariance. If the covariance between assets is zero, it is possible to diversify away all risk. However, stocks do co-vary because they are exposed to several risk factors that has an impact on all firms to some degree. This risk should therefore be understood as the non-diversifiable risk known as the market risk (Bodie et al. 2011; 254).

2.2 CAPM

Contemporaneously derived by Sharpe (1964), Lintner (1965a) and Mossin (1966), the CAPM has been one of, if not the most popular asset pricing model since its inception. Building on the foundation of Markowitz (1952), it is a model predicting expected returns of risky assets.

Like all models it relies on assumptions about the world to function, four of the most important ones being: 1) a one period investment horizon; 2) all investors have the possibility for unlimited borrowing and lending at the risk free rate; 3) all investors have homogenous expectations of assets' return, variance and covariance; and 4) zero transaction costs and taxes (Zylar, 2014; 102).

Having these assumptions in place imply that all investors will have the same preference in risky assets, choosing the same portfolio. Their risk aversion will determine how they will allocate their wealth between the risk free asset and this risky portfolio, located on the capital market line. The reason all investors will hold the same portfolio, the market portfolio, is twofold. Aggregating the portfolios of all investors borrowing and lending cancel out to a net sum of zero and the value of these aggregated portfolios equal the entire wealth of the economy. This means that the sum of all investor's portfolios will be the market portfolio. Since the weight of each asset in the market portfolio is determined by its market value, the proportion of all stocks in all single portfolios will be the same and as a result the optimal portfolios is a share of the market portfolio (Bodie et al, 2014; 292).

According to assumption (3), there is no reason for stocks to be mispriced as expectations of the market is homogenous. In the extreme case, if a single asset were to be ignored by investors in the optimal portfolio, its demand would be zero, as all investors hold the same portfolio. If the demand is zero, then its price would consequently fall to zero too. Had this happened investors would understand that investing in the asset would give a risk free potential return, and acquire the asset. The price would increase from zero to equilibrium, as prices below equilibrium would continue attracting investors looking for underpriced assets. All this would result in the assets return to the optimal portfolio.

Two useful relationships can be derived from the CAPM, namely the Capital Market Line (CML) and the Security Market Line (SML). They are both lines determining equilibrium, but with different interpretations.

2.2.1 CML

The Capital Market Line is a straight line composed of the expected risk/return tradeoff for all combinations of the risk free rate and the market portfolio. The expected return $E(r_p)$ of these portfolios can be expressed as:

$$E(r_p) = r_f + \frac{E(r_m) - r_f}{\sigma_m} \sigma_p$$

Where r_f is the risk free rate, $E(r_m)$ the expected market return, $\sigma_m$the standard deviation of the market portfolio and σ_p is the standard deviation of a portfolio with a given combination of risk free assets and the market portfolio.

2.2.2 SML

Derived from CAPM, the security market line is a graphical representation of the risk-return tradeoff for all individual securities.

The golden nugget of the CAPM, namely Beta, and specifically how it is derived from SML is shown below. Mathematically the expected return of an asset $E(r_i)$ can be expressed as:

$$E(r_i) = r_f + \frac{E(r_m) - r_f}{\sigma_m^2} \sigma_{im}$$

Writing Beta as:

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2} = \frac{Cov(R_i, R_m)}{\sigma_m^2}$$

The SML equation will take the recognizable form:

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f)$$

Specifically, SML depicts individual security risk premiums as a function of sensitivity to this market risk, beta (Zylar, 2014; 110).

Being the most recognizable part of the CAPM, and truly its main contribution to asset pricing is the expected return-beta relationship. Stating that the return for a single asset can be explained by a constant proportion to the excess market return, plotting the securities on a straight line from the intercept which equal the risk free rate.

Empirically there are assets that are not located on the SML due to the flawed underlying assumptions. Based on the beta-return relationship these assets will be considered over- and underpriced in a CAPM framework. Underpriced assets will plot above the line, as they achieve a higher return than predicted by the CAPM. Overpriced assets will plot below the line, meaning a lower return than predicted.

Beta is the measure of systematic risk as shown, where the market portfolio by construction has a beta of 1. Values between 0 and 1, state that the asset is less volatile than the market, and with values above 1 the asset is more volatile than the market. A beta of zero means that the asset is uncorrelated with the market, and a negative beta will be negatively correlated with the market.

2.3 Arbitrage Pricing Theory

The Arbitrage Pricing Theory was developed by Stephen Ross in 1976. Like the CAPM it ties expected return to risk, but how it links these are different. The APT relies on several propositions, three of which being especially important. 1) Security returns can be explained by a factor model; 2) there are sufficient securities to diversify away idiosyncratic risk; and 3) well-functioning security markets do not allow for arbitrage opportunities (Bodie et al. 2014; 327). Assumption 1) and 3) will be the basis of this section, whilst 2) is not going be further explained. However, its relevance will be discussed later in connection to empirical evidence.

The Law of One Price is intrinsically entangled with the APT, and will be enforced by arbitrageurs in a well-functioning market. Should there be a violation of the law, arbitrageurs will buy underpriced assets and sell overpriced ones, consequentially adjusting their prices, and the arbitrage opportunity will be eliminated. There is however a crucial difference to the risk-return dominance argument in support of equilibrium pricing. The risk-return dominance argument states that the investors will only make limited portfolio changes to accommodate the mispriced asset and optimize the Sharpe ratio. The sum of these small changes from many investors is what brings the price back to equilibrium. This is different to the APT, where the mispricing is assumed to be an arbitrage opportunity and all investors will want to take the largest possible position (Bodie et al. 2014; 328).

The CAPM, as an example of a risk-return dominance argument, tells us that all investors hold mean-variance efficient portfolios. If mispricing exits in this universe, investors will only marginally shift their portfolios towards the underpriced securities. This is because the underpriced security is not considered an arbitrage opportunity, but only a shift in the risk-return relationship for that asset which changes the portfolio composition. When imposing the no-arbitrage condition however, investors given such an investment opportunity, would want to take an as large as possible position in the underpriced security (Bodie et al. 2014; 328). Therefore, it would only take very few investors, and not a large group to bring the price back to equilibrium.

Essentially the APT is an attempt at improving on the CAPM and they are very different, even though the CAPM is a special case of the APT. While the CAPM is based on the risk free rate and market beta, the APT states that prices can be affected by other factors as well. In its general form, the APT can be written as:

$$R_i = \alpha_i + \sum_{k=1}^{K} \beta_{ik} f_k + \varepsilon_i$$

The expected return, R_i, is dependent on the intercept, α_i, which is a measure of the expected return when the risk factors are 0. That is the expected return when there is no risk, or for all relevant analyses, the risk-free rate. Furthermore, all factors f_k have their corresponding factor loading, $\beta_{ik,}$ as a measure of how sensitive each return is to each factor. There can be a variety of factors like commodity prices, interest rates and GDPs to name some. Unlike CAPM however, the APT does not require all securities to be explained by one factor like market risk. The models do not even require there to be a specific number of factors, but leaves the rather challenging job of defining these up to the investor. A key point however is that all securities inside a market need to be affected by the chosen factors. (Zylar, 2014; 117).

Investors will use the model to identify mispriced securities based on their defined factors. Mispriced securities will have a market price that differs from the APTs prediction, and thus create an arbitrage opportunity. The APT implies that investors will want to hold infinite positions in this arbitrage opportunity, and quickly restore the equilibrium price. In other words, the APT finds relations among expected returns that rule out riskless profit.

The factors should follow some prerequisites to make them applicable to the model. 1) their impact on the asset price must be in unexpected moves; 2) they should not be diversifiable, namely they should be market wide; 3) accurate and dated data must be available for these factors; and 4) the relationship between the factors and assets need to be established economically (Zylar, 2014; 118).

Using some possible factors like commodity prices and GDP, certain changes would have to be made to accommodate the first requirement. It would be necessary to use the variation in GDP and commodity prices, since the level of the factor should not affect its factor loading and predicted return. The explanation of why this is the case can be found in the APT equation. The goal of the model is to have factors that take advantage of variation in their values (Bodie et al. 2014; 338). This is the reason for why using variation input, such as changes in the coal price, is needed. If there is no variation in the factor, a stationary price, then expected return will equal the risk-free return. If the beta of the asset is 0 however, there is no reason to include it in the model as it does not contain systematic risk.

The benefit of creating the factors this way is their usefulness in making portfolios more or less sensitive to unexpected changes in different factors. This way, portfolios can bear less risk toward for example the development in coal prices, choosing assets with low factor loading on such a factor. Similarly, the factors can be used for sensitivity analysis, making it clear ex ante how a portfolio will react to the large unexpected drop in coal prices.

Probably the main fault of the APT is the fact that no factors are prespecified, making this the responsibility of the investor. If the investors were to misspecify these factors, and use the model to take advantage of a possible arbitrage opportunity, the results might be catastrophic. Leaving the investors with this uncertainty in using the model, might explain why the APT have not devoured the CAPM, even though the CAPM time and time again have been proven lackluster.

3 Empirical research on CAPM anomalies

The CAPM model have since its inception received criticism for its inability to explain the cross section of returns on stock markets. Lintner (1965b) and Miller & Scholes (1972) presented tests that showed the slope to be flatter empirically than the CAPM predicts. This have persisted and the relationship between beta and returns have become even less significant in the period from 1966-2010 (Brealey et al. 2011; 197). Black (1972) showed that one of the main reasons for the slope being too flat was the unrealistic assumption about unlimited borrowing at a risk free rate. By deriving a CAPM where the risk free rate was substituted with a zero-beta portfolio, he showed how the assumption of a risk free rate overestimates the beta slope. This was because the zero-beta portfolio on average would have a higher return than the risk free asset. The adjusted CAPM has a higher explanatory power of assets return compared to the regular CAPM. However, the extension of the model did not rescue the CAPM from empirical rejection (Black, 1972).

Further research into the anomalies the CAPM cannot explain, have led researches to question if a market risk factor is the only risk factor investors need compensation for. Basing the research on a multifactor model founded on Ross' (1976) APT model, researches have investigated if there are systematic risk factors that investors need compensation for that are outside the scope of the market risk. In the following section, the main empirical findings of risk premiums will be discussed. Focusing on firm characteristic factors that is assumed to be proxies for underlying risks not captured by CAPM.

3.1 The Fama & French three factor model

The first researchers to present an asset pricing model which claimed to explain the CAPM anomalies were Fama & French (1993). They presented a multifactor model for explaining stock return based on firm characteristics. Based on previous research like Banz (1981), Stattman (1980) and Rosenberg, Reid & Lanstein (1985), they argued that the expected return of a portfolio in excess of the risk free rate ($E(R_i) – R_f$) could be explained by three factors: The excess return of a broad market portfolio ($R_m – R_f$), the difference between return on a portfolio of small stock and large stocks (SMB) and the difference between the return on a portfolio of high-book-to-market stocks and low-book-to-market stocks (HML). How these portfolios are made will be explained in greater detail in the section about portfolio and factor creation. The expected return on portfolio i is expressed as:

$$E(R_i) - R_f = b_i\left[E(R_M) - R_f\right] + s_i E(SMB) + h_i E(HML)$$

Where $E(R_m) – R_f$, E(SMB) and E(HML) are the expected risk premiums and the factor loadings b_i, s_i and h_i are the slopes in the time series regression:

$$R_i - R_f = a_i + b_i\left(R_M - R_f\right) + s_i SMB + h_i HML + \varepsilon_i$$

By adding the size and book-to-market factors they were able to capture risk premiums the single factor model could not. In fact, by correcting for size, Fama & French (1992) showed that the beta did not have any significant explanatory power on stock returns. Furthermore, their research showed how other factors that have been found having explanatory power in isolation lost it when they are combined with B/M and size. In later years Fama & French (2012) expanded their research to international stock markets researching both global and local models. The empirical evidence of factor premiums is in various degrees persists all over the world, although global models have lower explanatory power.

Empirical asset pricing models have received criticism for not being founded on a theoretical foundation. Fama & French (1993, 1996) addressed this issue by suggesting fundamental reasons for why B/M and size are common risk factors that demand a premium. Building on the research of Chan and Chen (1991) they argued that relative distress is a risk factor that is not captured in the CAPM. These firms have low profitability, high leverage ratio, low operational efficiency and have often reduced dividend payment in recent years (Chan & Chen, 1991). In addition, these firms are struggling to get external financing because of the reasons above. Chan & Chen (1991) found that firms with low market cap have these characteristics related to relative distress.

Fama & French (1995) argue that HML is a good proxy for relative distress because distressed firms tend to have high-book-to-market ratios. Through the HML proxy other CAPM anomalies that can be explained with relative distress are captured. Firms with low Earnings to price ratio, low cash flow to price ratio and high sales growth have been identified as receiving a lower average return than the CAPM predicts. These characteristics are associated with strong firms with low relative distress. However, why relative distress is not captured by CAPM are uncertain. Fama & French (1996) suggest an explanation that relative distress is a state variable of special hedging concern. Investors with specialized human capital will have an incentive to avoid investing in firms that are distressed. A negative shock will most likely reduce the need for specialized human capital, thus these employees will avoid holding stocks in their firm. If such negative shocks are correlated between distressed firms, then employees have the incentive to avoid investing in all distressed firms. This is not the case for growth firms since a negative shock will most likely only lead to slower expansion and not layoffs.

Although Fama & French have found that these factors are fairy persistent throughout the world and argues for some fundamental economic reasons for the factors, they still receive criticism. Black (1993) argues that by investigating the CAPM anomalies the patterns of risk premiums could be sample specific. Others argue that the CAPM cannot be empirically tested as data for the market portfolio is not available (Roll, 1977). Using market proxies like the publicly traded stocks are therefore considered to not be sufficient as a proxy for all assets. The last major argument is that investors are irrational and the factors are premiums based on irrational decision making. This have led to a huge research field in behavioral finance that tries to explain anomalies found in the asset pricing models which is based on economic reasons that assumes investors are rational. In particular, have these arguments been used to explain the momentum premium discussed in the next section.

3.2 Momentum

The momentum factor discovered by Jegadeesh and Titman (1993) was the only factor known at the time, which Fama & French (1996) did not have a fundamental reason for why existed. For that reason, they did not include it as a fourth factor in their multi factor model. Jegadeesh and Titmans (1993) findings revealed that by sorting portfolios based on the 3 to 12-month past performance, could indicate how well they did in the next 3 to 12-month period. Buying stocks that performed well and shorting stocks that had poor recent performance generated a significant positive return. Based on these findings and the Fama & French three factor model, hereafter FF three factor model, Carhart (1997) created a four factor model to explain mutual funds' performance over time. The model is written the same way as the three factor model with the addition of the momentum factor. The expected return $E(R_i)$ on portfolio i can be expressed as:

$$E(R_i) - R_f = b_i\left[E(R_M) - R_f\right] + s_iE(SMB) + h_iE(HML) + p_iE(PR1YR)$$

Where $E(R_m) – R_f$, E(SMB) and E(HML) and E(PR1YR) is the risk premiums and b, s, h and p is the factor loading calculated from a time series regression. The PR1YR risk premium is defined as the difference in expected return between the past winners and losers over the previous year.

In Carharts (1997) investigation on persistence in mutual fund performance, he finds that the four factors have low correlations with the market proxy and each other. Moreover, the factors have high mean returns suggesting that they can account for much cross-sectional variation in asset returns. This is further emphasized when the new model substantially improves on the CAPM and three factor models pricing errors.

Although this model has higher explanatory power, there is not provided a fundamental economic reasoning for why momentum should be a risk premium. Fama & French (1996) used the relative distress argument for explaining long term momentum reversal discovered by DeBondt and Thaler (1985), but did not have any explanation for the short-term momentum effect. The most prevalent reasoning for why such a momentum effect exists is based on the investors irrationality and behavioral finance. Before presenting the behavioral finance arguments, a discussion on what this reasoning implies for the efficient market hypothesis is necessary.

The efficient market theory suggests that price movements in stocks follows a random walk. This have led to the efficient market hypothesis stating that all information about a stock is incorporated in the price and that only new and unexpected information would make the price move. Thus, no person has information about stocks they can use in a trading strategy to make abnormal returns (Brealey et al, 2011; 314f). There are three different levels of this theory where the weakest form states that it is impossible to consistently make abnormal returns studying past returns. According to this theory, momentum premiums or momentum reversals should not exist. However, such momentum effects and other anomalies have weakened the theory of efficient markets and have paved the way for the research field of behavioral finance.

Explaining the momentum effect both Jegadeesh and Titman (1993) and DeBondt and Thaler (1985) argues that the behavioral phenomenon of overreaction is the reason. By overreaction to information a short term momentum is created that last for a time period for about 1-2 years before the market revers the overreaction when it realizes the mispricing. This will be the same for negative information leading to a negative short term momentum with a long term reversal. As an extension of this theory Lakonishok, Shleifer & Vishny (1994) found that investors had an excessive tendency to extrapolate recent growth rates into the future. By relying on past growth, a momentum is created in the short term for growth stocks and negative momentum for value stocks. However, growth has the tendency to be mean reverting which implies that the momentum has mispriced the stocks. Slowly investors realize the growth expectation is flawed and this lead to the reversal.

Institutional factors like window dressing and investors time horizon are other explanations believed to strengthen the momentum effect. As the stocks with good past performance and growth prospects seems like prudent investments, money managers tilt their portfolio towards these (Lakonishok et al, 1994). Buying stocks that have performed good and sell the ones that have performed poorly, the money managers create an illusion of competence and risk reduction. Such behavior is found to be common, and can be a reason for why stocks get mispriced in the short term. Adding to this argument, the money managers are concerned with the time horizon of their investors. They are pressured to get results fast which incentivizing tilting the portfolio towards growth stocks (Lakonishok et al, 1994). Although they know value stocks will generate a higher return on a 3-5-year horizon, they do not have the time and trust from investors to first possibly suffer a short down turn.

3.3 Liquidity

The CAPM assume trading occurs frictionless where there is no transaction cost and an investor can trade any number of stocks instantly without affecting the price (Bodie et al, 2011; 306). This is not a realistic assumption as investors in the real world prefer assets that are highly liquid, and can therefore easily be traded at a low cost. Illiquidity arises from three different sources. The first source of illiquidity is the transaction costs like brokerage fees, order-processing cost and transaction taxes that occurs whenever a trade is executed. The second sources of illiquidity are search friction or inventory risk. Since not all investors are present in the market at all times, the natural buyer is not immediately available. The solution is to sell to a market maker which will buy at a lower price as he faces inventory risk, or wait until you can get the expected price from a natural buyer. Finally, asymmetry of private information is the last source of illiquidity. Trading a security to investors that have private information could result in a trading loss to the uninformed part (Amihud, Medelson & Pedersen, 2006). Thus, investors will take a margin of safety, which increases the bid-ask spread, to defend against informed counterparties.

The term liquidity contains four interrelated dimensions; the cost of executing a trade, the quantity that can be traded, how quick a trade can be executed and how much the price is affected given the size of a trade (Bodie et al, 2011; 306). These dimensions will have different effects depending on what kind of investor is trading the asset. For instance, the trading cost measured as the spread between bid and ask will affect long term traders differently than frequent traders. The cost does only matter when a trade is executed, thus the long term trader will be less affected. The depreciation of trading cost over time pushes frequent traders towards trading in assets that have a low spread, while long term investors will still invest in assets with higher spread (Bodie et al, 2011; 308). An effect like this, called the clientele effect, is expected to make the relationship between expected return and the spread to be increasing, but in a concave shape. Amihud & Mendelson (1986) calculated this relationship and found it to be exactly as predicted. The observed return in excess of the return on a zero-spread asset, in relation to the relative bid-ask spread, had a concave relationship.

In addition to how liquidity affect investors, stocks can also be liquid along one dimension and at the same time illiquid along another. For instance, an asset can be traded frequently but only in small quantities. Since these dimension is not necessarily correlated, it is difficult to find a measurement that captures the underlying liquidity or the liquidity that matters for investors.

Therefore, researches have suggested numerous different liquidity measures that either explain one or several dimensions combined. As mentioned above, the bid-ask spread have been used to account for transaction cost. While other measures like volume, turnover, zero-trade ratio, the Amihud measure, liquidity ratio, the Liu measure and size has also been used to capture liquidity (Liu, 2006).

Empirically it has been found that variation in liquidity seems to be correlated across assets. Such a correlation implies that liquidity has a systematic component that cannot be diversified away. Investors will therefore demand a compensation for their exposure to liquidity risk in form of a higher expected return (Bodie et al, 2011; 309). This has been proven to be true according to several research studies done over the last decades. As already mentioned, Amihud et al (1986) found that increased relative spread lead to high return. Pastor and Stambaugh (2003) calculates liquidity risk as how sensitive the stock liquidity is to a market wide liquidity measure. They also find that liquidity is priced as stocks with higher sensitivity, or beta, to the market liquidity have higher average return. In a Norwegian context, Næs, Skjeltop and Ødegaard (2008) found liquidity, measured as the relative spread, is priced on the OSE. In addition, they find that the liquidity factor and the SMB has a 0,51 correlation, which leads to liquidity not being a priced factor in a multifactor model containing market return, SMB and liquidity. The turnover ratio will therefore be used in this thesis as the liquidity measure because it is expected to have a lower correlation with the SMB factor. That will be explained in greater detail in the section about factor creation.

4 Methodology

To be able to investigate how risk factors can explain the returns of the OSE, several different methods can be used. We have chosen to use two simple methods that present the results in an easy and understandable way, but still achieves high accuracy in the statistical calculations. Sorting is the first method applied, which is an informal test presenting an overview of the results in an intuitive way. The second method is a statistical method developed by Fama & MacBeth (1973) to test the CAPM. This is a two stage regression model that can easily be applied to factor models. The FM regression have since its inception been the standard model for these kinds of tests because of its intuitive appeal and simplicity.

4.1 Sorting

Sorting assets into portfolios based on their value of the factor tested is a way of investigating anomalies related to the CAPM. However, an asset’s level of a given factor tends to change over time which makes it necessary to rebalance the portfolios. Doing so will increase the spread in the portfolios level of the factor which create more robust tests (Black, Jensen & Scholes, 1972). Most researchers rebalance the portfolios annually, but some chose to do the rebalancing every month. It is often practical reasons for the rebalancing frequency based on the anomaly tested.

For instance, the audited book value is only published once a year which makes it practical to rebalance yearly. It can also differ depending on what kind of factor you want to investigate. When the momentum factor is tested, the rebalancing frequency is determined by the length of the momentum period tested. If the test is for a one-year momentum, the rebalancing is done annually. Similarly, if a 3-month momentum is tested, the rebalancing has to occur every three months.

The informal test is to investigate how average return varies across portfolios sorted on an anomaly. Although this cannot produce a statistical significant answer to whether the anomaly is a priced risk factor, it can highlight if there is a trend where the anomaly is generating returns higher than expected. By including standard deviation and Sharp ratio, the findings can be further interpreted. If standard deviation is similar for all portfolios, thus making it likely that the changes in average return is dependent on the anomaly the portfolios were sorted on.

In addition to be an informal test of return anomalies, the sorting is also the first step in a statistical test. Sorting is necessary to create the portfolios that is the dependent variable in the regression, but also to create the factors that serves as a proxy for the underlying risk factor which is the regression's independent variable. These two inputs are the main data used in a FM regression explained in the next section.

4.2 Time series and Fama & MacBeth Regression

The FM regression is a statistical test that can be used for testing asset pricing models. It was introduced by Fama & Macbeth (1973) where they empirically tested CAPM using this model. Although they used it for testing the CAPM, it can be used for testing all factor and multifactor models. It is a two-step procedure which start by calculating factor loadings in a time series regression, and then use the factor loadings to estimate the risk premium, intercept and t-statistics.

The first step is to estimate the factor loading. This could either be the beta in a CAPM test or it could be any other factor. The factor loading interpretation remains the same regardless of what is tested. It is how sensitive the return of an asset or portfolio is to the changes in the factor return. This could either be the market return or portfolios created as proxies for the tested factor. The factor loading is estimated using an ordinary least square, hereafter OLS, time-series regression, where the return of an asset or portfolio is the dependent variable R_t^{ei} and the return on the portfolio used as a proxy for the factor is the independent variable f_t:

$$R_t^{ei} = \alpha_i + \beta_i f_t + \varepsilon_t^i, \qquad t = 1,2 \dots, T. \qquad \text{For each i.}$$

Where α_i is the intercept, ε_t^i is the pricing error in each time period and the β_i is the factor loading to factor f_t . Besides being the first step in a FM regression, the time series regression could also be used to test asset pricing models. Black et al (1972) demonstrated how the CAPM can only be true if the intercept is zero when using excess return. If the intercept is significantly different from zero, the model is rejected. The same is true for multifactor models provided that all the risk factors affecting asset returns in a given market are included in the model.

The second step in the FM regression is to use the factor loading estimated in step one to do a cross sectional regression for each time period. This is almost the same as a regular cross sectional regression, but with one important change. Instead of doing one cross sectional regression with the sample averages of the returns and the factor loadings, the FM regression runs a cross sectional regression in each time period (Cochrane, 2001; 228). In the cross sectional regression, the returns across portfolios or assets are the dependent variable and the factor loading is the independent variable. It is therefore possible to use a factor loading that is constant for the entire test period or changing through a rolling time series regression. Let R_t^{ei} be the excess return at time t for asset i and β_i' is the factor loading to asset i. Then the FM regression can be written as:

$$R_t^{ei} = \beta_i' \lambda_t + \alpha_{it} \qquad i = 1,2 \dots, N. \quad \text{For each t.}$$

Where λ_t is the regression coefficient which is interpreted as the estimated risk premium for the factor. α_{it} is the intercept which is interpreted as the pricing error in each time period (Goyal, 2011). This second step creates a time series vector of risk premiums and pricing errors. To get the risk premium and pricing error estimates for the entire period the average of these time series vectors are calculated:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_t, \qquad \qquad \hat{\alpha} = \frac{1}{T}\sum_{t=1}^{T} \hat{\alpha}_t$$

The result will be the same as in a single cross sectional regression. However, the benefit of using this method is that the standard errors can be calculated from the time series vectors:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T^2}\sum_{t=1}^{T} (\hat{\lambda}_t - \hat{\lambda})^2, \qquad \qquad \sigma^2(\hat{\alpha}) = \frac{1}{T^2}\sum_{t=1}^{T} (\hat{\alpha}_t - \hat{\alpha})^2$$

By using this method to calculate the standard errors, one of the biggest deviation from the underlying OLS assumptions when using cross sectional regression is mitigated. The standard error in a cross sectional regression is only unbiased when the residuals are independent and identically distributed (Petersen, 2009). However, there is good evidence in empirical asset pricing literature that these residuals are correlated across assets, called the time effect, and through time, called the firm effect. The firm effect will have a downward biased effect in the standard error because the FM regression do not adjust for this. Although that will bias the t-statistics, it is only expected to have a minor effect due to asset returns having a low correlation over time (Cochrane, 2001; 231). Instead the FM regression was developed to account for the time effect. This effect is much more prevalent in asset returns. When one stock's return is unusually high in a given time period it is highly likely that another stock's return is also unusually high (Cochrane, 2001; 231). By adjusting for this cross correlation effect the standard error will be less biased which in turn will lead to t-statistics and p-values that have high accuracy.

Another problem related to the two-step regression model, is that the second regression assumes that the beta is given and corresponds to the true unobservable betas. This is of course not the case as the betas are estimated through the first regression. Using the time series regression to estimate betas will lead to estimation errors of beta, called error in variables, hereafter EIV. Furthermore, using betas with estimation errors in the second regression will lead to an underestimation of market risk related to the beta. It will overestimate other risk premium for factors that are observable like size and book-to-market ratio (Kim, 2010). When testing the CAPM a similar effect occurs where the market risk premium is biased downward and the intercept biased upwards (Bodie et al. 2014; 412).

To minimize this EIV problem Fama & MacBeth (1973) formed assets into portfolios. Their argument was that if the estimated betas were less than perfectly correlated, bunching assets into portfolios would reduce the EIV, thus produce betas that were more precise estimates of the true betas. To emphasize their point, they found that the standard deviation in the error term for individual assets was 3-7 times higher than the standard deviation in the error term for the portfolios (Fama & MacBeth, 1973). This showed that the portfolio beta had a significant lower estimation error than individual assets. Using portfolios when calculating betas and testing factor models have since then become the standard method. However, using portfolios to reduce this problem will create low precision in the risk premium estimate. This is because of the reduced number of data points in each cross sectional regression (Bodie et al. 2014; 413). There is therefore a tradeoff between the number of assets in each portfolio to reduce EIV and the number of portfolios to increase the precision in the risk premium estimates.

To further reduce the EIV problem, Fama & MacBeth (1973) separated the betas used for portfolio sorting and the betas used in the second regression to estimate the risk premium. Since the extreme beta values, both high and low, tend to be more extreme than their true beta, it would be a mistake to use the same beta in the cross sectional regression. Portfolio sorting would bunch these sampling errors into the portfolio with the highest and lowest beta estimates which would bias the results. To overcome this problem, the subsequent period after the portfolio formation is used to estimate portfolio betas. Using the fresh data should mitigate the problem which again will minimize the sampling error. In addition, the beta estimation time is also a source to reduce EIV provided that as the true beta is presumed to be constant over time (Kim, 2010). This is due to an increasing number of data points will converge the estimate towards the true value. To accommodate both these solutions we have chosen to use a one year rolling beta estimate for portfolio sorting were portfolios are rebalanced every year. Then we use the full sample beta estimate in the FM regression. This will ensure that we minimize the EIV problem without using a quarter of our data only on portfolio sorting.

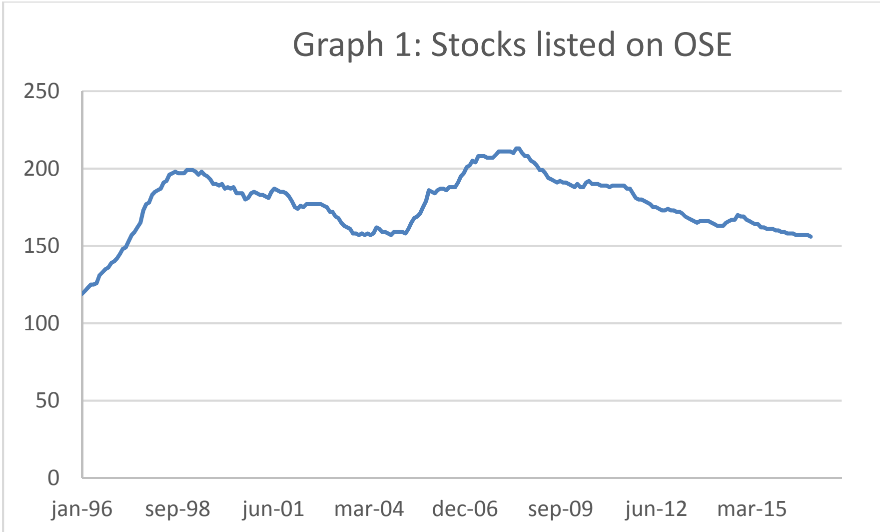
5 Data

When comparing the results of this thesis with previous research, differences in results can possibly come from the characteristics of the Norwegian market. The following section will therefore give an overview of the exchange and the composition of stocks listed on it. Moreover, the data collection and technicalities of sorting and preparing the FM regressions will be explained. This is done so that the results can be replicated, or for comparing results dependent on the method and delimitations of data across research.

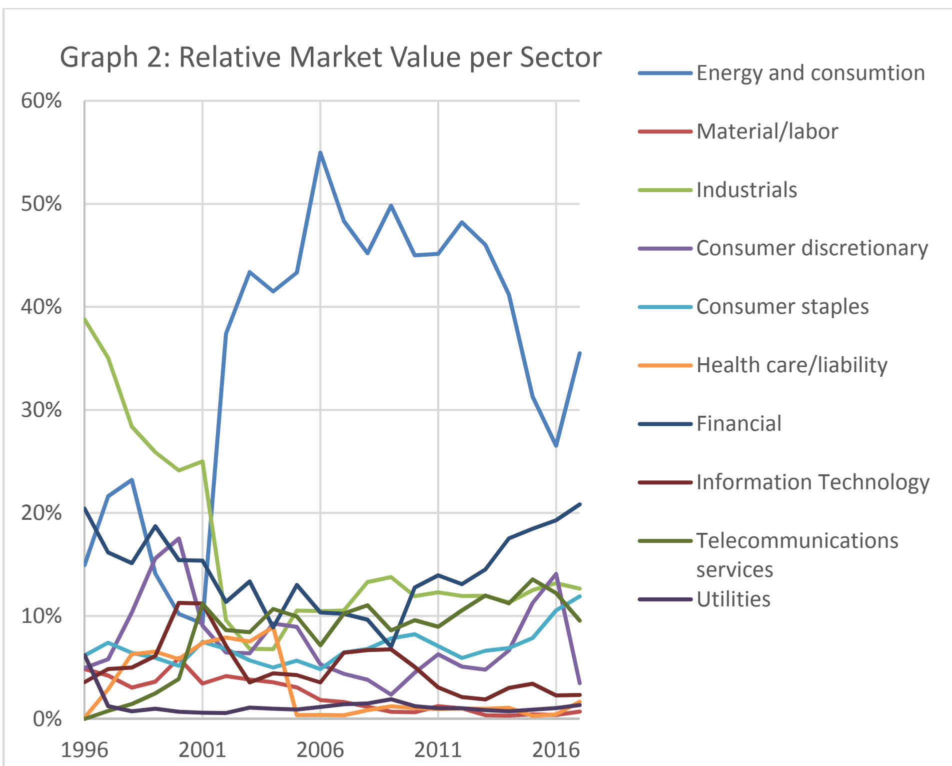
The focus of this thesis is on the Norwegian stock market, and hence on the stocks of the OSE. Founded in 1819, it is now recognized as a premier stock exchange of energy, shipping and seafood companies (Om Oslo Børs, n.d.). This section will include some statistics to paint a clear picture of the characteristics of the OSE, and hopefully give an understanding to some of our results later on. All data used next was either retrieved from the website of the OSE (Oslo Børs, n.d.) or from DataStream.

The Norwegian stock market is relatively small compared to countries like United States, United Kingdom, Japan, Australia or even Germany and France. Consequently, there are not that many stocks to be included in the analysis. To be included in our analysis we set the criteria that a stock needed to be listed on the stock exchange for two consecutive years in the period from 1/1/1996 to 31/12/2016. This is for consistency and making it more likely that the stocks could be included in a one-year formation and one-year portfolio for the factors calculated.

Using DataStream, all stocks currently listed and all delisted stocks for the period which fulfilled the first criteria was identified. This left a list of 385 stocks in total, with daily stock returns, volume, number of shares, market value and yearly book value. The development of the number of stocks listed on the exchange relevant to this thesis is shown in graph 1 below.



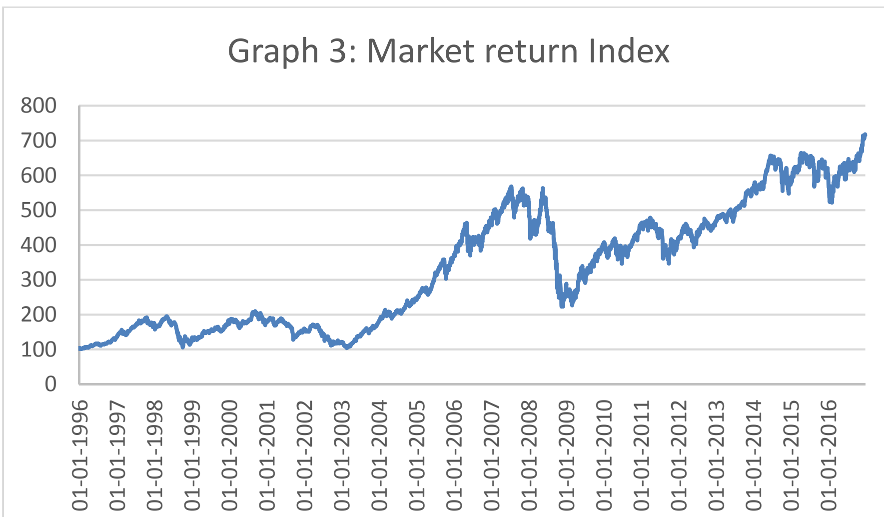
From the website of Bernt Arne Ødegaard, a professor currently at the University of Stavanger, sector data was collected for all stocks on the OSE. Ødegaard has for several years conducted research on the exchange and keeps updated statistics of the OSE readily available (Empirics on the OSE, n.d.). The sectors follow the Global Industry Classification Standard (GICS) created by Morgan Stanley Capital International.



Clearly it has been the Energy sector which has been dominant on the exchange ever since Statoil entered in 2001.This year the previously largest company Norsk Hydro, was also reclassified from

Industrial to Energy, further signifying the opposing trends. The other side of this trend is the steep drop of the Industrials sector at that time, a sector which in the years after have been situated around 10-15%, and is currently the third largest. The financial sector has historically been one of the largest with a natural low point in 2009, and is currently the second largest sector. This sector segmentation can be relevant to keep in mind, whenever comparing the results of this thesis with other markets.

A unique index was created with the stocks that was included after the two-year criteria had been applied. With a base of 100 in 1/1/1996 and tracking its development through our period, it is clear that it hardly varies from the OSE All Share Index. However, by using a market index equal to the stock universe tested will lead to better results of how risk factors effect asset returns. No noise from other assets will affect the beta estimation, and therefore not the risk premium. This is in line with the argument made by Shanken (1987), that the market proxy can be used provided it captures the variation in market return that is correlated with returns of the assets used in this thesis.



This index was created based on return data collected from Datastream. All shares in the database get its own index, created to take capital actions into account. The index theoretically reinvests dividends, to show how a certain stock moves over time regardless of payouts to the investors. Like the standard indexes, the ones provided by Datastream are cumulative as it adds any changes to the previous day's values, beginning at 100. To get the return data, the change from day t-1 to day t, the percentage change was calculated.

Weighting the index is based on market value from the previous day's closing value. The return data is from the previous day's closing value to the present day's closing value. This way the weights are decided pre-opening the day of the return which is in line with how the OSE calculates its indices. Having all this data, it was simply the case of weighting every return on its stock's share of total market value, and summing up for each day. As adding percentage returns over time will cause errors in the overall return, a basic transformation took place.

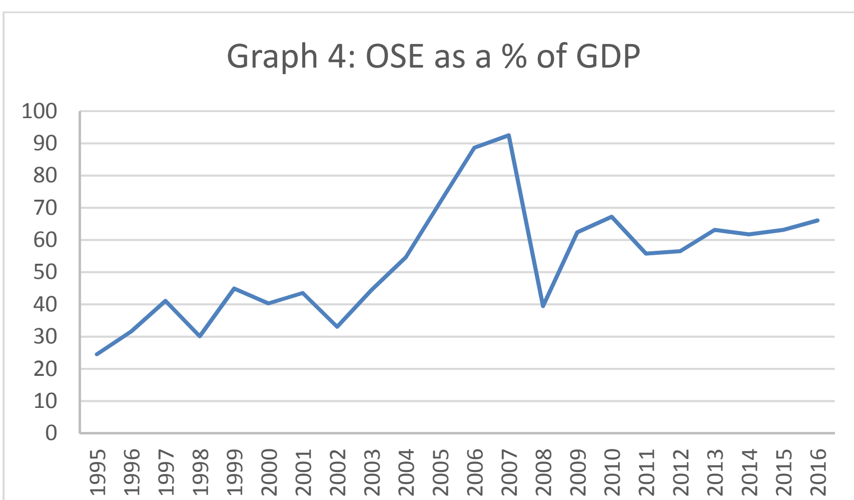
$$Total\ Return = \left(\prod_{t=1}^{T} (1 + \overline{return}_t) \right) - 1$$

Where the return at time t, represents the value weighted average of returns from all stocks on the exchange each day. The market value data is price per share times the number of shares outstanding. Shares outstanding is updated whenever a change takes place.

Being a crucial input in the test of CAPM, it is worth noting a few aspects about the market portfolio calculated. Roll (1977) argued that as the true market portfolio must include every single asset throughout the world and it is meaningless to test the expected return – beta relationship when this is not the case. This would make it meaningless to test the CAPM in the first place, and the results would naturally also be useless.

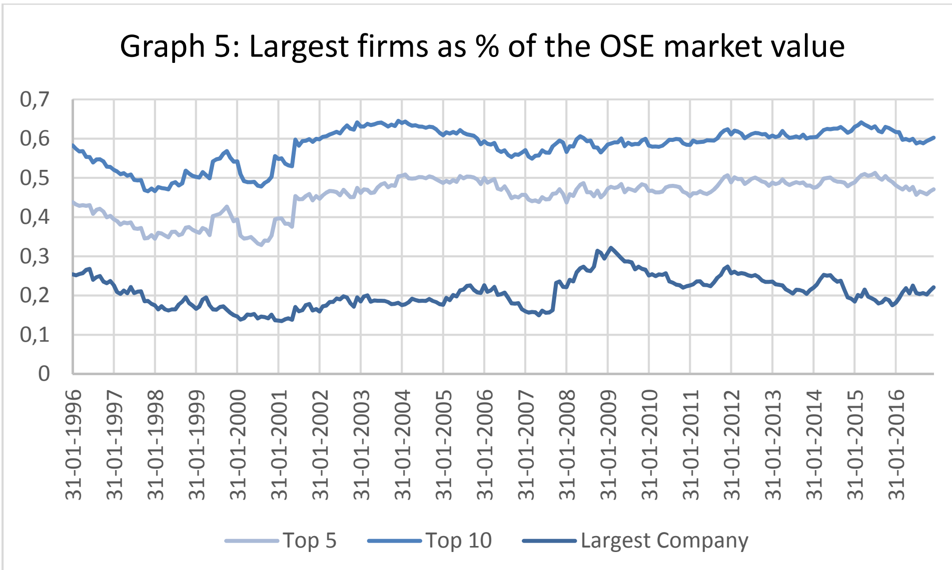
Work has been done to explore the claims of Roll. In fact, Shanken (1987) claims that the inability of the proxy to be perfectly correlated with the true market portfolio is unimportant. It is much more important that the proxy can capture variation in the market return that is correlated with the assets used in the test. Further, Kandel and Stambaugh (1987) states that as long as the proxy is highly correlated with the true market, rejection of the CAPM will not be affected by using the proxy. Even though the actual correlation of the true market portfolio and the proxy is not possible to find, the insight of Shanken (1987) shows that using a market portfolio like the one used here, has merit.

When comparing the total value of stocks present at the OSE in a given year, compared to the GPD of Norway the relative magnitude of the exchange and how it develops over time is illustrated.



The graph shows how the value peaked at over 90% of the Norwegian GPD. That said, it has the general shape of the Index, showing that the development is mostly due to changes in value at the exchange, as unsurprisingly the GDP has had a more stable development. Still it is clear that the relative value of the exchange is growing over time from 31% in 1996 to 66% in 2016. This should have a positive effect on how well the market portfolio proxy represents the economy, as the relative value of the two are moving closer together.

It is shown in graph 5 how the OSE is dominated by the its largest companies.



From the graph it is clear that the five largest companies make up close to 50% of the total value of the exchange ever since Statoil went on the exchange mid 2001. Before Statoil, Norsk Hydro was the largest firm, and although its relative size has dropped significantly since then, it is still in the top five. This definitely affects the indices as the return of just five companies will account for almost half of the return on the index at any given time, and a single company at times more than 30 %. The effects this value concentration can have will be discussed further later on.

For volume data the "Turnover by Volume" is used. It is defined as number of trades per day per stock. This is adjusted for subsequent capital actions and reported in thousands. By comparing volume data and return there are some cases where the price changed although the volume was zero. The matrix below shows how big a portion each combination makes up of the total amount of observations.

	Volum = 0	**Volum ≠ 0**
Return = 0	19,8%	12,0%
Return ≠ 0	1,5%	66,7%

In an ideal world most observation would fall into the top left or bottom right cell. Here is where the stock is traded and the return is different from zero, or alternatively, the stock is not traded and the price does not move. Some would be expected to be top right, as trading does not strictly need to affect the price of a stock. Few, if any, should fall into the bottom left category. Ideally there are trades going on to give a trustworthy picture of the stock's price, but the price can change even though there are no trades. The problem is that DataStream is not forthcoming with how the price and return are decided. The Return Index, which is partially based on "adjusted price" was used return-volume comparison above. The adjusted price is defined as either closing price of the day or an official price fixing according to DataStream, without any further explanation. This could be a problem with the data and therefore the results of the analyses later on. Nevertheless, as it is both technically possible for the price to change without trading, and this is only true for 1,5% of the data, this should not be too big of a problem.

Volume data was used for determining the number of trading days each stock had. This was used as criteria when calculating betas where the cut off was set at 20 and 50 trading days per year.

Finally book value was collected yearly from DataStream. Quarterly data was considered as an alternative, to obtain more data points. However, consistent quarterly data was not available for the majority of assets. Therefore, yearly data is used, with the added benefit of being audited values which increase the reliability. Book values for 1995, which are used in calculating book-to-market for 1996 were missing for some firms. This is used as sorting base for the portfolios of 1997, meaning the basis of returns from July 1997 to July 1998, is thinner than in the other years. This is a known flaw, but unfortunately the data was not available, so there was little to be done.

6 Portfolio and factor construction

The portfolios used for the analysis will be described in this section. As explained earlier creating portfolios is the bread and butter when it comes to analyzing assets returns and CAPM anomalies. The different portfolios are made to maximize the spread of the factors they are created to represent. This way, the difference between the portfolio with the highest values, and the one with the lowest values will be as large as possible.

Portfolios are created for each of the factors relevant to the analysis. That is Beta, Size, Book-to-Market, Momentum and Liquidity. The portfolios are sorted based on the same measures as earlier research of the FF three factor model, and Carharts four factor model. For liquidity turnover rate was used, a choice which will be discussed later. The specifics of the data, and data collection is described in the previous section.

6.1 Portfolio creation

When creating portfolios, one main method was used. This consisted of creating 10 portfolios, each with one tenth of the stocks available in each period. Creating 10 portfolios ensures that the differences between the values of the top and bottom portfolios are sizable, while still maintaining several stocks in each portfolio. The argument for both lower and higher amounts of portfolios can be made, but as the number of stocks is limited, dividing into deciles create some robustness while keeping a good spread of values.

Return data was then sorted based on the underlying factors. These portfolios were created the first trading day of July, and used until rebalancing took place a year later. For stocks entering the market in year t, they would not be included in a portfolio until t+1. Stocks who exit the market in year t, will be included until their exit and then eliminated from the portfolio for the remainder of the year. This is done to avoid survivorship biases which might enter the data, by eliminating stocks that went bankrupt and left the stock exchange during the year. Any possible selection biases will also be avoided, for the stocks that is taken off the exchange for reasons other than bankruptcy.

The return of a portfolio is the average return for the stocks included each day, generating a daily return value for each portfolio. There will also be created market weighted portfolios for comparison, and will be the portfolios used through the regressions. Here the return of each stock is weighted with its relative size within the portfolio. The specifics of each portfolio is explained below.

6.2 Beta

When calculating beta for stock i, the market portfolio discussed earlier is used. The beta of a stock is:

$$\beta_i = \frac{cov(r_i, r_{m)}}{var(r_m)}$$

Where r_i is the return of the stock and r_m is the return of the market. When estimating the betas, one year's historic data is used. In practice this means that for any given sort at time t, the year t-1 is used to estimate beta. Previous research typically uses more than a single year's basis for their beta estimation and sorting. In this thesis, the one-year estimation period is chosen from a practical perspective. Using only data from the past 20 years, on a relatively small stock exchange already puts pressure on the amount of data points available. Although not ideal, a one-year estimation period will not exclude considerable parts of the data.

Like stated in the data description section, there are different cut off values for including stocks when estimating beta. In this thesis both a 50 trading day cut off, as well as a 20 trading day cut off is used. As returns are used as input, some movement in the price is essential for the estimates a beta to be precise and a trading day cut off will promote this. The 50 days cut off will be the main path followed, but having two different cut offs is helpful as a comparison.

The beta portfolios were then created by putting the returns from the 10 % of stocks with lowest betas in the first portfolio, then the next 10 % and so on.

6.3 Size

The size portfolios have returns sorted on the absolute market value of the stock form the last day in the previous period. The stocks are sorted in ascending order where the returns of the stocks with the 10% lowest market values is put in the first portfolio and so on.

6. 4 Book-to-market

Book to market values is created in accordance with Fama & French (1992). Book value for the firm at Q4 was matched with the firm's market value at the first trading day of July. This is done to ensure that accounting data is known before the returns they are used to explain (Fama & French, 1992). Consequently, rebalancing of all the portfolios will take place the first trading day of July. Like earlier, the stock returns are sorted in ascending order based on book-to-market values, and divided into ten equal parts.

6.5 Momentum

Momentum is sorted based on Ln returns. The reason for using ln returns is their superiority when summing over time, which is the goal of this sort.

$$r_{it} = \sum_{t-12}^{t-2} lnReturns_{it}$$

For every stock i, the return from t-12 to t-2 is summed. The sum is taken for the 12 last months, not including the most recent one. Past research like Fama & French (1996) and Carhart (1997) both focus mainly on the one-year momentum factor. Further, Grundy and Martin (2001) also find that the one-year horizon is the strongest one for individual stock. Therefore, this will be the main momentum factor explained here.

The stock must have been present in the market for the entire year the sorting is based, t-12 to t-2. If a stock only has been on the exchange three months, it is likely that it will be placed in the wrong portfolio. For example, a stock which shows a strong development for three months, but is compared with stocks which have a full year to accumulate, will be put in portfolios which represents too low of a momentum.

The reason for not including the last month, is that several studies argue that this causes considerable noise in the factor. "A significant component of shortterm return reversals is driven by liquidity effects and microstructure biases" (Grinblatt, 2004; 546). The bid-ask bounce, where the stock price is moving rapidly up and down, could be such an effect. This would give a very volatile price, which can skew the momentum basis. Therefore, leaving out the last month has become standard when using a one-year base for ranking assets on momentum.

The thesis will look at several different momentum factors, which will be sorted mostly in the same way as described above. A six-month momentum, will use a six-month formation period also leaving out the last month, and a six-month rebalancing period. A three-month momentum, will use a three-month formation period without the last two weeks, and a three-month rebalancing period. Momentum factors of more than a year will use the same formation as the one-year momentum and just be rebalanced less frequently.

6.6 Liquidity

As discussed in the theory section, there are many different measures for liquidity that incorporates different liquidity dimension. Although it would have been great to test different liquidity measures and how they affect a multifactor model, due to the scope and aim of the thesis only one liquidity measure is tested. Since liquidity measures have proven to be correlated with the SMB factor a measure that is believed to have the lowest correlation is selected. This is to test the liquidity risk not captured by the SMB factor. Based on a previous master thesis by Jerkø & Morken (2012) share turnover as a percentage of total shares have a correlation of 0,4 with SMB, which is the lowest of any liquidity measure they tested. This intuitively makes sense, because the turnover ratio will capture liquidity independent of size, while the size will better capture the total value of shares traded. That is why the correlation between total value traded and size was 0.9 (Jerkø & Morken, 2012)

Turnover ratio is calculated as number of traded shares divided by total number of outstanding shares. This result in a daily turnover ratio number, which is averaged over one year to form the base for sorting. When sorted, the 10% of stocks with the lowest average turnover in the previous year are put in portfolio 1. The next 10% is put in portfolio 2 and so on, creating a total of 10 portfolios.

6.7 Factors

In this section the creation of factors is explained in detail. The SMB and HML factors of Fama & French, along with the PR1YR momentum factor of Carhart and the liquidity factor. To get the return of the factor, the average of the portfolios included are taken like earlier. The reason for the subtraction of one portfolio or group of portfolios from another, is to create zero investment strategy where the investor is long one group of assets and short another. In that way the investor will not be dependent on wealth.

When calculating the Fama & French factors, it is necessary to do a double sort. The goal of this sort is to get return data for stocks which fulfill two criteria simultaneously. The double sort will create six portfolios, each with a combination of two characteristics, based on size and book-to-market value. The argument for double sorting is that SMB and HML will have about the same weighted average book to market and market value, respectively. Thus creating a SMB factor largely independent of HML, and vice versa (Fama & French, 1993).

To get the six portfolios size is divided in two, and book-to-market in three. Size is split down the middle by finding the median and defining all stocks above this as Big, and all below as Small. Book-to-market is split in three where stocks with the lowest 30% book-to-market value is set as Low. The stock with the highest 30% is set as High, and the remaining 40% set as Medium (Fama & French, 1993).

All stocks which are both Small and Low, will then be put in the SL portfolio. All stock which are both Small and Medium, put in the SM portfolio and so on, resulting in the six portfolios SL, SM, SH, BL, BM and BH. The factors are then calculated as:

$$SMB = \frac{SL + SM + SH}{3} - \frac{BL + BM + BH}{3}$$

$$HML = \frac{SH + BH}{2} - \frac{SL + BL}{2}$$

The PR1YR factor of Carhart is created in the same fashion as book to market above, although not weighted the same way as when double sorting. The stocks are split into three, where the stocks with the lowest 30% return the previous period is put in the Down portfolio and the top 30% in the Up portfolio. To generalize the factor can therefore be called Up Minus Down, UMD where PR1YR is the special case of one-year formation and rebalancing interval used Carhart.

$$UMD = Up - Down$$

The turnover factor is created like momentum, where the lowest 30% were put in the Illiquid portfolio, and the top 30 % in the Liquid portfolio. This then created the factor:

$$Turnover = Illiquid - Liquid$$

7 Results

In this section are the results from the empirical investigation on the OSE presented. First will a statistical test of the CAPM be presented. The CAPM is tested against portfolios sorted on all risk factors discussed in the theory section. This is to test if the CAPM predicted asset returns holds empirically on the Norwegian stock market. Another reason for testing the CAPM is to establish a benchmark when testing multifactor models. Then different multifactor models can be compared to the CAPM which will determine if additional risk factor in fact improves the model. Further, the additional risk factors will be tested by first presenting descriptive results from factor creation and portfolio sorts. The descriptive results are presented in different periods to investigate how they change over time. Then a statistical test is conducted using time series- and FM regression to determine if the tested risk factors are priced the OSE. Meaning if each factor is a significant risk factor investors need compensation for. Finally, results will be presented for different multifactor models with the objective to find a model that can best explain asset returns.

7.1 Estimation of the CAPM

The first test is designed to determine whether the CAPM is a good model to explain asset returns. By using a time series- and FM regression the models explanatory power can be investigated. The time series regression described in the methodology section produces a constant and a beta for each portfolio. In addition, the time series regression calculates the standard error of both variables. These can be used to determine the precision of the estimates. Further calculations can produce t-statistics and p-vales which tell us the probability of the intercept and beta being different from zero. Furthermore, the time series regression also produces a R^2 statistic, which is interpreted as the model's goodness of fit (Brooks, 2008; 106). It is the squared correlation coefficient of the y and $\hat{y}$, which is the dependent variable and the corresponding fitted value in the regression. Since the correlation coefficient is between -1 and 1, the squared correlation coefficient is between 0 and 1 where a higher R^2 means the models fits the observations better. It is not ideal to compare R^2 across different dependable variables (Brooks, 2008; 110), and therefore it will be of less importance in the following statistical analysis.

A more interesting measure to determine if the CAPM can be used to explain asset returns is the intercept. Black, Jensen and Scholes (1972) proposed to test portfolios of assets in a time series regression on the market return. By using excess market return and excess portfolio return, the intercept in the regression should be zero if the model is true. This should hold for all portfolios of assets as long as the portfolio is large enough to diversify away idiosyncratic risk. Ødegaard (2006) tested this empirically on the OSE which showed most of the diversification effect was achieved after 10-15 stocks in each portfolio. This is the low end of number of shares this study have in each portfolio. Leading to the conclusion that results from a CAPM estimation will be contributed to systematic risk factors.

To further test the probability that the intercepts are zero, Gibbons, Ross and Shanken (1989) proposed a test to determine the probability that all intercepts are jointly zero. This is done with a specific F-test, called a GRS test after the researches, which are calculated the following way:

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

Where:

$E_T(f)$ = expected return of the factor
$\hat{\alpha}$ = estimated intercept in the time series regression
$\widehat{\Omega}$ = Covariance matrix of the factors
$\hat{\Sigma}$ = covariance matrix of the residuals
T = number of time periods
N = number of portfolios
K = number of factors

The GRS test assumes that the errors are normally distributed as well as uncorrelated and homoscedastic over time (Cochrane, 2001; 216). This is exactly the same assumptions that the t-statistics used to calculate p-values for the portfolio intercepts. As discussed in the methodology sections, this assumption is not entirely true, although the firm effect is inconsequential for asset returns.

Testing if the model produces intercepts equal to zero is best if the beta dispersion is high. An increasing dispersion will lead to increased precision of the regression estimates. This is not an issue for portfolios sorted on beta. However, some of the portfolios sorted on the other risk factor have a lower dispersion which increases the standard errors leading to lower precision of the estimates. With high standard error it will be more difficult to reject the hypothesis that the intercept is zero.

The intercept in the time series regression can only be used to determine if the model is good. For further analysis of the risk premium, the FM regression is used to calculate the size of the risk premium and the precision of estimate. By calculating the FM regression, the final result is an intercept and a risk premium. The intercept should be zero given that all risk factors affecting stock returns are incorporated in the model and the risk premium describes the historic return given one unit of the risk factor. In addition, the regression provides standard errors and t-statistics, which can be used to determine the precision of the estimate. The risk factor is said to be priced if the risk premium is significantly different from zero (Næs et al. 2009). The significance level is often set at 5 %, meaning there is only a 5% chance that the actual risk premium is zero given the risk premium estimated. However, by having a small universe of stocks, thus limiting the number of portfolios, will increase the standard error in the regression. This will make it more difficult to reject a null hypothesis with 95% certainty. Ang, Liu and Schwarz (2008) have therefore argued for using individual stocks to increase the dispersion of the factor loading which in turn reduces the standard error. This could be a good way to get higher precision, although it is not practical for both the time series and FM regression. Using individual stocks would increase the idiosyncratic risk and estimation errors in betas which would bias the results in the time series regression.

In the following paragraphs the CAPM test is presented. Table 1 through 5 will contain the time series- and FM regression sorted on beta, size, B/M, momentum and liquidity. Before analyzing the results in each table there is some main points to notice right away. Depending on which type of portfolio sort, the results vary substantially. In addition, the results are often different for value weighted and equally weighted portfolios. It is therefore extremely difficult to draw a general conclusion about CAPM, but the test gives us a deeper understanding of how well the model works on different portfolio sorts.

Table 1: Estimation of the CAPM on portfolios sorted on beta

Panel 1 shows the results from estimating the CAPM using an OLS regression for portfolios sorted on beta. The beta is calculated using a one-year estimation period where only assets with at least 50 trading days are used. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values. The first part shows the result from the time series regression and the second part shows the results from the FM regression. Portfolios in both panels are rebalanced every year, but in panel 1 the return of each asset in the portfolio is equally weighted while it is weighted based on market value in panel 2. Column 1 and 2 shows the estimated intercept and the corresponding p-value. Column 3 and 4 shows the estimated beta and the corresponding p-value. The last column presents the models R squared which is how much of the variance the model can explain. The second part of the table show the GRS test and the corresponding p-value and the last part contains the alpha and risk premium (λ) in daily and annual form with its corresponding t-statistic.

Panel 1: Equally weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00063	0,1%	0,26	0,0%	7%
Portfolio 2	0,00051	0,1%	0,32	0,0%	16%
Portfolio 3	0,00035	2,8%	0,40	0,0%	21%
Portfolio 4	0,00042	0,4%	0,44	0,0%	27%
Portfolio 5	0,00028	11,2%	0,52	0,0%	26%
Portfolio 6	0,00021	19,8%	0,65	0,0%	39%
Portfolio 7	0,00008	62,0%	0,73	0,0%	48%
Portfolio 8	0,00003	85,2%	0,90	0,0%	52%
Portfolio 9	0,00008	65,9%	1,03	0,0%	58%
Portfolio 10	0,00023	54,4%	1,21	0,0%	30%

	F-test	P-value
GRS	2,86	0,15%

	Return Daily	Return annualized	T-stat
α	0,0598%	16,3%	3,62
λ_{EW}	-0,0217%	-5,3%	-0,64

Panel 2: Value weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00034	3,2%	0,26	0,0%	9%
Portfolio 2	0,00017	23,1%	0,32	0,0%	16%
Portfolio 3	0,00018	19,0%	0,44	0,0%	30%
Portfolio 4	0,00024	9,3%	0,55	0,0%	37%
Portfolio 5	0,00002	89,7%	0,61	0,0%	42%
Portfolio 6	-0,00004	79,7%	0,79	0,0%	46%
Portfolio 7	0,00014	37,6%	0,94	0,0%	59%
Portfolio 8	0,00003	83,2%	1,02	0,0%	63%
Portfolio 9	-0,00004	82,0%	1,23	0,0%	66%
Portfolio 10	-0,00024	23,0%	1,40	0,0%	67%

	F-test	P-value
GRS	0,98	45,43%

	Return Daily	Return annualized	T-stat
α	0,0357%	9,4%	2,61
λ_{EW}	-0,0094%	-2,4%	-0,37

Table 1 shows the CAPM estimation of portfolios sorted on beta with 50 minimum days of trading volume. The first point to notice is that the beta values have a good dispersion and is in ascending order for both equally- and value weighted portfolios. The ascending order is a good indication that sorting beta portfolios on only one year of previous returns is sufficient. Even with only a minimum of 20 trading days the estimated betas seem to have these properties as well (appendix 2: table 26). The good dispersion will, as discussed above, lead to precise estimates of the risk premium. With a significance level of 5%, the CAPM have a significant intercept different form zero for the value weighted portfolio 1 and portfolio 1-4 for the equally weighted portfolio. This is also reflected in the GRS test's p-value. Equally weighted portfolios have a significant intercept when tested jointly, while it cannot be rejected that all the intercepts could simultaneously be zero for the value weighted portfolios.

In general, the CAPM is struggling to price low beta portfolios. With a positive intercept the beta can only explain part of the variation and the rest is absorbed by the intercept. For high betas the model fits quite well, although if this is because the model in fact can price the high beta portfolios or just a coincident because the high betas is not far from 1 is not clear. Nevertheless, there is a clear trend in the intercept which could indicate that even higher beta portfolios would have increasingly negative intercepts.

The descending intercepts result in a negative risk premium for both types of weighted portfolios. These are far from significant, meaning that the risk factor is not priced and investors do not need compensation for exposure to market risk. The FM regression also show a high intercept which can indicate that not all risk factors the portfolios are exposed to are incorporated in the model.

Table 2: Estimation of the CAPM on portfolios sorted on market value

Panel 1 shows the results from estimating the CAPM using an OLS regression for portfolios sorted on market value. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values. The first part shows the result from the time series regression and the second part shows the results from the FM regression. Portfolios in both panels are rebalanced every year, but in panel 1 the return of each asset in the portfolio is equally weighted while it is weighted based on market value in panel 2. Column 1 and 2 shows the estimated intercept and the corresponding p-value. Column 3 and 4 shows the estimated beta and the corresponding p-value. The last column presents the models R squared which is how much of the variance the model can explain. The second part of the table show the GRS test and the corresponding p-value and the last part contains the alpha and risk premium (λ) in daily and annual form with its corresponding t-statistic.

Panel 1: Equally weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00134	0,0%	0,35	0,0%	4%
Portfolio 2	0,00050	2,0%	0,41	0,0%	13%
Portfolio 3	0,00035	3,2%	0,43	0,0%	21%
Portfolio 4	0,00018	30,2%	0,46	0,0%	23%
Portfolio 5	-0,00003	82,3%	0,54	0,0%	35%
Portfolio 6	0,00013	35,7%	0,60	0,0%	43%
Portfolio 7	0,00017	20,2%	0,67	0,0%	51%
Portfolio 8	0,00013	25,0%	0,69	0,0%	59%
Portfolio 9	0,00002	87,7%	0,80	0,0%	67%
Portfolio 10	0,00003	67,6%	1,12	0,0%	89%

	F-test	P-value
GRS	2,36	0,90%

	Return		
	Daily	annualized	T-stat
α	0,0907%	25,7%	4,17
λ_{EW}	-0,0758%	-17,4%	-2,30

Panel 2: Value weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00032	20,7%	0,40	0,0%	9%
Portfolio 2	0,00000	99,3%	0,46	0,0%	14%
Portfolio 3	0,00001	92,8%	0,43	0,0%	21%
Portfolio 4	-0,00008	66,4%	0,47	0,0%	20%
Portfolio 5	-0,00016	29,3%	0,52	0,0%	33%
Portfolio 6	-0,00001	96,4%	0,59	0,0%	43%
Portfolio 7	0,00022	9,0%	0,64	0,0%	49%
Portfolio 8	0,00011	38,8%	0,70	0,0%	53%
Portfolio 9	-0,00004	71,6%	0,78	0,0%	67%
Portfolio 10	0,00001	73,9%	1,09	0,0%	98%

	F-test	P-value
GRS	1,01	42,84%

	Return		
	Daily	annualized	T-stat
α	0,0086%	2,2%	0,41
λ_{EW}	0,0195%	5,0%	0,64

The results for the CAPM estimation was not promising when sorting for beta. Still, additional tests will be performed against the various anomalies identified in previous research. This is to further investigate the validity of the CAPM and identify risk factors that are not incorporated in the model. Table 2 show the results of the CAPM estimation for portfolios sorted on size. The size portfolios have similar beta values as the portfolios sorted on beta. This is reflected in the correlation coefficient where market return and beta have a correlation of -0.66 and -0,5 for value weighted and equally weighted portfolios, respectively. The negative correlation is due to the SMB factor is long the small stocks and short big stocks. Since the betas are similar, the model is rejected on almost the same portfolios. However, the intercepts descending trend is not as clear for the size portfolios. Finally, the GRS test show similar characteristics as for beta portfolios.

The intercepts are jointly significantly different from zero for equally weighted portfolios, while it cannot be rejected that the intercepts are simultaneously zero for value weighted portfolios.

The FM regression further illustrates the big difference for equal and value weighted portfolios. For the equal weighted portfolios, the intercept from FM regression is significantly above zero and the risk premium is priced as a negative risk factor. This is surprising considering the results from value weighted portfolios tell a completely different story. As seen later on in table 8 the average returns in all the portfolios are lower in the equally weighted portfolios compared to the value weighted ones. This is consistent with a size premium, as the smallest stocks in each portfolio will have the highest return, but have the lowest weights when value weighting. However, the lack of a clear trend, or even reversal of trend across portfolios when value weighting signals large variation and randomness in the portfolio creation. The reversal of the trend is random in the sense, that by creating 10 portfolios and not another arbitrary number, the high return stocks can become the highest in one portfolio, rather than the lowest in the next one.

One solution could be to increase the number of assets in each portfolio to reduce the idiosyncratic risk, thus reducing this phenomenon. Nevertheless, we chose not to run the test with more assets in each portfolio. This is because it will reduce the number of portfolios and make the FM regression results less precise due to a smaller spread in beta.

As a final note, the R^2 have an increasing ratio which occurs because the portfolios are sorted on size. By doing so, the larger portfolios will be increasingly similar to the market return, which will lead to higher R^2 and also a beta closer to 1. Especially will portfolio 10 be very similar to the market index since it incorporates 50%-70% of the market value on the OSE.

Table 3: Estimation of the CAPM on portfolios sorted on B/M ratio

Panel 1 shows the results from estimating the CAPM using an OLS regression for portfolios sorted book-to-market ratio. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values. The first part shows the result from the time series regression and the second part shows the results from the FM regression. Portfolios in both panels are rebalanced every year, but in panel 1 the return of each asset in the portfolio is equally weighted while it is weighted based on market value in panel 2. Column 1 and 2 shows the estimated intercept and the corresponding p-value. Column 3 and 4 shows the estimated beta and the corresponding p-value. The last column presents the models R squared which is how much of the variance the model can explain. The second part of the table show the GRS test and the corresponding p-value and the last part contains the alpha and risk premium (λ) in daily and annual form with its corresponding t-statistic.

Panel 1: Equally weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00049	2,1%	0,92	0,0%	43%
Portfolio 2	0,00000	98,8%	0,86	0,0%	54%
Portfolio 3	0,00026	7,5%	0,70	0,0%	48%
Portfolio 4	0,00032	2,4%	0,57	0,0%	40%
Portfolio 5	0,00030	2,3%	0,55	0,0%	42%
Portfolio 6	0,00017	17,3%	0,51	0,0%	40%
Portfolio 7	0,00029	2,8%	0,50	0,0%	37%
Portfolio 8	0,00048	0,0%	0,46	0,0%	32%
Portfolio 9	0,00013	41,6%	0,48	0,0%	27%
Portfolio 10	0,00048	16,9%	0,52	0,0%	8%

	F-test	P-value
GRS	2,51	0,52%

	Return		
	Daily	annualized	T-stat
α	0,0355%	9,4%	1,48
λ_{EW}	0,0167%	4,3%	0,39

Panel 2: Value weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00013	52,5%	1,24	0,0%	61%
Portfolio 2	-0,00024	17,0%	1,12	0,0%	62%
Portfolio 3	0,00001	93,3%	1,02	0,0%	66%
Portfolio 4	0,00015	32,4%	0,89	0,0%	57%
Portfolio 5	0,00011	39,1%	0,74	0,0%	56%
Portfolio 6	0,00019	23,4%	0,97	0,0%	60%
Portfolio 7	0,00013	38,3%	0,78	0,0%	51%
Portfolio 8	0,00009	57,1%	0,78	0,0%	51%
Portfolio 9	-0,00023	16,6%	0,68	0,0%	42%
Portfolio 10	-0,00031	10,7%	0,68	0,0%	34%

	F-test	P-value
GRS	1,15	31,67%

	Return		
	Daily	annualized	T-stat
α	0,0009%	0,2%	0,03
λ_{EW}	0,0237%	6,2%	0,61

For portfolios sorted on B/M, the results vary across portfolios. Table 3 shows the CAPM estimations when sorting on book-to-market ratio. For these portfolios the beta spread is smaller than for sorts done on beta and size, although it still has a relatively greater spread than momentum. The beta is only explaining part of the variation for the equally weighted portfolios due to the positive intercept for all portfolios. Furthermore, the intercept is significant for five of the equally weighted portfolios, which implies a badly specified model. This is further emphasized with a p-value of 0,52% in the GRS test. The FM regression produces a high intercept and a too low risk premium compared to the excess market return which is at 7,08%. The low risk premium has a small t-statistics which further illustrate the market risk premiums inability to explain returns for equally weighted B/M sorted portfolios.

The same is true for the value weighted portfolios which has a t-statistic for the risk premium at 0.61. Although this is fairly close to excess market return which can be somewhat confusing. The reason for the low t-statistic is the high variance found when investigating the HML. Presented in table 10, it is clear that especially the high portfolios have experienced large variations in returns. This could be contributed to the effect of the financial crisis and the drop in the price of crude oil. How high B/M and these events are connected will be explained in greater detail later. In addition to high variation can the use of portfolios, which limits the beta spread and the number of data points in each cross sectional regression, reduce the estimates precision (Ang, Liu and Schwarz, 2008). Moreover, the firm effect can have a small downward biased effect on the standard error which further reduces the t-statistics.

For the value weighted portfolios, the intercept is close to zero for both the time series regression and the FM regression. For the time series regression, the intercept is never significantly different from zero and varying around zero indicates that the CAPM can better explain these portfolio returns.

Table 4: Estimation of the CAPM on portfolios sorted on one-year momentum

Panel 1 shows the results from estimating the CAPM using an OLS regression for portfolios sorted on each asset's return in the previous one-year period. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values. The first part shows the result from the time series regression and the second part shows the results from the FM regression. Portfolios in both panels are rebalanced every year, but in panel 1 the return of each asset in the portfolio is equally weighted while it is weighted based on market value in panel 2. Column 1 and 2 shows the estimated intercept and the corresponding p-value. Column 3 and 4 shows the estimated beta and the corresponding p-value. The last column presents the models R squared which is how much of the variance the model can explain. The second part of the table show the GRS test and the corresponding p-value and the last table contains the alpha and risk premium (λ) in daily and annual form with its corresponding t-statistic.

Panel 1: Equally weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00036	36,3%	0,71	0,0%	12%
Portfolio 2	0,00023	24,8%	0,58	0,0%	25%
Portfolio 3	0,00013	45,1%	0,57	0,0%	32%
Portfolio 4	0,00024	17,4%	0,59	0,0%	31%
Portfolio 5	0,00021	11,3%	0,52	0,0%	39%
Portfolio 6	0,00041	0,1%	0,51	0,0%	42%
Portfolio 7	0,00040	0,1%	0,43	0,0%	36%
Portfolio 8	0,00031	0,7%	0,61	0,0%	53%
Portfolio 9	0,00037	0,4%	0,66	0,0%	52%
Portfolio 10	0,00022	15,9%	0,86	0,0%	55%

	F-test	P-value
GRS	2,78	0,20%

	Return		
	Daily	annualized	T-stat
α	0,0394%	10,4%	1,43
λ_{EW}	0,0093%	2,4%	0,18

Panel 2: Value weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00054	8,3%	0,91	0,0%	25%
Portfolio 2	-0,00045	9,2%	0,91	0,0%	32%
Portfolio 3	-0,00055	1,0%	0,92	0,0%	43%
Portfolio 4	0,00014	42,1%	0,92	0,0%	54%
Portfolio 5	0,00013	39,8%	0,85	0,0%	56%
Portfolio 6	0,00013	35,5%	0,80	0,0%	56%
Portfolio 7	0,00024	7,3%	0,68	0,0%	50%
Portfolio 8	-0,00008	56,5%	0,95	0,0%	66%
Portfolio 9	0,00018	23,5%	1,01	0,0%	64%
Portfolio 10	0,00019	34,8%	1,18	0,0%	59%

	F-test	P-value
GRS	2,20	1,53%

	Return		
	Daily	annualized	T-stat
α	0,0028%	0,7%	0,07
λ_{EW}	0,0174%	4,5%	0,34

For portfolios sorted on momentum, the alpha and risk premium in the FM regression is similar for those sorted on B/M. Presented in table 4, the equally weighted portfolios risk premium is fairly low and far from significant. This is true for value weighted portfolios as well, even though the risk premium is 2,1% higher and the intercept is closer to zero. The low t-statistics can both be attribute to returns close to zero, but also a relative low spread in betas. For value weighted portfolios the beta has only a 0,21 spread if you exclude the highest and lowest beta value. For equally weighted portfolios the spread is better because of the absolute spread and better variance in beta between portfolios.

For the time series intercept, several are significantly different from zero. This is primarily true for the equally weighted portfolios, but by increasing the significance level to 10%, four value weighted portfolios would also have an intercept significantly different from zero. Additionally, the GRS test is significant for both types of weighted portfolios. Accordingly, this can indicate that momentum is a risk factor that investors need compensation for which is not captured by the market risk factor, thus the CAPM is a badly specified model. The momentum portfolios the CAPM is struggling to explain are different for the equally weighted and value weighted portfolios. For the equal weighted portfolios, the intercept is significantly different from zero for portfolios with a high momentum. When looking at table 12 that is logical since the average return is high for these portfolios and the beta value is only around 0,5. For the value weighted portfolios, CAPM have no problems with high momentum portfolios. The issue is with portfolios with low momentum where the intercept is below zero for portfolio 1-3. This is because they have a negative average return even though the beta is close to 1.

Table 5: Estimation of the CAPM on portfolios sorted on turnover ratio

Panel 1 shows the results from estimating the CAPM using an OLS regression for portfolios sorted on trading volume measured as the number of stocks traded divided by the number of outstanding stocks. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values. The first part shows the result from the time series regression and the second part shows the results from the FM regression. Portfolios in both panels are rebalanced every year, but in panel 1 the return of each asset in the portfolio is equally weighted while it is weighted based on market value in panel 2. Column 1 and 2 shows the estimated intercept and the corresponding p-value. Column 3 and 4 shows the estimated beta and the corresponding p-value. The last column presents the models R squared which is how much of the variance the model can explain. The second part of the table show the GRS test and the corresponding p-value and the last part contains the alpha and risk premium (λ) in daily and annual form with its corresponding t-statistic.

Panel 1: Equally weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00024	20,0%	0,38	0,0%	14%
Portfolio 2	-0,00007	68,9%	0,43	0,0%	19%
Portfolio 3	0,00033	3,0%	0,46	0,0%	27%
Portfolio 4	0,00038	1,2%	0,46	0,0%	27%
Portfolio 5	0,00033	2,1%	0,49	0,0%	32%
Portfolio 6	0,00047	0,1%	0,56	0,0%	37%
Portfolio 7	0,00043	1,5%	0,63	0,0%	34%
Portfolio 8	0,00025	8,4%	0,72	0,0%	50%
Portfolio 9	0,00030	4,7%	0,89	0,0%	59%
Portfolio 10	0,00068	1,9%	1,02	0,0%	33%

	F-test	P-value
GRS	3,04	0,08%

	Return		
	Daily	annualized	T-stat
α	-0,0184%	-4,5%	-0,86
λ_{EW}	0,1049%	30,2%	2,57

Panel 2: Value weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00041	3,2%	0,39	0,0%	14%
Portfolio 2	-0,00039	2,7%	0,48	0,0%	23%
Portfolio 3	0,00003	84,4%	0,67	0,0%	41%
Portfolio 4	0,00002	91,5%	0,58	0,0%	34%
Portfolio 5	0,00001	96,7%	0,72	0,0%	39%
Portfolio 6	0,00019	24,9%	0,76	0,0%	46%
Portfolio 7	0,00017	23,8%	0,84	0,0%	57%
Portfolio 8	-0,00005	75,6%	0,98	0,0%	60%
Portfolio 9	0,00015	28,3%	1,08	0,0%	71%
Portfolio 10	0,00000	98,5%	1,19	0,0%	78%

	F-test	P-value
GRS	1,40	17,53%

	Return		
	Daily	annualized	T-stat
α	-0,0423%	-10,1%	-2,19
λ_{EW}	0,0786%	21,9%	2,70

The last CAPM estimation is done on portfolios sorted on liquidity, measured using the number for traded shares divided by the total number of shares. This is, as discussed in the methodology section, to test the liquidity risk that is not captured the size factor. Presented in table 5, the liquidity factor has one similarity with size. The betas are almost exactly the same which is not that strange considering both should have some liquidity risk incorporated in the factor. This can again be found in the correlation between turnover and SMB which is 0,58 for the value weighted factors and 0,22 for the equally weighted factors. Although the betas are similar, the CAPM is a better specified model when sorting on size than for turnover. Seven equally weighted portfolios and two value weighted portfolios have an intercept significantly different form zero. This is because the portfolios actually have an increasing trend where higher turnover yields a higher return. In isolation this is will not make the model poor, considering betas are also increasing. However, the returns of equally weighted portfolios are high above the expected return – beta relationship. The same is true for value weighted portfolio 1 and 2, where the return is far below the CAPM's expectations. This could imply that high turnover ratio is a proxy for underlying risk factors investors need compensation for or that stocks with high turnover have a behavioral explanation for having a high return.

The FM regression estimations for turnover is the only portfolio sorts to price market risk as a significant risk factor. However, it may be that other risk exposures are incorporated in risk premium which is resulting in a significant risk factor. With an annualized return of 30,2% and 21,9%, the return is way above the excess market return of 7,08%. In fact, the risk premium is almost significantly different from zero even if the market risk is deducted from the estimated risk premiums. Most likely, the reason for this is the increasing return not because of the risk premium related to market risk, but to the high volume return premium (Gervais et al. 2001). Such a premium will make the estimated risk premium large and significant. This is because our proxy for the high volume return premium is correlated with the market return showed in the correlation matrix in table 7. The correlation is negative because the turnover factor for high volume return premium is long high turnover stocks and short low turnover stocks. The factor presented in the correlation matrix is exactly the opposite of such a proxy. If turnover ratio is a better proxy for high volume return premium than liquidity will be further discussed and tested in a later section.

7.1.1 Summary

The CAPM have proven to be a well specified model for most of the value weighted portfolios. Only four portfolios in total had an intercept significantly different from zero, where two of the portfolios were in the turnover sorts. The GRS tests also concludes that the model is good for portfolios sorted on beta, size and B/M. Conversely, the test shows that for momentum the intercepts are simultaneously significantly different from zero. This can indicate that momentum is a proxy for underlying risk factors the investors need compensation for. For turnover the GRS test does not show a significant intercept, although the results could be biased due to high correlation between turnover and market return.

The FM regression's intercepts could not be rejected for three types of sorts while it was significantly different from zero for the beta and turnover sorts. The risk premium was positive in all portfolios except the beta sorts, but only significant for the turnover portfolios. When considering that the beta sorting should provide the most accurate results for the market risk premium there are few signs that there is such a risk premium in the Norwegian market. At least there is a big possibility that it has shrunk in the latest decades considering Næs et al. (2009) found such a premium in their test period.

Throughout the tests there is a contradiction in results between time series and FM regressions. Frequently, the results show that the CAPM cannot be rejected and at the same time is the market risk premium far from significant. This contradiction is particular apparent for value weighted portfolios sorted on beta where the risk premium in negative, but the CAPM is still not rejected. The reasons for why this occurs could be several, but mainly it is due to lack of precision of the estimates. This is largely because of a small stock market and only a test period of 20 years. It was assumed ex ante that using daily data could mitigate the problem, however it seems like the increased noise in daily data offset the positive effects of the increased number of data points.

For the equally weighted portfolios, the CAPM is a poorly specified model. There are at least two reasons for the big discrepancy between equally weighted and value weighted portfolios. First of all, the equally weighted portfolios have on average higher return than the value weighted ones. A plausible explanation for that anomaly is that assets with the lowest market value, which have high returns, is randomly distributed across portfolios when they are sorted on a different factor. This will result in higher returns for equally weighted portfolios compared to the value weighted companion because their contribution is greater for equally weighted portfolios. This argument is flawed from a theoretical view, as the CAPM should be able to estimate all asset returns just dependent on the beta and the risk free rate.

To further investigate the problem, all the same CAPM estimations are done using an equally weighted market portfolio. As expected the results changed dramatically. Appendix 3 shows that the CAPM improves as a model in regards to the equally weighted portfolios and become worse for the value weighted portfolios. For the FM regression the generally high intercept decreased for equally weighted portfolios and a generally low intercept increased for value weighted portfolios. The risk premium also had some of the same effects which indicates that by using equally weighted market return the results almost reversed itself. These findings do not necessarily indicate that the CAPM is a well specified model. It only implies that the results are more reasonable by being consistent in how portfolios and market return are weighted.

7.2 Risk factors

This section contains tables and graphs made from portfolios sorted on the different factors included in this thesis. The tables are followed by a brief explanation of the numbers, and how they relate to the expected results. A more rigorous statistical test of the factors will be presented later, but this section should give an overview of what the data contains and what to expect from the factor models explanatory powers. Further, the size effect from equally weighted to value weighted portfolios will be obvious in sorted data, like it was earlier. Some deeper discussion of this effect will be given in the end of the section, when summarizing.

Table 6: Annualized factor returns

The table shows the annualized return and p-value for each factor. The second part of the table breaks up the return into four sub periods where the first period is four years and the remainder is five. The returns are annualized using the formula $(1+r)^n - 1$, where n is the number of trading days in a year.

Table 6A: Equally weighted portfolios

	SMB	HML	Mom factor	Turn factor
Annualized mean	7,4%	-1,7%	9,0%	-12,5%
p-value	3,1%	67,7%	5,2%	0,4%

	SMB	HML	Mom factor	Turn factor
1997-2001	2,3%	1,4%	0,7%	-9,0%
2001-2006	16,5%	15,0%	11,3%	-2,0%
2006-2011	1,9%	-4,1%	-1,1%	-20,9%
2011-2016	8,5%	-15,9%	25,4%	-16,2%

Table 6B: Value weighted portfolios

	SMB	HML	Mom factor	Turn factor
Annualized mean	-5,0%	-4,9%	13,1%	-10,6%
p-value	17,2%	18,9%	1,3%	1,1%

	SMB	HML	Mom factor	Turn factor
1997-2001	-5,9%	6,7%	18,1%	-13,5%
2001-2006	-3,2%	2,9%	23,2%	-6,4%
2006-2011	-5,9%	-7,4%	1,8%	-17,9%
2011-2016	-5,4%	-17,9%	11,5%	-4,5%

Table 6 gives an overview of the factors that are going to be investigated for the remainder of the thesis. For equally weighted portfolios, it turns out that SMB is a significant risk premium, while there is a negative risk premium for the turnover factor. The momentum factor has a p-value of 5,2% which makes it likely that it is also priced on the Norwegian stock market. The same is true for value weighted portfolios in regards to turnover and momentum, but not for SMB. In addition to the results from the entire test period, the table includes factor returns divided into four sub periods. From these table it is clear that the factors have high fluctuation from period to period which can make it more difficult to say anything definite about the risk factors. In the following section an in depth investigation of the sorted returns is conducted. Of special interest is to identify trends, return fluctuation over time and the deviation between equally weighted and value weighted portfolios.

Table 7: Correlation tables

Table 7A: Equally weighted portfolios

	Market return	SMB	HML	Mom factor
SMB	-0,50			
HML	-0,32	0,23		
Mom factor	-0,01	-0,31	-0,35	
Turn factor	-0,50	0,22	0,08	0,19

Table 7B: Value weighted portfolios

	Market return	SMB	HML	Mom factor
SMB	-0,66			
HML	-0,32	0,11		
Mom factor	-0,02	-0,03	-0,14	
Turn factor	-0,66	0,58	0,25	0,05

The correlation table is containing the calculated factors of each set of portfolios. The first point to notice is that all correlations are in the same direction unaffected by whether they are equally weighted, or value weighted. Furthermore, the correlations show how the factors are only proxies for different risk in the market. Not being able to capture truly unique systematic risk, the factors will be correlated with each other. This is because some of the factors is exposed to the same underlying factor.

SMB should by construction have a low correlation with HML, as they are double sorted portfolios. There is still some correlation left, but if they had not been double sorted and calculated like the other factors, the correlation would have been roughly twice as high as in table 7. The double sorts are only done for SMB and HML because the hypothesis is that they are exposed to much of the same relative distress risk. Although the correlation matrix show that other factors have a high correlation they are still not part of the dependent sorting. This is because with a small number of stocks, including more factors could result in very few stocks for some portfolios used to construct the factors. This would be troublesome because of idiosyncratic risk and the diversification effect.

Table 8: Return on portfolios sorted on market value

Panel 1A show ten portfolios daily and annualized returns sorted on each company's market value. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and Sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1st of July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 has exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Anualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,15%	45%	57%	0,78	10	17	21
portfolio 2	0,07%	18%	30%	0,61	13	17	21
Portfolio 3	0,05%	13%	23%	0,56	12	17	21
Portfolio 4	0,04%	11%	23%	0,46	13	17	21
Portfolio 5	0,02%	5%	21%	0,23	13	17	21
Portfolio 6	0,04%	10%	22%	0,43	12	17	21
Portfolio 7	0,04%	10%	23%	0,45	13	17	21
Portfolio 8	0,04%	10%	22%	0,45	12	17	21
Portfolio 9	0,03%	7%	23%	0,32	13	17	21
Portfolio 10	0,04%	11%	29%	0,37	13	18	21

	Anualized returns			
B	1996-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	39%	93%	3%	60%
portfolio 2	14%	54%	9%	2%
Portfolio 3	6%	30%	4%	13%
Portfolio 4	17%	25%	7%	-4%
Portfolio 5	10%	18%	-4%	-3%
Portfolio 6	19%	28%	-12%	7%
Portfolio 7	12%	31%	3%	-3%
Portfolio 8	13%	26%	1%	1%
Portfolio 9	0%	16%	5%	9%
Portfolio 10	13%	14%	7%	9%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Anualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,05%	13%	34%	0,40	10	17	21
portfolio 2	0,02%	5%	29%	0,17	13	17	21
Portfolio 3	0,02%	4%	21%	0,19	12	17	21
Portfolio 4	0,02%	4%	24%	0,18	13	17	21
Portfolio 5	0,01%	2%	20%	0,09	13	17	21
Portfolio 6	0,02%	6%	21%	0,29	12	17	21
Portfolio 7	0,04%	11%	22%	0,51	13	17	21
Portfolio 8	0,04%	9%	23%	0,40	12	17	21
Portfolio 9	0,02%	6%	22%	0,26	13	17	21
Portfolio 10	0,04%	9%	27%	0,36	13	18	21

	Anualized returns			
B	1996-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	15%	21%	-10%	32%
portfolio 2	7%	38%	-10%	-8%
Portfolio 3	-5%	19%	-5%	9%
Portfolio 4	16%	9%	0%	-6%
Portfolio 5	10%	7%	-4%	-5%
Portfolio 6	16%	18%	-13%	5%
Portfolio 7	11%	29%	4%	3%
Portfolio 8	14%	22%	-3%	6%
Portfolio 9	-2%	16%	1%	8%
Portfolio 10	7%	17%	5%	8%

Table 8 shows the daily return of 10 portfolios sorted on market value. The highest returns for equally weighted portfolios are found in the two portfolios containing the stocks with the lowest market value This indicates that there is a positive SMB factor, as suggested by the earlier empirical studies. This is further supported by the descending trend in the Sharp ratio. This is mainly due to the standard deviation being more stable across portfolios compared to the average return, resulting in highly correlated Sharp ratio with returns. Moreover, the standard deviations are at similar levels for both types of weighting and the average returns are higher for equally weighted portfolios. This is causing an on average higher Sharp ratio for the equally weighted portfolios compared to the value weighted ones. Such a trend is identified on all types of sorts and is attributed to the anomaly that very small firms have extremely high returns. A comprehensive explanation of this phenomenon will be presented in the summary.

From the value weighted panel 2, there is no clear trend in the returns of the different size portfolios. If anything, it could be argued that by dropping the first portfolio, it would be a slight upwards trend, in opposition to what earlier studies and the equally weighted results indicate.

The annualized returns presented for four sub-periods show sporadic signs of trends. The first and second period is similar to the overall period for equally weighted portfolios. For the last period portfolio 1 have an extremely high return compared to the others, but beside that portfolio it is not possible to detect any trend. For the value weighted portfolios, it is more difficult identifying any trends. For periods 1 and 4 there seem to be no size effect, although in the last period the smallest firms have experienced extremely high returns compared to the remainder of the assets. For the second period it can be argued that there is a small declining trend, even though this trend is small and highly varying.

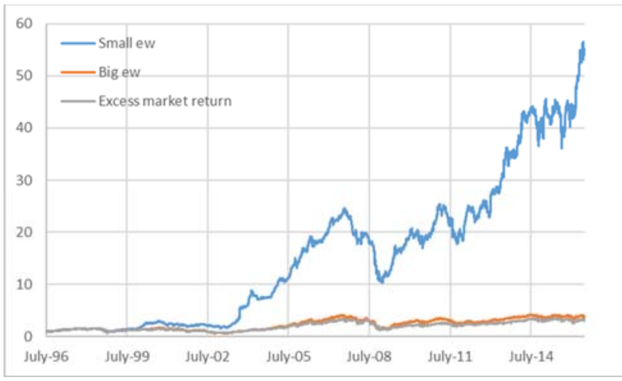
In period three where the recent financial crisis is situated, the returns are overall low. Here is it hard to argue for a trend in the equally weighted portfolios, but there can be a positive trend in panel 2B, although this is not convincing results.

Some cherry picking would be needed to claim obvious signs of a positive small minus big factor, as the value weighted portfolios show very few signs of this. In fact, it can be argued that the value weighted portfolios actually have a slight inclining trend. However, for equally weighted portfolios there are some signs of a SMB effect, but this is largely due to the very high returns of the smallest firms.

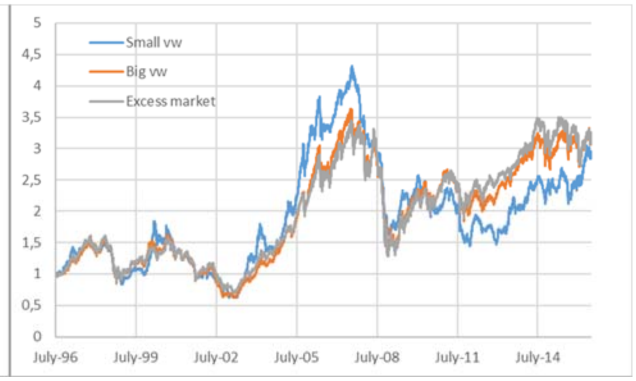
Graph 6: Return index created for portfolios sorted on market value

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 6A: Equally weighted portfolios



Graph 6B: Value weighted portfolios



Like seen in the table data, equally weighted small portfolios can create a positive return compared to the market. This is not the case for value weighted portfolios, as the three indices follow each other closely, where at some point all of them would give the highest return up to that time.

Table 10: Return on portfolios sorted on book-to-market ratio

Panel 1A show ten portfolios daily and annualized returns sorted on each company's B/M ratio. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and Sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1st of July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 has exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean				Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,08%	22%	38%	0,57	9	17	22
portfolio 2	0,03%	8%	28%	0,29	10	17	21
Portfolio 3	0,06%	15%	25%	0,60	10	17	21
Portfolio 4	0,05%	14%	23%	0,62	9	17	20
Portfolio 5	0,05%	14%	21%	0,65	10	17	21
Portfolio 6	0,04%	10%	20%	0,49	10	17	21
Portfolio 7	0,05%	12%	20%	0,60	9	17	20
Portfolio 8	0,07%	18%	21%	0,87	10	17	21
Portfolio 9	0,03%	8%	22%	0,36	10	17	21
Portfolio 10	0,07%	19%	48%	0,39	10	17	21

	Anualized returns			
B	1996-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	27%	24%	14%	22%
portfolio 2	16%	17%	-3%	5%
Portfolio 3	19%	29%	1%	15%
Portfolio 4	3%	30%	3%	22%
Portfolio 5	6%	30%	-1%	22%
Portfolio 6	11%	29%	-2%	3%
Portfolio 7	4%	25%	8%	13%
Portfolio 8	21%	44%	10%	2%
Portfolio 9	16%	36%	-12%	-3%
Portfolio 10	20%	67%	3%	-3%

Panel 2: Value Weighted returns

A	Mean		Annualized		Number of stocks		
	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,02%	6%	38%	0,17	9	17	22
portfolio 2	0,01%	3%	32%	0,10	10	17	21
Portfolio 3	0,04%	10%	30%	0,33	10	17	21
Portfolio 4	0,04%	11%	29%	0,39	9	17	20
Portfolio 5	0,04%	10%	24%	0,43	10	17	21
Portfolio 6	0,05%	14%	31%	0,43	10	17	21
Portfolio 7	0,04%	10%	26%	0,39	9	17	20
Portfolio 8	0,04%	10%	26%	0,37	10	17	21
Portfolio 9	0,00%	1%	23%	0,03	10	17	21
Portfolio 10	-0,01%	-2%	25%	-0,07	10	17	21

B	Anualized returns			
	1996-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	1%	13%	22%	-8%
portfolio 2	10%	2%	-9%	12%
Portfolio 3	5%	24%	3%	10%
Portfolio 4	5%	19%	-1%	25%
Portfolio 5	18%	11%	4%	8%
Portfolio 6	15%	25%	9%	5%
Portfolio 7	5%	16%	2%	18%
Portfolio 8	19%	22%	3%	-2%
Portfolio 9	11%	13%	-7%	-12%
Portfolio 10	9%	26%	-12%	-24%

Table 10 show the daily return of 10 portfolios created on book-to-market ratios. The highest values of the equally weighted portfolios are portfolio 1, and portfolio 8 and 10. This is not in line with previous studies, where the higher the book-to-market ratio, the higher the return should be. The value weighted portfolios are also troublesome as the highest return values appear in the middle portfolios.

Table 11: Return on portfolios sorted on book-to-market ratio pre financial crisis

The table show the average return, standard deviation and Sharp ratio for B/M sorted portfolios in the period July 1996 to July 2007. The results are annualized based on daily data and presented for both equally weighted and value weighted portfolios.

Panel 1: Equally weighted portfolios

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8	Portfolio 9	Portfolio 10
Mean	27%	17%	24%	17%	18%	21%	16%	32%	26%	41%
Std.dev	39%	30%	28%	23%	19%	20%	20%	23%	22%	63%
Sharp	0,70	0,56	0,86	0,76	0,95	1,07	0,83	1,42	1,17	0,65

Panel 2: Value weighted portfolios

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8	Portfolio 9	Portfolio 10
Mean	12%	6%	15%	12%	14%	22%	13%	21%	13%	20%
Std.dev	39%	29%	31%	27%	24%	29%	25%	25%	24%	26%
Sharp	0,31	0,21	0,50	0,45	0,58	0,75	0,53	0,85	0,56	0,75

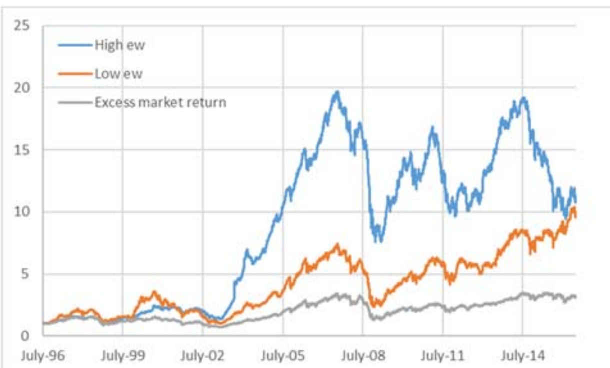
The overall results presented in table 10, which have no clear trend, can indicate that book-to-market is not a proxy for any underlying risks. However, by eliminating the period with the financial crisis and the drop in the oil price the results paint a completely different picture. Table

11 shows the period from 1996 to July 2007. In this test period there is a clear trend which is in line with the theory and the findings from Næs et al. (2009). The period from July 2007 have been affected by two major crises which have resulted in almost a reversal of the effect, although with great variance within the trend.

Graph 7: Return index created for portfolios sorted on book-to-market

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 7A: Equally weighted portfolios



Graph 7B: Value weighted portfolios

The returns of equally weighted portfolios of high and low book-to-market ratios, are in fact both above market return over time. The reason is because the return is highest for the portfolios in the top and bottom, and lower for the ones in the middle. This is of course in addition to the small sized assets with high return problem which often will make equally weighted returns higher than the market weighted index.

Market weighted portfolios show more expected results up to winter 2011. Before this point, the high book-to-market portfolios have higher returns than the low ones, and the market index is between the two. From 2011 however, both returns of the portfolios is lower than the market index and high B/M is even lower than low B/M towards the end. Notably, the high B/M portfolios experience a large downturn in this period while the low B/M portfolios approximately continue their relation to the market index. The possible reason can be hard times for oil related companies because of a stagnation and decline in the oil price. Sorting all stocks on book-to-market values in this period, show indeed that most companies in the highest range of book-to-market are directly related to the oil sector. Quickly declining stock prices for companies where the depreciation of assets often lags behind the market value will put an increasing number of oil related companies in the top portfolios.

High book-to-market portfolios experience very high returns when the market is rising, and take very large losses when the market is declining. This happens all the way up to July 2014, after which the market is relatively stable, but the high portfolios suffer negative returns.

Table 12: Return on portfolios sorted on one-year momentum

Panel 1A show ten portfolios daily and annualized returns sorted on each asset's return in the previous one-year period. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and Sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1st of July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 has exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,05%	15%	55%	0,27	11	15	19
portfolio 2	0,04%	10%	29%	0,36	12	16	20
Portfolio 3	0,03%	7%	24%	0,30	12	16	20
Portfolio 4	0,04%	11%	26%	0,41	12	16	19
Portfolio 5	0,03%	9%	20%	0,45	13	16	20
Portfolio 6	0,05%	15%	20%	0,74	12	16	20
Portfolio 7	0,05%	14%	18%	0,77	12	15	19
Portfolio 8	0,05%	13%	21%	0,61	12	16	20
Portfolio 9	0,05%	15%	23%	0,64	12	15	20
Portfolio 10	0,05%	12%	29%	0,42	13	16	20

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	21%	61%	-10%	1%
portfolio 2	14%	26%	1%	2%
Portfolio 3	6%	17%	1%	5%
Portfolio 4	3%	32%	7%	1%
Portfolio 5	11%	23%	-1%	5%
Portfolio 6	21%	30%	3%	8%
Portfolio 7	1%	24%	11%	17%
Portfolio 8	-3%	34%	6%	15%
Portfolio 9	2%	33%	7%	17%
Portfolio 10	3%	40%	-4%	13%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	-0,03%	-7%	38%	-0,19	11	15	19
portfolio 2	-0,02%	-5%	35%	-0,14	12	16	20
Portfolio 3	-0,03%	-7%	29%	-0,25	12	16	20
Portfolio 4	0,04%	10%	31%	0,33	12	16	19
Portfolio 5	0,04%	9%	28%	0,34	13	16	20
Portfolio 6	0,03%	9%	26%	0,35	12	16	20
Portfolio 7	0,04%	11%	24%	0,48	12	15	19
Portfolio 8	0,02%	5%	27%	0,17	12	16	20
Portfolio 9	0,05%	12%	32%	0,38	12	15	20
Portfolio 10	0,05%	14%	40%	0,34	13	16	20

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	6%	-2%	-17%	-12%
portfolio 2	4%	0%	0%	-20%
Portfolio 3	0%	-14%	8%	-19%
Portfolio 4	3%	22%	2%	13%
Portfolio 5	9%	15%	0%	14%
Portfolio 6	11%	19%	-2%	10%
Portfolio 7	4%	12%	19%	9%
Portfolio 8	-3%	22%	3%	-3%
Portfolio 9	1%	21%	4%	22%
Portfolio 10	13%	37%	2%	5%

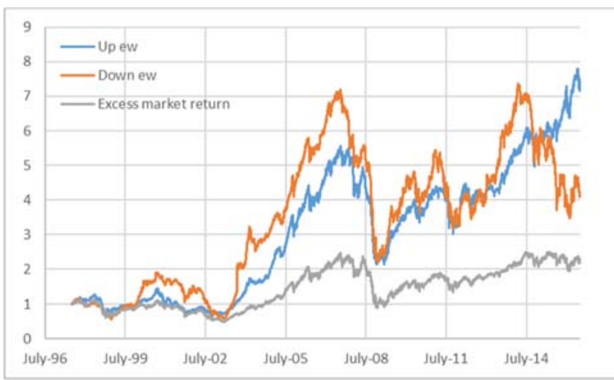
Table 12 show the daily return of 10 portfolios created on one-year momentum. There are no signs of trends in either direction when looking at equally weighted portfolios. These results are not aligned with the previous empirical studies, where increasing momentum equals higher return. However, the Sharp ratio has a slight upwards trend because of the high volatility for low momentum assets. This could either be a sign of low diversification effect or actually high risk for low momentum assets. When considering that the betas are generally lower for low momentum portfolios indicates that the high standard deviation is only because high correlation between asset, thus a low diversification effect.

Value weighted portfolios are more in line with previous studies. There is a clear trend upwards from negative returns in the low momentum portfolios, to high returns for the high momentum portfolios. For value weighted portfolios the standard deviation is more stable which also leads to an upwards trend for the Sharp ratio.

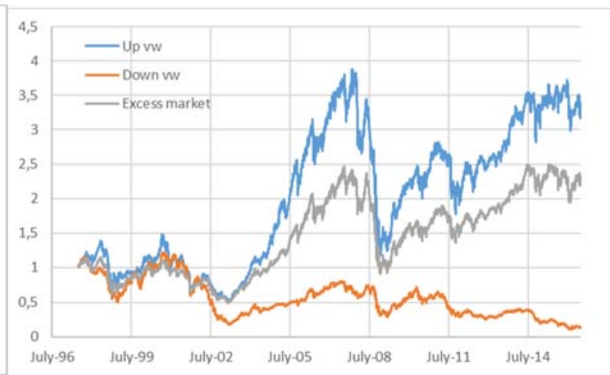
Graph 8: Return index created for portfolios sorted on one-year momentum

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 8A: Equally weighted portfolios



Graph 8B: Value weighted portfolios



Equally weighted portfolios have the considerable problem of having low momentum portfolios outperforming, both the market and high momentum portfolios over time. This happens all the way up to the fall of 2014. This essentially means that stocks who did bad last year, outperform the stocks who did good for the following year, completely in opposition to the empirics on the subject.

Graph 8B is much more in line with earlier studies, as high momentum stays above the market, and low momentum stays below. Further, the time period where "everything" is falling during the financial crisis, high momentum portfolios also decline rapidly, which is as expected. If this was not the case, it would suggest stocks with high momentum coming into a crisis, would not be affected by it, which has shown itself not to be the case empirically when comparing with data for the US (French, 2017). As the factor is relative to low momentum portfolios, it can still be positive in these crises and this is the case in the US market, but it is slightly negative in Norway.

Even though the empirical analysis of Carhart and others, suggest the one-year momentum is the clearest momentum measure, this thesis investigates other possibilities. Both shorter formation and rebalancing periods, as well as longer ones where tested. Six-month formation with six-month rebalancing, and the same for three months were tested. One-year formation with two- and three-year rebalancing were also tested, to investigate possible mean reversion.

Six-month formation with six-month rebalancing showed the clearest signs of momentum in the dataset and will be the alternative presented here. All other momentum tests, will be presented in the appendix 4.

Table 13: Return on portfolios sorted on six-month momentum

Panel 1A show ten portfolios daily and annualized returns sorted on each asset's return in the previous six-month period. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and Sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1st of July, and 1. January. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 has exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,05%	15%	53%	0,28	11	16	20
portfolio 2	0,03%	8%	26%	0,31	12	17	21
Portfolio 3	0,03%	7%	23%	0,30	12	17	20
Portfolio 4	0,04%	10%	21%	0,47	12	17	21
Portfolio 5	0,05%	12%	21%	0,58	12	17	20
Portfolio 6	0,03%	7%	19%	0,36	12	17	21
Portfolio 7	0,06%	15%	20%	0,74	12	16	20
Portfolio 8	0,05%	12%	20%	0,62	12	17	21
Portfolio 9	0,08%	23%	25%	0,90	12	17	20
Portfolio 10	0,09%	27%	32%	0,84	12	17	21

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	20%	45%	10%	-6%
portfolio 2	16%	19%	7%	-5%
Portfolio 3	13%	12%	7%	-3%
Portfolio 4	21%	25%	2%	-3%
Portfolio 5	6%	21%	12%	10%
Portfolio 6	14%	18%	-1%	-1%
Portfolio 7	11%	27%	9%	13%
Portfolio 8	3%	28%	5%	14%
Portfolio 9	20%	42%	14%	17%
Portfolio 10	39%	51%	1%	23%

Panel 2: Value weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	-0,02%	-5%	38%	-0,13	11	16	20
portfolio 2	0,00%	1%	36%	0,03	12	17	21
Portfolio 3	0,02%	4%	28%	0,15	12	17	20
Portfolio 4	0,03%	9%	27%	0,33	12	17	21
Portfolio 5	0,03%	8%	29%	0,28	12	17	20
Portfolio 6	0,03%	8%	27%	0,29	12	17	21
Portfolio 7	0,04%	11%	28%	0,39	12	16	20
Portfolio 8	0,04%	11%	28%	0,40	12	17	21
Portfolio 9	0,03%	9%	30%	0,31	12	17	20
Portfolio 10	0,07%	19%	40%	0,49	12	17	21

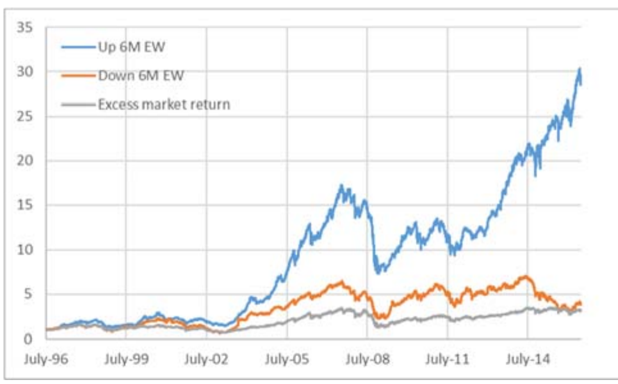
	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	8%	-16%	10%	-16%
portfolio 2	-1%	2%	5%	-3%
Portfolio 3	6%	12%	9%	-7%
Portfolio 4	19%	4%	8%	7%
Portfolio 5	5%	19%	0%	8%
Portfolio 6	15%	15%	-9%	12%
Portfolio 7	6%	14%	2%	22%
Portfolio 8	6%	21%	6%	12%
Portfolio 9	14%	12%	11%	0%
Portfolio 10	43%	41%	8%	-3%

Table 13 shows the daily return of 10 portfolios created on six-month momentum. The equally weighted portfolios show some signs of a trend, although this is largely due to the return of the portfolios with highest momentum. The return of the three top portfolios, is considerably higher than the bottom three laying the grounds for a large positive momentum factor. The same goes for value weighted portfolios, where the trend is more stable than for the one-year momentum. In the one-year momentum, the factor largely came from the fact that the three lowest portfolios had a considerably lower return than the others. The remaining seven however, showed low degree of a trend. Now the case is different. Except for two portfolios, the next portfolio returns are higher or equal to the previous, indicating a trend where the there is a closer to linear relationship between the past six-month return and the next six months.

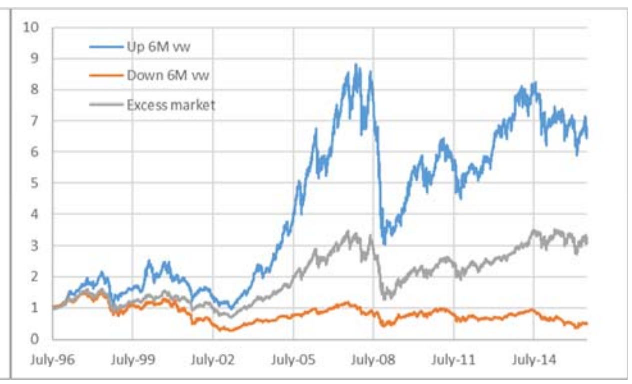
Graph 9: Return index created for portfolios sorted on six-month momentum

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 9A: Equally weighted portfolios



Graph 9b: Value weighted portfolios



The graph for equally weighted portfolios, is in line with what previous studies suggest as the high momentum portfolios outperform the low momentum ones. This trend is continuous throughout the period which is in contrast to the one-year momentum, where low momentum outperformed high momentum portfolios over long time spans.

The graph for value weighted portfolios generally holds the same shape as in the one-year momentum one. The absolutes return values are considerably higher than before for the high momentum portfolios, and the same is true for low momentum in large parts of the sample.

Table 14: Return on portfolios sorted on beta with 50-day cut-off

Panel 1A show ten portfolios daily and annualized returns sorted on beta. The beta is calculated using a one-year estimation period where only assets with at least 50 trading days are used. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and Sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1st of July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 has exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,07%	19%	25%	0,76	10	15	19
portfolio 2	0,06%	16%	21%	0,78	10	15	19
Portfolio 3	0,05%	12%	22%	0,55	11	15	19
Portfolio 4	0,05%	15%	22%	0,67	12	15	20
Portfolio 5	0,04%	11%	25%	0,44	11	16	19
Portfolio 6	0,04%	10%	25%	0,40	12	15	19
Portfolio 7	0,03%	7%	25%	0,28	12	15	20
Portfolio 8	0,03%	7%	30%	0,24	12	15	19
Portfolio 9	0,04%	9%	33%	0,28	11	16	19
Portfolio 10	0,06%	15%	59%	0,25	11	16	20

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	8%	50%	8%	24%
portfolio 2	9%	33%	12%	22%
Portfolio 3	12%	33%	-1%	19%
Portfolio 4	13%	34%	9%	15%
Portfolio 5	9%	41%	9%	0%
Portfolio 6	27%	25%	0%	5%
Portfolio 7	13%	27%	-2%	4%
Portfolio 8	5%	27%	0%	9%
Portfolio 9	8%	41%	3%	-1%
Portfolio 10	12%	73%	6%	-7%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,04%	11%	21%	0,53	10	15	19
portfolio 2	0,03%	7%	19%	0,36	10	15	19
Portfolio 3	0,03%	8%	19%	0,40	11	15	19
Portfolio 4	0,04%	10%	22%	0,47	12	15	20
Portfolio 5	0,02%	5%	22%	0,22	11	16	19
Portfolio 6	0,02%	4%	27%	0,16	12	15	19
Portfolio 7	0,04%	10%	30%	0,34	12	15	20
Portfolio 8	0,03%	8%	31%	0,26	12	15	19
Portfolio 9	0,03%	8%	37%	0,21	11	16	19
Portfolio 10	0,01%	4%	41%	0,09	11	16	20

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	2%	37%	4%	12%
portfolio 2	4%	21%	-4%	18%
Portfolio 3	9%	31%	-7%	12%
Portfolio 4	8%	26%	3%	16%
Portfolio 5	7%	19%	-3%	8%
Portfolio 6	14%	6%	-4%	16%
Portfolio 7	19%	17%	12%	7%
Portfolio 8	8%	17%	7%	11%
Portfolio 9	8%	32%	1%	3%
Portfolio 10	-14%	31%	13%	-3%

Table 14 shows the daily returns for 10 portfolios sorted on beta with 50 trading day cutoff. Equally weighted there is a descending trend in return as the betas in the portfolios gets higher. This is not the case for value weighted portfolios, where there is no apparent trend even though the largest and lowest returns are in the top and bottom portfolio respectively. The Sharpe ratio follows the same patterns as earlier, being higher for equally weighted portfolios mostly because of higher returns. It also shows a descending trend because of increasing volatility. The volatility is closely correlated with beta which indicates a declining trend for risk adjusted returns.

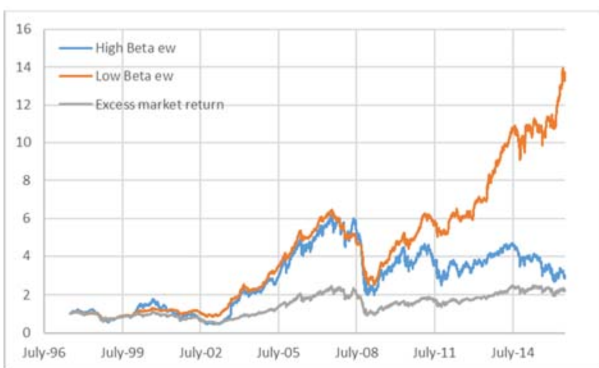
Over time all portfolios vary significantly, the overall trends, or lack of, stay similar half of the periods for both weights. Both weights show a clear negative trend in the final period, and some slight sings of a positive trend in the first period. Finally, the second period for value weighted is trend free.

A point with the beta sorting is the number of stocks in each portfolio. When choosing to use 50 trading days as cutoff, part of the argument was the precision of the beta estimates mentioned in an earlier section. Another part is that the number of stocks in each portfolio is always within two, and mostly only one, apart from a beta using 20 days as cutoff. This leaves no real reason for using 20 cut off days, because of worries regarding a large data base.

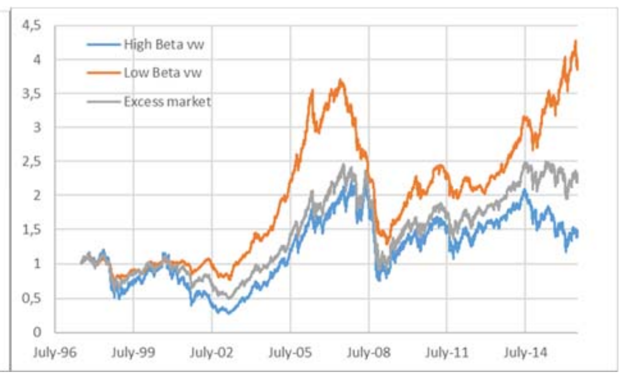
Graph 10: Return index created for portfolios sorted on beta with 50-day cutoff

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 10A: Equally weighted portfolios



Graph 10B: Value weighted portfolios



The graph with equally weighted portfolios show a familiar problem, where both high and low sorting values are above the market. When value weighting high beta stays just below the market, and low beta stays well above. The difference accelerating in the last period from July 2014.

Table 15: Return on portfolios sorted on turnover

Panel 1A show ten portfolios daily and annualized returns sorted on trading volume measured as the number of stocks traded divided by the number of outstanding stocks. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and Sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1st of July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 has exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	-0,01%	-3%	22%	-0,16	11	16	19
portfolio 2	0,00%	1%	22%	0,05	13	16	20
Portfolio 3	0,05%	12%	22%	0,55	12	16	20
Portfolio 4	0,05%	14%	22%	0,61	13	16	19
Portfolio 5	0,05%	13%	22%	0,57	12	16	20
Portfolio 6	0,06%	17%	24%	0,71	12	16	20
Portfolio 7	0,06%	16%	28%	0,58	12	16	19
Portfolio 8	0,04%	12%	25%	0,47	12	15	20
Portfolio 9	0,05%	15%	30%	0,49	12	15	20
Portfolio 10	0,10%	27%	51%	0,53	11	16	20

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-8%	31%	-15%	-15%
portfolio 2	4%	17%	-12%	-3%
Portfolio 3	5%	47%	-9%	10%
Portfolio 4	13%	38%	4%	2%
Portfolio 5	10%	19%	2%	19%
Portfolio 6	19%	35%	9%	8%
Portfolio 7	4%	28%	11%	21%
Portfolio 8	1%	28%	12%	6%
Portfolio 9	12%	19%	10%	17%
Portfolio 10	18%	57%	12%	24%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	-0,03%	-7%	21%	-0,35	11	16	19
portfolio 2	-0,03%	-6%	21%	-0,31	13	16	20
Portfolio 3	0,02%	6%	25%	0,22	12	16	20
Portfolio 4	0,02%	4%	23%	0,20	13	16	19
Portfolio 5	0,02%	5%	27%	0,19	12	16	20
Portfolio 6	0,04%	11%	28%	0,38	12	16	20
Portfolio 7	0,04%	11%	28%	0,39	12	16	19
Portfolio 8	0,02%	6%	30%	0,19	12	15	20
Portfolio 9	0,04%	12%	32%	0,37	12	15	20
Portfolio 10	0,03%	8%	33%	0,26	11	16	20

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-16%	7%	-15%	-5%
portfolio 2	-4%	-4%	-10%	-7%
Portfolio 3	2%	25%	-7%	4%
Portfolio 4	22%	5%	-5%	1%
Portfolio 5	5%	4%	-4%	17%
Portfolio 6	1%	23%	8%	9%
Portfolio 7	-7%	22%	1%	26%
Portfolio 8	13%	16%	3%	-7%
Portfolio 9	8%	10%	19%	9%
Portfolio 10	5%	22%	3%	4%

Table 15 shows the daily return for 10 portfolios sorted on turnover rate. Both panels show signs of a positive trend across the portfolios. The Sharpe ratio is lower in panel 2 than in panel 1, due to overall higher returns of equally weighted portfolios while the standard deviations between them stay similar.

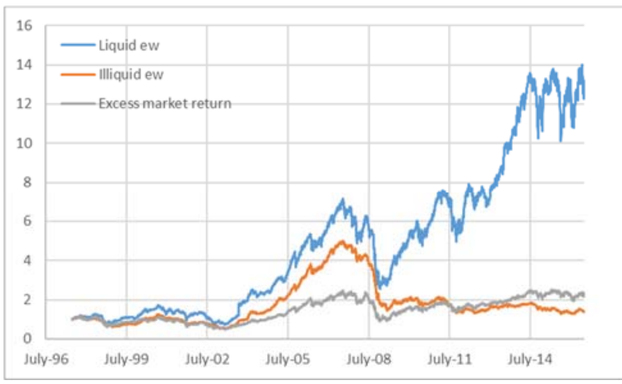
Panel 1B and 2B, show that compared to many of the other factors, variation over time is smaller. In most periods the trend is overall positive, albeit with some odd values disrupting a perfect incline. The second period in equally weighted and the last period in value weighted, is where it is hardest to make the case for increasing values overall.

The theory predicts low liquidity should be a measure of systematic risk and therefore in the end give a higher return, not the other way around like this table show. Although turnover is not the only measure of liquidity, the same logic should hold true for these portfolios. The fact that this is not the case in these portfolios, is peculiar.

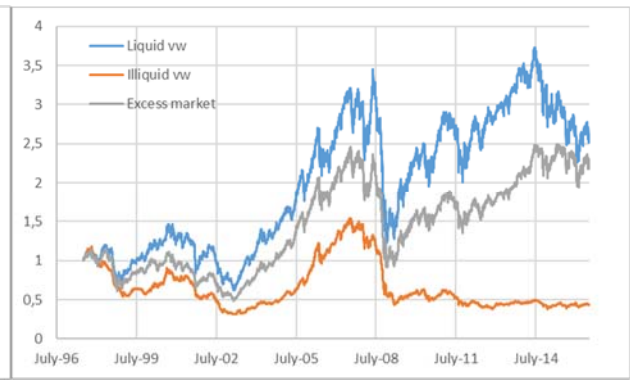
Graph 11: Return index created for portfolios sorted on turnover rate

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 11A: Equally weighted portfolios



Graph 11B: Value Weighted portfolios



The graphs show the same as the tables, where the portfolios with high turnover rates give higher returns than both the market and portfolios with low turnover. In graph 11A both liquid and illiquid portfolios stay above the market in the first periods, but around winter 2012 illiquid stocks fall below and the liquid stocks experience extremely high returns. This is in contrast to the value weighted liquid stocks which actually have a negative return from 2014 and onwards.

As mentioned in an earlier section, turnover ratio is related to a high volume return premium in addition to being a liquidity measure. However, the surprising results from above raise the question how well turnover ratio works as liquidity measure. Either do not the investors on the OSE need any compensation for illiquidity or the turnover ratio is a poor proxy for the underlying liquidity risk. Based on the results from the SMB factor, which previous research have found to be correlated with other liquidity measures, there is no demand for compensation for the liquidity risk. To further investigate if this is actually the reality, another portfolio sort is conducted on relative spread which should capture another dimension of liquidity for comparison.

Table 16: Return on portfolios sorted on relative spread

Panel 1A show ten portfolios daily and annualized return sorted based on the average relative spread for the previous year. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1. July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 have exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,05%	12%	24%	0,51	14	17	20
portfolio 2	0,04%	12%	22%	0,53	14	17	21
Portfolio 3	0,04%	11%	24%	0,45	14	17	21
Portfolio 4	0,07%	18%	28%	0,65	13	17	21
Portfolio 5	0,07%	19%	45%	0,41	14	17	21
Portfolio 6	0,04%	10%	24%	0,40	14	17	21
Portfolio 7	0,03%	9%	23%	0,37	14	17	21
Portfolio 8	0,03%	7%	22%	0,32	14	17	21
Portfolio 9	0,05%	12%	26%	0,47	12	17	21
Portfolio 10	0,04%	10%	23%	0,41	14	18	21

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	2%	44%	1%	5%
portfolio 2	1%	41%	-2%	9%
Portfolio 3	10%	22%	4%	8%
Portfolio 4	18%	31%	12%	13%
Portfolio 5	1%	60%	3%	15%
Portfolio 6	3%	32%	1%	5%
Portfolio 7	12%	13%	4%	6%
Portfolio 8	16%	23%	-4%	-2%
Portfolio 9	0%	32%	5%	11%
Portfolio 10	10%	29%	-5%	7%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,03%	7%	28%	0,27	14	17	20
portfolio 2	0,02%	5%	25%	0,20	14	17	21
Portfolio 3	0,04%	11%	33%	0,32	14	17	21
Portfolio 4	0,04%	11%	30%	0,37	13	17	21
Portfolio 5	0,02%	4%	28%	0,16	14	17	21
Portfolio 6	0,03%	7%	28%	0,23	14	17	21
Portfolio 7	0,02%	6%	27%	0,21	14	17	21
Portfolio 8	0,01%	3%	26%	0,12	14	17	21
Portfolio 9	0,04%	11%	31%	0,34	12	17	21
Portfolio 10	-0,02%	-4%	24%	-0,16	14	18	21

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-13%	39%	6%	0%
portfolio 2	-17%	25%	-1%	13%
Portfolio 3	5%	12%	11%	14%
Portfolio 4	8%	11%	11%	14%
Portfolio 5	-7%	21%	2%	0%
Portfolio 6	4%	24%	-5%	5%
Portfolio 7	5%	11%	2%	5%
Portfolio 8	-5%	26%	-7%	0%
Portfolio 9	-2%	34%	15%	-2%
Portfolio 10	-15%	-1%	-12%	13%

Table 16 shows the results from sorting the portfolios on the average relative spread from the previous year. where the relative spread is defined as the bid minus ask divided by midpoint between bid and ask. This is a cost measure of liquidity interpreted as the cost of illiquidity as the percentage of the trading price (Næs et al. 2008). The measure incorporates another dimension of liquidity than turnover ratio which can explain the correlation of only 0,03 and 0,08 for equally and value weighted factors. Moreover, 0,11 and 0,13 correlations between size and relative spread indicates that the already tested liquidity measures do not account for the cost dimension.

The low correlation between relative spread and the other liquidity measures helps to determine if there is a liquidity risk premium in the Norwegian stock market. Neither the two previous liquidity measures, nor the relative spread measure identified such a risk premium. For value weighted portfolios, it can be argued for a slight declining trend in returns as the spread increases. Equally weighted portfolios show no trend, with the highest returns for the middle portfolios. When testing the relative spread factor, the results are similar. With an estimated risk premium of -1,9% and -4,1% it could be argued that higher liquidity leads to higher return. However, with t-statistics of -0,59 and -1,13 this is rejected as a risk premium for liquid stocks.

7.2.1 Summary

There is a clear gap between expectations and the results of the sorting for many of the factors. Part of the reason can be because of the size effect briefly discussed in the CAPM tests earlier. From the size portfolios, it is clearly portfolio 1 with the lowest market value firms, which has the highest daily return. This stocks in this portfolio has an average return of about 45% per year, and have a median number of stocks in the portfolio is 17. As an experiment, it can be assumed that the stocks will spread randomly throughout portfolios sorted on other factors than size. If this is the case, all portfolios will get a higher equally weighted return, than value weighted, as these stocks are always the smallest of the portfolios they enter. This is in line with the results where almost all equally weighted portfolios have higher returns than value weighted ones. The only other possibility would be if the value weighted portfolios sorted on market value had a clear descending trend in returns from small to big stocks. Then all portfolio sorts would have the smallest firms within each portfolio with the highest return which would produce a similar effect. However, this is not the case as discussed above. The value weighted portfolios sorted on size have almost no trend, and if any, the trend is upwards where big firms have higher returns.

Another important aspect to mention is the lack of clear trends in many of the factor portfolios. If the trend across portfolios is not linear, this will have large effects of how the final factors calculated for testing behave. How many portfolios are included from the two extreme sides when calculating a factor like one-year momentum, is based on the hope of giving a large spread, as well as some robustness. Robustness here being averaging out small differences from a linear trend amongst the portfolios. However, when there is no linear trend, the number of portfolios to include can dramatically affect the results. Continuing with value weighted one-year momentum, the returns are negative for the first three portfolios, but largely positive for the fourth. This gives reason for some skepticism towards the calculation of PR1YR, as including four and not three portfolios on each side would give largely different results. This thesis will use the same factor calculations as previous studies, but the lack of linearity is good to keep in mind nonetheless, showing the choices would have been somewhat arbitrary if the data presented here would be the only basis.

7.3 Factor risk premium

In the previous section only some of the portfolio sorts showed any clear trends which can indicate a systematic risk factors. To further investigate these factors, the following section will contain statistical test to determine if any risk premiums are significant. These test are similar to the CAPM estimations, although the results should be interpreted slightly differently. The time series regression results will not be presented because the test is not to determine if the risk factor is the only systematic risk factor affecting asset returns. By only testing one factor, the expectation is that the model is not correctly specified and the intercept will therefore often be different from zero.

In the FM regression, the intercept is affected for the same reasons as for the time series regression. Thus, the only results that matter and will be presented is the risk premium calculated in the FM regression. The aim is to determine if any of the risk factors are priced on the Norwegian stock market. An issue to keep in mind when testing risk factors with no clear trend, is how the risk factor is constructed in terms of which portfolios to include. As discussed in the last section, this could affect the results when there is not a clear trend for the risk factor.

Table 17: Factor risk premium

The table show the risk premium and the corresponding t-statistics calculated from the FM regression. Equally weighted portfolios are regressed on equally weighted factors, while the value weighted portfolios are regressed on value weighted factors. The results only show the calculation for portfolios sorted on the same factor as tested.

	Equally weigted		Value weighted	
Factor	Yearly return	t-statistics	Yearly return	t-statistics
Size	12,8%	3,20	-3,6%	-0,90
B/M	0,5%	0,11	-3,4%	-0,60
Momentum	2,9%	0,58	14,3%	2,73
Turnover	-12,7%	-2,75	-11,7%	-2,78

In table 17 the risk premium and t-statistics from the FM regression is presented. The results are mostly consistent with the results presented in the section above. The turnover rate has negative risk premium, meaning that investors require compensation for holding stocks with high turnover rate. Additionally, the t-statistics reveal that these results are significant which means that the risk factor is priced. As mention above is this a direct contradiction of previous empirical findings in liquidity research.

The B/M and the value weighted size portfolios are as expected not significantly different from zero. This is in line with the findings of no trend for all the ten portfolios. However, equally weighted size is a priced risk factor with a t-statistic of 3,2. This is due to the high returns of the smallest sized assets in portfolio 1. The big difference in risk premium for size, depending on how the returns are weighted, makes it difficult to conclude if there is a size premium in the Norwegian stock market. Nevertheless, it is clear that the smallest sized firms in portfolios 1 have on average performed extremely well in the last 20 years.

The momentum factor is the only risk factor that does not have the same result as expected. For value weighted momentum, the risk premium is large and significant which is in line with expectation. However, it is surprising that there is no significant factor premium when the portfolios and factor are equally weighted. The portfolios show an upwards trend in return and the factor is positive with an average yearly return of 9,61%. The most likely reason for the results is that portfolio 1 have a big effect both on the momentum factor and the risk premium calculation. When the momentum factor is calculated using the top three portfolios minus the bottom three, the factor loading spread between portfolio 2 and 10 is quite small. Furthermore, the negative factor loading is huge for portfolio 1 which is strange considering the return is 15% annually. This outlier does not follow the momentum trend, but is still having a high negative factor loading. The most viable reason for this high return is that some of the smallest firms with high return have ended up in this portfolio. This have had a large impact on the return considering the value weighted portfolio have a negative return of -5%.

Table 18: Factor exposure momentum factor

The table shows the ten portfolio's, factor loading for portfolios sorted on momentum. With 1 is the factor loading with portfolio 1 as part of the momentum factor. Without 1 is factor loadings when the momentum factor is calculated using the average return of the top three portfolios minus the average return of only portfolio 2 and 3. The second table shows the risk premium and the corresponding t-statistic when portfolio 1 is and is not used in the momentum factor calculation.

Factor loadings

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8	Portfolio 9	Portfolio 10
With 1	-1,582	-0,452	-0,342	-0,095	-0,064	-0,015	-0,004	0,121	0,195	0,308
Without 1	-0,118	-0,707	-0,541	-0,060	-0,003	0,033	0,063	0,264	0,345	0,519

	Risk premium	T-stats
With 1	2,9%	0,58
Without 1	12,3%	3,10

To analyze this phenomenon further, a new calculation is presented where the momentum factor is calculated without portfolio 1. Meaning the momentum factor is the average return of the top three portfolios minus the average of portfolio 2 and 3. Table 18 shows how the factor loading spread is larger and more intuitively correct when portfolio 1 is excluded. In addition, the risk premium is significant with an annual return on 12,3% and a t-statistic of 3,1. This is more in line with what is expected when only looking at the trend from the last section.

If the improved results from the FM regression by excluding portfolio 1 is proving that there is a momentum effect is questionable. By comparing market weighted and equally weighted momentum portfolios it is clear that there are some very small stocks in portfolio 1 that have a high return. This is because when portfolio 1 is value weighted the average return is negative. Therefore, the assets with high market weights must have low returns and the small stocks with low weights have high returns. If this is just by chance or investors demanding a risk premium for small stocks with low momentum is difficult to answer. A more thorough analysis must be conducted to make such a conclusion, but that is outside the scope of this master thesis.

7.4 Multifactor models

After testing the CAPM and different anomalies related to the model, the results are ambiguous. The CAPM model do a poor job explaining asset returns for equally weighted portfolios, but could not be rejected based on the GRS test for all but one of the value weighted portfolios. In this section, the objective is to create a multifactor model which can better explain all asset returns observed on the Norwegian stock market. Drawing on the insights from the previous section, only value weighted factors and portfolio sorts will be used in the remainder of this thesis. This is because of the small firms with extremely high returns have a large effect on the equally weighted portfolios.

Based on large amount of empirical research the FF three factor model and the Carhart four factor model is first presented. Building on these results and the findings in this thesis, other multifactor models expected to explain the returns well are constructed. For practical purposes only two additional models besides the FF and Carhart model is presented. These are the models that can best explain results of our empirical investigation.

All the multifactor models are tested against portfolios sorted on all factors. This is to easily compare the multifactor models with the CAPM and each other. It will also make it possible to identify if the model has problems explaining a specific type of risk constructed in the sorted portfolios. Furthermore, only the GRS test and an average absolute intercept is presented from the time series regression. For the FM regression, the risk premiums and the intercepts are presented. This is to reduce the amount of data presented for each test making the results more comprehensible to the reader. The average absolute intercept is added to better differentiate the multifactor models. By comparing both the absolute intercept and GRS test between different models, it is easier to get an understanding of how well they fit and their variance.

Before presenting the results there are a few important point that must be made. All p-values from the GRS test are above a 5% significance level. This is not that strange considering the CAPM only had one significant p-value. As discussed before, the high p-vales could be because of the low spread and small sample size in the Norwegian stock market. For that reason, the absolute intercept and GRS test in combination must be used as a guide for the ability of the model to explain asset returns.

The second problem with multifactor models is multicollinearity. The correlation between factors can have effects on the multifactor model which can seem strange when keeping in mind the risk premiums found when testing factors in isolation. The regressions will often have problems determining which of the independent variables are affecting the dependent variable if they are highly correlated. This will result in varying results in the risk premiums when testing on different portfolio sorts. It will also increase the standard errors which makes the precision of the risk premium low (Brooks, 2008; p. 172). The final problem is that some portfolio sorts give very low factor loading spreads for factors in the multifactor model. The result is often a risk premium which is way too high compared to what was found when the factors were tested in isolation. The variance of course also increases because of the low exposure which leads to much lower precision on the factor premium estimates. This problem is most prevalent for the momentum factor where the factor loading is often close to zero for all portfolios. However, the problem can also occur for the other factors depending on the sorts.

The problems will in combination result in risk premiums and intercepts from in the FM regression which often are large, but at the same time not significant. It is therefore important to investigate both the significance level for intercepts and risk premiums combined with the variation within the model when testing different portfolio sorts. Using these results and the time series regression results, a decent picture of how good the model is should emerge, even though the tests are not significant.

Table 19: Estimation of the FF three factor model

The table shows the estimation of the FF three factor model. The sorted portfolios and factors are value weighted and rebalanced each year. The FM regression statistics show annualized return for the intercept and risk premiums, in addition to the corresponding t-statistics. The time series regression shows the absolute intercept for the model and the GRS test's p-value.

	FM regression								Time series intercept	
Portfolio sorts	Intercept	t-stat	Beta	t-stat	SMB	t-stat	HML	t-stat	$\lvert\alpha\rvert$	GRS p-value
Beta	11,3%	0,78	-3,7%	-0,27	-4,1%	-0,18	1,9%	0,05	0,00016	25,7%
Size	21,8%	1,73	-13,0%	-1,05	-5,4%	-1,30	9,5%	0,52	0,00010	42,0%
BM	12,0%	0,75	-3,1%	-0,19	-27,7%	-2,24	-0,1%	-0,01	0,00016	25,9%
Momentum	11,2%	0,46	0,0%	0,00	-18,8%	-0,81	-34,7%	-2,48	0,00016	47,0%
Turnover	15,0%	0,77	-2,7%	-0,15	-29,6%	-1,28	-20,9%	-0,96	0,00014	22,8%

The estimation of the FF three factor model is presented in table 19. Since neither of the factors in this factor model was significant when tested in isolation, the model is only expected to be a slight improvement on the CAPM. When looking at the GRS statistic it is performing almost as expected. The model is not rejected when tested on momentum portfolios which is an improvement from the CAPM. This can indicate that SMB and HML could incorporate some of the same underlying risk factors the momentum factor is exposed to. However, the correlation between those factors are lower than expected for this to be the case. Further investigation show that SMB have a relatively high exposure to portfolio 1 and 10 compared to the other portfolios where the exposure is close to zero. These are the portfolios which have the extreme values and does not fit within the CAPM framework. This may be the reason for the high negative SMB premium and the improved GRS test when sorting on momentum.

Even though the model improved in the time series regression characteristics, the FM regression have produced high intercepts and highly varying risk premiums. The large changes in the risk premiums depending on which type of sorting the model is tested against is a bad sign. Factor loading close to zero for the SMB factor sorted on B/M and momentum, and for the HML factor sorted on momentum and turnover can be attributed some of the models extreme values. These lead to low precision in form of low t-statistics compared to the high return per unit of risk factor. Moreover, the intercepts in the FM regression is high and even higher on average than for the CAPM, although the variance in the model results in a generally lower t-statistic when testing for the intercepts probability of being zero. The high positive intercept for all portfolios indicates that there are risk factors relevant for the investor that are not captured by the model. This is of course not that surprising when considering the momentum and turnover effect documented in the previous sections.

Table 20: Estimation of the Carhart four factor model

The table shows the estimation of the Carhart four factor model. The sorted portfolios and factors are value weighted and rebalanced each year. The FM regression statistics show annualized return for the intercept and risk premiums, in addition to the corresponding t-statistics. The time series regression shows the absolute intercept for the model and the GRS test's p-value.

	FM regression										Time series intercept	
Portfolio sorts	Intercept	t-stat	Beta	t-stat	SMB	t-stat	HML	t-stat	Mom	t-stat	$\|\alpha\|$	GRS p-value
Beta	8,0%	0,54	0,4%	0,03	-3,1%	-0,14	5,7%	0,13	26,8%	0,61	0,00015	32,7%
Size	27,3%	1,87	-16,7%	-1,25	-5,1%	-1,22	0,9%	0,05	75,5%	1,15	0,00010	47,1%
BM	-16,1%	-0,82	33,8%	1,22	-29,2%	-2,39	13,0%	1,18	121,2%	1,82	0,00015	29,0%
Momentum	11,1%	0,45	-0,3%	-0,01	-16,6%	-0,60	-30,6%	-1,14	13,3%	2,47	0,00010	93,7%
Turnover	22,7%	1,04	-7,7%	-0,42	-38,3%	-1,56	-12,0%	-0,47	40,5%	1,22	0,00015	20,1%

The Carhart four factor model is presented to investigate if adding the momentum factor is the solution to create a better model. Table 20 shows that by adding momentum as a factor the intercepts came closer to zero and GRS test slightly improved. The biggest improvement is for the momentum sorted portfolios which now have a GRS p-value of 93,7%. This is a good indication that momentum is a risk factor in the Norwegian stock market and a momentum factor must be part of a model to capture this risk. For the remainder of the sorted portfolios the added momentum factor only slightly improves the GRS test. This is due to momentum having low correlations with the other factors and will not encapsulate other risk factors these are exposed to. Moreover, the momentum exposure when sorting on other factors it is surprisingly low. This indicates that momentum is an important risk factor, but investors are unlikely to have high exposure to this factor if they hold a large diversified portfolio.

The FM regression results have even higher variation than the FF model. This implies the model has a problem with multicollinearity and low factor loadings which in combination makes the results difficult to interpret. Especially the beta and HML factors are very inconsistent which makes the intercepts often far from zero. However, the variance in the model makes the average absolute t-statistics similar for the three and four factor model. This is an indication that the model is not much better and there's still risk in the Norwegian stock market the model has not incorporated.

The momentum factor is always very high for portfolios sorted on other factors than momentum. This is due to the low exposure which makes the values extreme and also results in very high variance. Even for the B/M sorted portfolios where the momentum premium is 121,2% is the t-statistic not significant. however, it is significant when the return is only 13,3% because the factor loading when sorting on momentum have a larger spread with a smooth inclining trend.

From the results of the three and four factor model, there is reason to believe that it is possible to create a better model with less variation in the risk premiums. The GRS tests are not significant, but this have been a problem throughout the thesis. In addition, there is good evidence that the turnover factor incorporates underlying risks investors demand compensation for. This have led to the testing of a different three factor model where both momentum and turnover are two of the three factor. It turns out that there are small differences regarding what factor is chosen as the last factor, but using market risk makes all FM regression intercepts insignificant. The small difference between HML, SMB and market risk indicates that all three factors are not important risk factors on the Norwegian stock market. This will be further investigated later.

Table 21: Estimation of a three factor model (Beta, Mom and turnover)

The table shows the estimation of a three factor model consisting of SMB, momentum and turnover. The sorted portfolios and factors are value weighted and rebalanced each year. The FM regression statistics show annualized return for the intercept and risk premiums, in addition to the corresponding t-statistics. The time series regression shows the absolute intercept for the model and the GRS test's p-value.

	FM regression								Time series intercept	
Portfolio sorts	Intercept	t-stat	Beta	t-stat	Mom	t-stat	Turnover	t-stat	$\lvert\alpha\rvert$	GRS p-value
Beta	16,4%	1,24	-7,3%	-0,53	39,1%	0,84	-14,6%	-0,55	0,00017	13,9%
Size	9,8%	0,84	-1,6%	-0,13	55,0%	0,84	-7,3%	-0,48	0,00013	33,3%
BM	16,7%	1,69	-8,2%	-0,77	11,6%	0,35	-24,1%	-1,75	0,00013	51,1%
Momentum	15,8%	0,83	-7,5%	-0,39	14,2%	2,62	1,6%	0,05	0,00010	91,0%
Turnover	7,3%	0,56	2,0%	0,14	50,3%	1,48	-11,7%	-2,81	0,00013	54,6%

Table 21 show the results from the estimation of a three factor model using beta, momentum and turnover. From the intercepts and GRS tests the model better explains portfolios sorted on turnover and B/M. An improvement in the model for portfolios sorted on turnover is as expected, but the interesting result stems from the increased p-value when sorted on B/M. This could be because of the correlation between HML and turnover which indicates that turnover have some exposure to the same underlying risk as the HML factor.

The model is better when looking at the FM regression as well. The variation in the factor premiums and intercept are lower when testing different portfolios. The risk premium is also positive for momentum and negative for turnover and market risk. This is as expected from the previous test which can indicate lower multicollinearity. The low variation is additionally a good sign that each factor actually are proxies for different risk factors.

The intercepts in the FM regression are all insignificant. Meaning the model cannot be rejected no matter what portfolio sorts is tested. However, all intercepts are positive which can be a sign that there are parts of the return not explained by the model. It is therefore risk factors outside the model that explain some of the return. Considering this is a reoccurring problem for all multifactor models, there is a good chance that there are risk factors besides the ones tested which investors needs compensation for.

The t-statistics for the market risk are very low for portfolio sorts. This can be an indication of the factor being redundant in the multifactor model. When considering the market risk have a correlation of -0,66 with the turnover factor, it is reasonable to assume a two factor model could equally well explain the asset returns. The last model tested in therefore a two factor model with momentum and turnover as the factors.

Table 22: Estimation of a two factor model (Momentum and turnover)

The table shows the estimation of a two factor model consisting of momentum and turnover. The sorted portfolios and factors are value weighted and rebalanced each year. The FM regression statistics show annualized return for the intercept and risk premiums, in addition to the corresponding t-statistics. The time series regression shows the absolute intercept for the model and the GRS test's p-value.

	FM regression						Time series intercept	
Portfolio sorts	Intercept	t-stat	Mom	t-stat	Turnover	t-stat	$\|\alpha\|$	GRS p-value
Beta	8,4%	2,74	29,9%	0,67	0,8%	0,11	0,00017	17,6%
Size	5,8%	1,11	56,4%	0,86	-1,2%	0,90	0,00011	46,4%
BM	4,0%	0,58	52,5%	1,52	-4,3%	-0,40	0,00014	68,2%
Momentum	14,6%	0,84	14,3%	2,63	10,2%	0,39	0,00009	96,8%
Turnover	-0,2%	-0,06	40,4%	1,40	-11,4%	-2,72	0,00013	64,4%

For the final test, a model with only momentum and turnover is presented in table 22. The results show GRS and time series intercepts which is similar to the three factor model when market risk was the third factor. This shows that the market risk had little impact in making the model better. The changes are so small that it can with high certainty be concluded that the market risk factor had no effect.

The FM regression show some changes from the three factor model. This is not surprising considering the correlation between market risk and turnover is -0.66. By removing the market risk factor, the high negative risk premium for the turnover factor becomes closer to zero. Moreover, the momentum sorts lead to a positive turnover risk premium which is not as expected. However, the t-statistics show that it is far from significant which can be attributed to a very small spread in the factor loading.

The intercept in the FM regression is similar, but the two factor model have an intercept significantly different form zero for beta sorted portfolios. This may suggest that market risk had some explanatory power which makes the model slightly better. Considering the lower variance and simplicity of a two factor model we conclude that the two models are equally good at explaining asset returns on the OSE.

8 Factor explanation

The thorough analysis above has led to results that are both similar and different to results presented in the empirical research section. The result section has made no attempt to explain why this is the case, but only determine the estimated factor risk premiums, the precision of these estimates, the factors development over time and which combinations best make up an asset pricing model for the OSE. This section will therefore attempt to explain these results in a theoretical context. Based on empirical investigations, theories and hypotheses the most reasonable explanations for the level and development of each factor is presented. For some factors, it will be conducted tests to further validate these theories. However, for other factors such tests are not possible or too comprehensive to be within the scope of this thesis. For these factors, the most validated and reliable explanation for the effect will then be presented by assuming the affect found in other markets will be similar in a Norwegian context.

8.1 Market risk

It has been found that the relationship between beta and return predicted by the CAPM does not hold empirically. Tests done in the 1970s by for instance Doulgas (1968), Black, Jensen and Scholes (1972), Miler and Scholes (1972), Blume and Friend (1973) and Fama and Macbeth (1973) presented results indicating the security market line was too flat. Further research into the issue have found instances where the market risk premium is negative, especially in the recent decades (Baker, Bradly and Wurgler, 2010; Karceski, 2002). These findings are similar to the results from this thesis where the risk premium is negative for beta sorted portfolios, although not significantly different from zero.

Numerous researchers have attempted to explain the flat or negative SML. Black (1972) first identify unlimited borrowing at a risk free rate as an unrealistic assumption. He found that the predictions of the CAPM was closer to empirical results with restricting borrowing. This was done by switching from a risk free asset to zero beta portfolio. Newer studies by Frazzini and Pedersen (2010) use Blacks insight to hypothesize a leverage aversion theory. The theory predicts that many investors are willing to increase the risk to get a higher expected return, but are not willing to use leverage to achieve their goal. Instead they tilt their portfolio towards high beta assets to achieve the higher returns. If the majority of investors follow the same investment strategy, the demand for high beta assets will increase and the demand for low beta assets will decrease. This will lead to the increased prices and lower expected returns for high beta assets compared to low beta assets.

Frazzini and Pedersen argues their case by presenting evidence that risk adjusted return is higher for low beta assets. This was found to be true for beta sorted stocks, but also between different asset classes like stocks, bonds, credits and commodities. To further investigate their claim, they tested a betting against beta (BAB) factor (Frazzini & Pedersen, 2014). Using a zero investment portfolio holding low beta stocks leveraged to a beta of 1, and short high beta stocks deleveraged to a beta of 1 a BAB factor was created. In both the U.S market and internationally across 20 developed equity markets this BAB factor was found to be significant. Although these findings do not necessarily indicate that the market risk premium should be zero or negative, it definitely proves that market premium slope is flatter than the CAPM predicts. This is in line with our findings which can indicate a high level of leverage risk aversion for Norwegian investors.

Another common argument for the flat market risk premium slope is a behavioral phenomenon and incentive problem in combination. Baker, Bradley and Wurgler (2011) found that stocks with low risk measured for both beta and volatility have a tendency to perform better than stocks with high risk. From a private investors perspective Baker et al. (2011) argue they are pushed towards risky investments like high beta stocks because of three behavioral biases; preference for lotteries, representativeness and overconfidence. The preference for lotteries bias predict that people are willing to invest if there is a possibility for a huge profit with only a small investment. This is the case even though the probability for making the huge profit is low enough for the expected return to be negative.

Representativeness further push investors towards risky investments. Easily observable risky investments that have experienced high return is often highlighted. Such exposure can lead investors to conclude that it is likely to happen for other risky investments. They therefore disregard all risky assets that have done poorly because these are not that widely reported. The last bias that pushes the price of high beta stocks up is overconfidence among investors. Miller (1977) found that investors buying stocks are more common than short selling, implying that overconfident optimistic investors have a greater impact on the price than overconfident pessimistic investors. Riskier stocks with a wider range of opinions will have more optimists among their shareholder and sell for a higher price, leading to lower future returns.

Baker et al. (2011) further argues that institutional investors do not have the right incentives to take advantage of this mispricing, but rather have the incentives to exacerbate it. This is due to the focus on benchmarking, maximizing the information ratio and at the same time avoid using leverage to achieve this objective. By focusing on a benchmark like the S&P500 they invest in assets that have a beta close to one and follows the index to reduce the tracking error, thus maximize the information ratio. Since private investors already are pushing the market towards high beta stocks, the institutional investors will continue this trend by investing similarly. Even though this keeps the risk adjusted return low, the focus is on high information ratio rather than on risk adjusted returns.

A last explanation argued by Karceski (2002) have some of the same characteristics, in regards to skewed incentives and behavioral biases. He argues that mutual fund investors chase returns across funds and thought time. Funds that have recently performed well will experience large inflows of funds. In addition, the chase of returns through time will lead to large inflows of funds into the mutual fund industry when it recently has experienced high returns. Thus, it is relatively more important to achieve high returns in a bull market than a bear market. When these effects are combined with the findings that high beta stocks tend to outperform low beta stocks in bull markets, incentives get skewed for mutual fund managers. Their objective turns into achieving high returns in bull markets no matter the level of risk or performance in bear markets.

Karceski finds good evidence for investors actually chasing returns across funds and through time. In addition, the theory implies an inverse relationship between risk premium and the size of the mutual fund industry. The evidence shows a flatter than expected market risk premium up until 1983, but from that time on, the market risk premium has been negative. In the same period the mutual fund industry has increased the ownership of shares on the US stock exchanges from about 30% to 60%. This further demonstrates that the theory is supported by evidence on the US market.

It is not easy to determine which reason that have caused the Norwegian stock market to have a slightly negative risk premium over the last 20 years. Most likely it is a combination of the reasons discussed above and maybe other dynamics that have caused this result. Leverage aversion and benchmarking is assumed to be prevalent in the Norwegian market, but testing the relationship between these phenomena and risk is outside the scope of the thesis. The mutual fund percentage has only been between 4%-8% in the estimation period which makes it difficult to test Karceski's theory. Furthermore, this thesis finds no decisive trend where high beta stocks outperform low beta stocks in bull markets making Karceski's theory less likely. In summary the best explanation for the negative risk premium is the leverage aversion and benchmark theories. However, as these are not tested it is not possible make a definite conclusion.

8.2 Size

Early on the questions regarding small company returns in comparison to large ones, were related to a positive premium. Most of the theories proposed was then concerning how the later defined SMB factor could be positive, as the evidence then was that small stocks outperformed large stocks. Fama & French were proponents of their factors showing relative distress in companies, although they argued book-to-market was a better exponent of this than size. Shumway (1996) however, argued size was a better factor for measuring the distress as he finds book-to-market only weakly correlated with default risk.

A meta study done by van Dijk (2011), explores how empirical results have changed since the size effect was first discovered. Studies in the period up to, and including Fama & French (1992), show a clear size premium on the US market (van Dijk, 2011). Van Dijk also reference how the size premium was significant in 17 out of 19 countries, in different time periods spanning from 1954-2000. Norway is not included in these studies. However, there is a possibility that size is indeed not a proxy for some systematic risk like these early studies would suggest. The early empirical research gave unquestionable evidence of a size factor, but after its discovery the evidence have faded and been questioned by a large group of researchers. Van Dijk reference how several studies like Eleswarapu and Reinganum (1993), Dichev (1998), Chan, Karceski & Lakonishok (2000), Horowitz, Longhran & Savin (2000), and Amihud (2002) declared the size effect "dead" after the early 1980s, when finding no evidence of it in their samples.

Dimson and Marsh (1999) investigates the relative underperformance of a small stock index to a large stock index in in the UK from 1989-1997. The authors were highly skeptical to earlier explanations of the size effect, as the explanations either only could explain a positive premium, or showed little explanatory power at all. As the size effect reversed in their sample, they wanted an explanation that could account for the effect. Concluding that most earlier explanations of the size effect to be flawed in some way. Moreover, the argument was made for that a correlation between size and sector might be the real underlying cause of the size effect. In the period of 1989-1997, the sectors with relatively higher number of small firms had underperformed in comparison to sectors with larger firms, which supported their theory.

Table 23: Sector return indices

	Energy	Materials	Industrials	Cons Discr	Cons Staples	Health Care	Financials	IT	Telecom	Utilities
1996	100	100	100	100	100	100	100	100	100	100
2001	175	211	162	174	238	124	289	132	193	90
2006	557	323	285	293	561	204	636	122	414	269
2011	596	452	211	313	516	234	696	166	555	294
2016	597	432	318	847	1769	391	1154	211	1105	453

Should SMB be a sector risk proxy, the sectors containing the smallest firms should consistently underperform relative to the other sectors in the data, as value weighted SMB is negative throughout the test period. From table 23 it is clear that the most consistent underperformers are Industrials, Materials, IT, Health Care and Utilities. On the OSE however, Health Care, Utilities and Materials sectors contain a low number of assets, in addition to some of these assets having a large market value. Industrials has numerous assets, but due to economies of scale many of them are very large making the argument that Industrials is a sector with a large proportion of small firms, wrong.

IT has a large number of firms with 42 in 2005, but decreases to 19 in the recent years. Since IT contains several small firms it could be used to argue a sector risk in the early periods, making SMB negative as the sector underperforms. However, as SMB is negative in every period, fewer IT firms over time should counteract their previous effect. Additionally, about a third of the IT firms which are currently listed, are above the median market value and will be defined as big when calculating SMB.

Currently Energy has the largest number of firms below the market value median, making this sector the largest contributor to the small portfolios in the SMB factor. This is not because of a natural tendency of these firms to be small, but rather the persistent fall in the sector. Such an effect highlights another problem with the sector theory. Sectors which experience large long lasting recessions, will automatically make out an increasingly higher proportion of the smallest firms. Such recessions can change the sector size relation which indicates that there is no stable relationship between sector and size over time.

A theoretical argumentation for firm's size being related to specific sectors, based on for example economies of scale, can complement the prediction, but the actual market values cannot be ignored. This is clear at the OSE, where if looking at recent years a large number of the smallest firms are in the Energy sector, and this sector has underperformed. Consequently, the sector risk argument suggested by Dimson and Marsh (1999) does not seem to hold at the OSE in the 1996-2016 period.

Comparing our results to more recent factor analyses, there is some ambiguity of the current health of the size effect. Although Fama & French (2015) still find SMB as a factor in the North American market, there is very little evidence of a size effect in Europe and Asia-Pacific in the period of 1990-2015 (Fama & French, 2015). Næs et al. (2009) finds that small companies outperform big ones in their data from the OSE in the period 1980-2006, although the effect is shrinking over time. This thesis finds that in the years since 2007, the effect has reversed, continuing the trend found in Næs et al. (2009). The data is showing no consistent evidence supporting a positive SMB factor when using value weighted portfolios. The effect is largely positive when equally weighted portfolios are used, but this effect is mainly due to the smallest portfolio. As the premium disappears when value weighting, the size effect is not a consistent relationship between return and size in general, but maybe only an effect of the absolute smallest firms relative to the rest. Hence, a positive SMB lacks conclusive evidence. This is still keeping in mind that as small stocks according to the model is riskier, they could underperform occasionally without it being a sign of a misspecified factor. But these periods should not be frequent or long lasting, like results from different sources show them to be.

It appears that in the Norwegian market at least, and according to Fama & French (2015) in the European market as well, the size effect is seemingly unrelated to any fundamental time-stable systematic risk, which could cause a premium on small stocks. Given that the time period in which the test is conducted is affecting the results significantly, makes any result questionable even within a given market. This makes the argument for a size factor to explain some underlying risk across markets, thin at best. Nonetheless, the Arbitrage Pricing Theory states that not all markets must be affected by the same factors. Further, factors should only be included in a model if they have some explaining power permeating all stocks in that market. From this, size can be perfectly in line with a model regarding North America, but left out when considering models in other markets.

Even though the APT requires the relationship between the factors and assets established economically (Zylar, 2014; 118), the pioneers seemed less concerned with this when proposing their factors. Even though Fama & French suggested the one size fits all relative distress explanation, researchers have caught on trying to explain the underlying causes ever since. The size effect appears to exist consistently in the US, but elsewhere in the past only. For any argument to hold, the underlying reason must explain why the SMB risk is present in the US, but not for several other markets.

8.3 Book-to-market

Fama & French (1992) state that the HML factor can capture the risk of relative distress studied by Chen and Chan (1991). Even though the relative distress might be more related to size like mentioned above, the possibility of distress to be captured by book-to-market will be discussed here.

Relative distress comes from marginal firms, which have several attributes. They have lost market value because of poor performance, they are inefficient producers, they are likely to have high financial leverage and cash flow problems (Chen and Chan, 1991). This makes them more sensitive to changes in the economy, and less likely to survive extreme economic conditions. Fama & French (1995) found High B/M to be correlated with sustained low return on book equity, being consistent with marginal firms as inefficient producers. A marginal firm, is a firm that is more sensitive to changes in the economy, and less likely to survive extreme economic conditions.

Sensitivity to changes in the economy need to be understood as a lack of adaptability. Chan and Chen (1991) exemplifies by relating marginal firms to a continual technological development in the economy. In this environment, efficient producers can prosper if the aggregate economy is growing slowly, while the inefficient marginal firms may not survive a low growth rate over time. The risk of marginal firms is in other words partly due to this inefficiency. Even though the firm might be able to endure in a slow growing environment for some time, extreme economic conditions will make the shortcomings of the marginal firms apparent, and they will be less likely to survive. Næs et al (2009) finds a positive HML factor in their study up to 2006, but this thesis finds that from the financial crisis' start in 2007 the HML factor has been increasingly negative.

If relative distress is a state variable like suggested by Fama & French (1996), then this helps separating HML from market risk. Investors with specialized human capital, do not want to invest in distressed firms as they want to hedge the risk for being laid off. Therefore, investors will demand a risk premium causing the distressed firms, high B/M, to have an above average return.

If the HML is indeed a proxy for systematic risk, then it will from time to time lead to substantial losses. Relying on the theory of marginal firms, this can happen in time of crisis. From Kenneth French website, where the factors calculated for the US market are updated frequently, comparable data can be downloaded (French, 2017). In the period from summer 2007 until January 2009, HML is negative for the US market as well, reaffirming the possibility of a risk factor related to marginal firms. The period starting in January 2009 and up till 2016, is positive for in the US, albeit much closer to zero than in the period from 1996 up until the summer of 2007. Conversely the HML factor on the OSE does not recover from the crisis and is negative the remaining years.

Table 24: Annualized returns for HML in different macroeconomic conditions

	1996-2007	2007-2009	2009-2011	2011-2016
High B/M	18%	-29%	4%	-13%
HML	2%	-6%	-12%	-18%

During the data analysis the overlap in the final period between high book-to-market and oil sector related companies was stated. In the final period the market value of these firms have been falling substantially due to consecutive years of a declining oil price. Being an industry with large capital assets, book-to-market values will be high until sufficient depreciations have taken place. This is assumed to be lagging behind the quick drop in market value, meaning that the B/M will remain high until the trend is reversed. The OSE being an exchange with a large number of firms in the Energy sector, the number of firms this rising B/M value is relevant for will be enough to have a significant negative effect on the factor.

The period in-between the financial crisis, and the oil crisis has no clear culprit explaining the negative HML factor. From table 24, it is obvious that the reason for a negative factor is that the low B/M firms perform very well. Although the reason for these results are not obvious, the short time period could lead to other effects than the risk-return argument of HML. Research by Guiso, Sapienza & Zingales (2013) find that investors risk aversion increases after financial crises which leads investors to shift their portfolios towards assets that are expend to be less risky. Such a shift in demand is likely to occur in a two-year period after the financial crisis, which would lead to increasing prices for low B/M stocks, thus high returns in the period. Treasury bills and bonds are usually the safe assets that experience increased demand in these periods (Coudert & Feingold, 2011), but it is possible that low B/M can serve a similar purpose.

The HML factor has been negative since the financial crisis, but the events that caused this effect is expected to lose their impact on the premium over time. Eventually, oil related firms should rise in value or have depreciated their assets enough to not be overrepresented in the high B/M portfolios. When this happens, it is possible the premium will return and therefore it is no reason for declaring the factor dead or reversed just yet.

8.4 Turnover

Turnover gave a surprising result; as higher turnover gave higher returns. Empirically, turnover ratio should be a measure, amongst many, of liquidity. Illiquid stocks have been documented to carry a risk premium and give a higher return than liquid stocks (Bodie et al. 2011; 309). The most likely explanation for the turnover results, is that it captures something other than the traditional liquidity risk. Additionally, this effect must overpower any liquidity risk contained by the proxy. A good candidate for explaining the results is the briefly mentioned high volume return premium. Not finding evidence of any other form of liquidity risk when testing relative spread and size, the turnover factor is also assumed not to have a liquidity effect. The high volume return premium is therefore considered to be the main underlying reason for the return trend. The following section will give a more complete explanation and analysis of the results, to corroborate the claim.

Gervais et al. (2001) find stocks which experience unusually high volume in the previous period, will have higher return than stocks with normal or unusually low volume in the same period. They find that stocks who experience this increased volume, receive a "high volume return premium" for at least 20 days, and possibly up to 100 trading days. This holds for all stock sizes (Gervais, 2001).

Gervais et al. (2001) sort stocks on volume shocks to find these effects. A volume shock is defined as a relatively high volume for the previous day, compared to the average volume of the stock in a previous period of 50 days. Stocks which experience a large increase in volume, compared to the average will then be sorted in the high portfolios. Those experiencing a low relative volume will be sorted in the low portfolios.

Both formation period and effect period is shorter than used in this thesis, but the arguments made by Gervais et al (2001), and further explored by Kaniel et al (2012) will be reviewed in this section for a possible explanation of the results. Gervais et al. (2001), further find that volume events over a week, lasts for longer than events for one single day. This could indicate that longer volume events will have effects on the average returns for a one-year period.

If volume shocks are to be the explanation of the turnover results, then a few relations between the two need to be present. Firstly, a volume shock in the last period before formation need to have a significant effect on the average turnover for the past year. Secondly, this effect need to be large enough to offset the general turnover level enough to change portfolio composition over time.

By doing a similar test to what Gervais et al. (2001) did, a correlation between a volume shock factor and the turnover factor used for this thesis can be calculated. Since the volume shock number is relative to its mean volume, an equivalent turnover number relative to its mean is used in this thesis for simplicity. Since the turnover factor used is a yearly measure, it makes sense to do the same to a turnover shock factor as well. Based on the results of Gervais et al. (2001), it is plausible that the effect can last even longer than 100 days if the formation period is longer than a week, although a shock lasting for a month might be stretching the term shock slightly.

To test the correlation between turnover ratio and turnover shocks, a new sorting is done. Here, the mean of the turnover for the last month before rebalancing, is compared to the average turnover for the last 12 months. Stocks with relatively high turnover in the last month will then be sorted into higher portfolios. Rebalancing is done yearly, so that each portfolio has a formation period of one month, June, and return data for the subsequent 12 months from July.

Having these portfolios, a factor similar to the turnover factor can be calculated. Taking the average of the top three portfolios and subtracting the average of the bottom three portfolios, a factor that according to the theory should be positive, is created. The correlation between the turnover shock factor, and the original turnover factor is -0,51. The correlation is negative, because the turnover factor is defined as low portfolios minus high portfolios. Although not perfectly correlated, it should be strong enough for the coming argument to have some merit, even though Gervais et al. (2001) and Kaniel et al. (2012), use a different measure.

The reason an increase in turnover will cause returns to increase comes from Merton's (1987) investor recognition hypothesis. The hypothesis states that as more analysts and traders becomes aware of the stock, it should increase in value due to reduction in estimation risk faced by traders and facilitates risk sharing among them.

Kaniel et al (2012) find evidence in support of the hypothesis stated by Merton (1987). They argue that markets with an initial low visibility among stocks, should experience a relatively higher magnitude of the "high volume return premium" compared to markets with high visibility. A reason for this higher magnitude, is that in markets where the number of potential investors to number of stocks is low, any given stock is less likely to be visible. In turn this increases the probability that a stock will need a visibility event to increase investors awareness. Therefore, the high volume return premium will be expected to increase (Kaniel et al, 2012).

Following the above line of though, the authors use the number of stocks on the exchange in a given country divided by potential investors, for which urban population is used as a proxy. They find that this measure has a significant explanatory power, in the expected direction. Their median ratio value is 22, with lows like China (1,5) and highs like Japan (93,7) on either side. They do not present results for all countries in their paper, but doing the same calculation, using the same database for Norway, results in a ratio of 45,0. It should therefore be expected to find a factor with relatively large effect on asset returns.

Further, the authors argue that a more educated urban population, should affect the accessibility to financial information and awareness of stocks, decreasing the visibility effect (Kaniel et al. 2012). Using ratio of students in secondary school, to the population in the same age range they should find a relative measure of education level. They do not however find the results statistically significant possibly because the proxy is too crude (Kaniel et al. 2012). The ratio in Norway for this proxy would be close to 1, as it is rare for youth not to attend school at this age. This should then have been an indicator of more informed investors overall, resulting in a lower effect of the volume premium. The fact that the authors do not find this to be a significant input, makes the high attendance of secondary school in Norway not contradictory to a large premium.

Kaniel et al. (2012), further investigates how market concentration affect the high volume return premium. The theory predicts that in markets with few very large companies, the premium should have a greater effect. This should be the case for the same reason as described above where stocks are more likely to need a volume event to become more visible. In their research, Kaniel et al. (2012) find the hypothesis to hold empirically. In a Norwegian context, where it was shown in the data description that the top 5 % of companies makes up roughly 60 % of the market, the effect is expected to be high.

The possible explanation that volume shocks is only a proxy for momentum is shown not to hold by Gervais et al (2001). They find that the return is not mainly generated by past winners with positive volume shocks, and past losers with negative shocks. This is in line with the results from this thesis, as the correlation between the turnover factor and momentum factor is only 0,05. Consequently, the turnover factor is clearly not a proxy for momentum.

Volume shocks being highly connected to announcements about earnings and dividend is another possible explanation for the premium. It could be expected that an announcement of high earnings, would make both price and volume rise. However, removing periods where such announcements happen, does not affect the premium (Gervais et al. 2001).

From the results it is feasible that turnover explains a large amount of the volume shock related visibility effect. High correlation between the turnover factor and a volume shock factor indicates that this is true. A relatively low number of urban population per stock and the OSE composition shows how this effect is likely to exist in Norway according to the hypothesis of Kaniel et al. (2012).

8.5 Momentum

This thesis finds consistently positive momentum effects across different formation periods and rebalancing intervals, and across time. This is in accordance with previous research, where a momentum effect typically is found up to a year from formation (Jegadeesh and Titnam, 1993; Rouwenhorst, 1998; Chen, Chou & Hsieh 2015). It is hard to argue against the effect, but explanations for why the effect occurs varies. As the results from this thesis coincide with all major research done earlier, it is unlikely to provide substantial new insights. Nevertheless, the most empirically validated explanations will be discussed.

Carhart (1997) makes no effort to explain the driving force behind his momentum factor, but other researchers try to answer this elusive question. Like mentioned in the theory section, the momentum effect being a behavioral phenomenon is widespread. DeBondt and Thaler (1985) along with Jegadeesh and Titman (1993) argue for an overreaction to information. The latter find that past winners have significantly higher stock return in the next 7 months surrounding their earnings statements compared to past losers, creating a positive momentum factor for up to two years (Jegadeesh and Titman, 1993). DeBondt and Thaler (1985) show that with longer formation periods, a negative momentum effect is found in a three- to five-year time span. The reason for this reversal they argue is overreaction in the formation period, and after 3 years the market realize the mispricing and the price starts falling. Finding a momentum factor for 3 months to two years, is therefore in accordance with this theory and it should be expected to be fully reversed and negative after three years.

Jegadeesh and Titman (1993) find reversal starts after 12 months, with negative abnormal returns from 12 to 31 months after formation. This is in agreement with a two-year factor tested on the OSE, presented in appendix 4. A two-year momentum is still positive, but smallest of the factors which were positive. There is some reversion 12 to 24 months after formation, just not enough to offset the first year's positive return. The actual contrarian effect in DeBondt and Thaler (1985), where a 3- to 5-year momentum is reversed in the next 3- to 5-year period, which could be similar in the Norwegian market. After three years the momentum effect is indeed negative, even though the formation period is shorter in the thesis.

The reasons for the overreactions stated by the momentum or contrarian pioneers can be several, and it is useful to see it in relation to underreaction. Some brief explanations are presented in "A Survey of Behavioral Finance" by Barberis and Thaler (2003; 1091f). These include

Barberis, Shleifer & Vishny (1998) and Daniel, Hirshleifer & Subrahmanyam (1998, 2001). The two differ in that the first is a model where an initial underreaction is corrected, before an overreaction happens. While the theory of Daniel et al is an overreaction followed by an even larger overreaction.

Barberis et al (1998) argue that conservatism makes the investor underreact to positive company news, not pushing the price up enough. As time goes by the investors realize this mistake and the price will steadily increase to its true level. Representativeness, where a small series of good news is mistaken for definite signs that the firm will continue in this fashion forever, will cause the investors to price the firm too high, and the price will continue rising from its true level. Eventually, as less good news than expected is presented by the firm, the price should fall again, which is what causes reversion.

Daniel et al (1998, 2001) argue the momentum effect is due to biases in private over public information. Investors doing some work in estimating for example the value of future cash flows, will be overconfident in this information over readily available public information. If the private information is positive the investors will overvalue the stock pushing the price upwards. Public information will slowly decrease the belief in the private calculations leading to long term reversals. Should this be the reasoning behind momentum, the investors must react asymmetrically to good and bad future public information. This asymmetry is called the self-attribution phenomenon and need to be prevalent in the investors to achieve the momentum effect. The phenomenon results in information that agrees with preexisting thoughts is overvalued. Good news will therefore make the investor more certain, than bad news will make him uncertain. This lead the investor to drive up the price more from good news, than down from bad news.

Determining which behavioral explanation is best fitting for the OSE, is no easy task and impossible to state with certainty without considerable testing. The two theories presented are some of many trying to give good explanations for why there is a momentum effect at all. Presenting the two here, was to show that Jegadeesh and Titman (1993) and DeBondt and Thaler (1985) had valid points when suggesting that overreaction was the cause for both momentum and the reversal.

9 Conclusion

In this master thesis an empirically investigation the OSE have been conducted to test the CAPM and anomalies related to the model. We have updated the findings after a period of two major crises affecting the Norwegian stock market. In addition, this thesis has had a greater focus on explaining the theoretical reasoning behind the results found. To our knowledge, this has never been done in the same magnitude for the Norwegian stock market before.

First the CAPM was tested on all portfolios sorted on previous empirically found factors. This showed that the model was rejected for all equally weighted portfolios. The main reason for the low ability to explain equally weighted returns was due to very small firms with high returns. This made all portfolios have high returns which resulted in positive intercepts for almost all portfolios within each sorting. For value weighted portfolios the CAPM had only a significant intercept in the GRS test for the momentum portfolios. This indicated that the momentum effect was not incorporated in the market risk which was further emphasized through sorting, risk premium estimations and the tests of different multifactor models. For the reminder of the portfolio sorts the GRS test were not significant, although the risk premium was negative when sorting on beta. This discrepancy in results could be because of the low precision in the time series estimates.

The descriptive statistic for sorted portfolios and risk premium tests showed that similar results as the CAPM test. The one-year momentum effect was prevalent, but it turned out that a six-month momentum effect gave even higher and more stable spread in returns. The turnover ratio had a trend in reverse of expectation which is explained by the high volume return premium. Further testing also concluded that liquidity was not a risk factor when relative spread was tested.

The tests found a slight negative slope for the market risk and value weighted SMB factor. The market risk and SMB have in the recent decades been similar to our results in several markets worldwide, although SMB is still prevalent in the US market. This led us to believe SMB is not proxying a systematic risk factor in Norway and a yet unidentified risk in the US market makes it still relevant there. Moreover, the market risk is believed to be close to zero because of the leverage aversion theory proposed by Frazzini & Pedersen (2010) in combination with biased investors and the pervasiveness of benchmarking for mutual funds (Baker et al 2011).

For HML the results were similar to SMB on average in the period. However, further investigation showed how the HML had reversed in the financial crisis and stayed reversed throughout the drop in the oil price. The HML factor was the only factor to change substantially in the test period. With better evidence backing the HML factor through time and across markets it is more likely that the negative HML is only due to the recent crises.

In conclusion we have found that the CAPM, and the empirically derived FF three factor model and the Carhart four factor model could be improved on when explaining returns of the OSE. A model containing momentum, turnover ratio and market risk proved to be the best model. However, the market risk factor had low impact and has high negative correlation with turnover which made it almost redundant. The last test showed that a two factor model with momentum and turnover had almost the same results as for the three factor model.

10 Perspective and further research

We believe our research has been able to provide an updated perspective on risk factors in a Norwegian context. In particular, has our investigation shed light on how different risk factors have developed through time and the effects of turbulence in the financial market. These findings can supplement existing research to achieve a better understanding of these risk factors. Furthermore, the focus on theoretical explanations have enhanced the understanding of the dynamics on the OSE.

Our findings suggest a large proportion of the CAPM anomalies are due to behavioral explanations. These findings are relevant for investors wanting to create trading strategies that exploit these biases and result in high risk adjusted returns. Additionally, it can be used for evaluation of mutual fund performance. By using the multifactor model we propose, the investor can get a deeper understanding of the driving forces behind the portfolio returns. Especially considering the market risk had low explanatory power, which is signaling that risk adjusting returns using the CAPM relationships will result in flawed conclusions. Although our model is believed to be better than the CAPM we advise readers to use it with caution due to the low precision in our results.

We suggest three main research paths that should be followed to further validate our findings. The first is to increase the statistical precision when estimating the CAPM, risk premiums and multifactor models. This can be achieved by increasing the test period, test different return frequencies and use generalized moments of methods (GMM). Increasing the test period could improve the precision in the results by smoothing out big financial events, which this thesis is heavily influenced by. Different return frequencies and GMM could also be a way to reduce standard errors although the return levels will remain the same.

The second path to further validate our findings is a comprehensive test of the theoretical explanations. Since the scope of this thesis only was to conduct simple tests to substantiate the theories, a more thorough investigation could make these theories more reliable in a Norwegian context. For instance, the question of how the effects of benchmarking and leverage aversion affects the market risk premium, needs answering. Additional investigations of the of how behavioral biases influence momentum, turnover and market risk premium is also of interest.

The last suggested area to conduct further research on, is in relation to the number of factors tested. Our findings revealed that the factors tested might not be all risk factors affecting the OSE. By testing more factors, it could be possible to get a better model which explain more of the variation in the returns.

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12 Appendix

12.1 Appendix 1: returns for portfolios sorted on beta with minimum 20 trading days

Table 25: Return on portfolios sorted on beta with 20 day cut-off

Panel 1A show ten portfolios daily and annualized return sorted based on each asset's return in the previous one-year period. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, Panel 1A shows the standard deviation and sharp ratio annualized based on daily returns. The portfolios are equally weighted and rebalanced each year at the 1. July. Panel 1B shows the annualized return of each portfolio divided into four sub periods. Panel 2 have exactly the same properties as panel 1, although the portfolios are value weighted based on the daily market value of the previous closing price.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,08%	24%	25%	0,94	12	16	20
portfolio 2	0,07%	18%	20%	0,91	11	16	20
Portfolio 3	0,05%	14%	20%	0,72	12	16	21
Portfolio 4	0,07%	19%	23%	0,82	13	16	20
Portfolio 5	0,05%	14%	24%	0,57	13	16	21
Portfolio 6	0,05%	14%	25%	0,57	13	16	20
Portfolio 7	0,04%	11%	25%	0,44	13	17	20
Portfolio 8	0,03%	8%	29%	0,29	13	16	21
Portfolio 9	0,07%	20%	53%	0,37	12	17	20
Portfolio 10	0,04%	10%	38%	0,27	14	17	21

	Anualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	10%	45%	10%	29%
portfolio 2	11%	31%	13%	17%
Portfolio 3	14%	36%	-1%	12%
Portfolio 4	13%	27%	13%	22%
Portfolio 5	11%	42%	8%	-2%
Portfolio 6	21%	30%	-1%	11%
Portfolio 7	15%	29%	-2%	6%
Portfolio 8	0%	26%	0%	7%
Portfolio 9	9%	76%	4%	2%
Portfolio 10	17%	28%	6%	-6%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,05%	12%	21%	0,58	12	16	20
portfolio 2	0,04%	9%	19%	0,50	11	16	20
Portfolio 3	0,04%	10%	19%	0,52	12	16	21
Portfolio 4	0,05%	13%	21%	0,60	13	16	20
Portfolio 5	0,03%	7%	22%	0,33	13	16	21
Portfolio 6	0,04%	10%	29%	0,34	13	16	20
Portfolio 7	0,05%	14%	30%	0,45	13	17	20
Portfolio 8	0,04%	10%	31%	0,33	13	16	21
Portfolio 9	0,05%	13%	39%	0,34	12	17	20
Portfolio 10	0,02%	6%	41%	0,16	14	17	21

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	0%	36%	5%	8%
portfolio 2	3%	20%	-2%	16%
Portfolio 3	5%	30%	-6%	12%
Portfolio 4	9%	26%	3%	15%
Portfolio 5	5%	21%	-4%	8%
Portfolio 6	17%	17%	-2%	10%
Portfolio 7	15%	18%	12%	10%
Portfolio 8	7%	18%	5%	11%
Portfolio 9	15%	36%	1%	3%
Portfolio 10	-14%	31%	13%	-3%

Graph 11: Return index created for portfolios sorted on beta with 20 day cutoff

The two graphs show a theoretical index created for the average excess return of the three portfolios with the highest values, and the three portfolios with the lowest values. The index is created the same way as explained in the data section for the market index.

Graph 11A: Equally weighted portfolios

Graph 11B: Value weighted portfolios

12.2 Appendix 2: Estimation of CAPM using beta sort with minimum of 20 trading days

Table 26: Estimation of the CAPM on portfolios sorted on beta

Panel 1 shows the results from estimating CAPM using a OLS regression for portfolios sorted on beta. The beta is calculated using a one-year estimation period where only assets with 20 days with trading volume. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values. The first part shows the result from the time series regression and the second part shows the results from the FM regression. Portfolios in both panels are rebalanced every year, but in panel 1 the return of each asset in the portfolio is equally weighted while it is weighted based on market value in panel 2. Column 1 and 2 shows the estimated intercept and the corresponding p-value. Column 3 and 4 shows the estimated beta and the corresponding p-value. The last column presents the models R squared which is how much of the variance the model can explain. In the second part the alpha and risk premium (λ) is presented in daily and annual form with its corresponding t-statistic.

Panel 1: Equally weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00069	0,0%	0,20	0,0%	5%
Portfolio 2	0,00048	0,1%	0,31	0,0%	17%
Portfolio 3	0,00033	1,8%	0,38	0,0%	23%
Portfolio 4	0,00047	0,2%	0,43	0,0%	24%
Portfolio 5	0,00027	9,6%	0,51	0,0%	28%
Portfolio 6	0,00026	9,5%	0,60	0,0%	37%
Portfolio 7	0,00013	38,2%	0,70	0,0%	48%
Portfolio 8	-0,00002	92,1%	0,87	0,0%	52%
Portfolio 9	0,00035	29,2%	1,00	0,0%	27%
Portfolio 10	-0,00003	88,9%	1,15	0,0%	57%

	F-test	P-value
GRS	3,48	0,01%

	Return Daily	Return annualized	T-stat
α	0,0647%	17,7%	4,72
λ_{EW}	-0,0304%	-7,4%	-1,00

Panel 2: Value weighted

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00030	6,5%	0,19	0,0%	5%
Portfolio 2	0,00017	24,1%	0,32	0,0%	17%
Portfolio 3	0,00015	23,2%	0,41	0,0%	29%
Portfolio 4	0,00024	7,6%	0,52	0,0%	37%
Portfolio 5	0,00001	95,6%	0,63	0,0%	46%
Portfolio 6	0,00005	75,5%	0,80	0,0%	47%
Portfolio 7	0,00015	31,7%	0,92	0,0%	60%
Portfolio 8	0,00002	91,7%	1,01	0,0%	64%
Portfolio 9	0,00005	76,4%	1,23	0,0%	66%
Portfolio 10	-0,00023	24,0%	1,39	0,0%	67%

	F-test	P-value
GRS	0,90	53,01%

	Return Daily	Return annualized	T-stat
α	0,0317%	8,3%	2,47
λ_{EW}	-0,0032%	-0,8%	-0,13

12.3 Appendix 3: CAPM estimation using equally weighted market portfolio

Table 27: Estimation of the CAPM on portfolios all risk factors using EW market return

The table shows a summary of CAPM estimation on all factors using an equally weighted market return portfolio. Panel 1 shows portfolios sorted on beta with minimum 20 trading days in the calculation period, while panel 2 shows portfolios sorted on beta with minimum 50 trading days. Panel 3 is sorted on size, panel 4 on B/M, panel 5 on momentum and panel 6 on turnover ratio. All panel A's are equally weighted, while all panel B's are value weighted. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values of the factor and portfolio 10 will therefore have the assets with the highest values

Panel 1A

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00054	0,2%	0,46	0,0%	13%
Portfolio 2	0,00031	1,5%	0,56	0,0%	28%
Portfolio 3	0,00014	27,9%	0,68	0,0%	38%
Portfolio 4	0,00026	6,3%	0,74	0,0%	38%
Portfolio 5	0,00003	85,4%	0,87	0,0%	43%
Portfolio 6	0,00000	98,5%	0,95	0,0%	50%
Portfolio 7	-0,00015	24,0%	1,07	0,0%	59%
Portfolio 8	-0,00036	1,3%	1,31	0,0%	63%
Portfolio 9	-0,00018	53,7%	1,79	0,0%	46%
Portfolio 10	-0,00047	0,9%	1,70	0,0%	66%

	F-test	P-value
GRS	2,71	0,26%

	Daily	Return annualized	T-stat
α	0,0617%	16,8%	3,74
λ_{EW}	-0,0155%	-3,8%	-0,70

Panel 1B

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00019	23,3%	0,37	0,0%	10%
Portfolio 2	0,00003	82,3%	0,50	0,0%	22%
Portfolio 3	-0,00002	87,3%	0,64	0,0%	38%
Portfolio 4	0,00006	65,4%	0,73	0,0%	38%
Portfolio 5	-0,00020	15,8%	0,84	0,0%	44%
Portfolio 6	-0,00019	27,8%	1,04	0,0%	43%
Portfolio 7	-0,00008	63,9%	1,10	0,0%	45%
Portfolio 8	-0,00025	17,1%	1,21	0,0%	49%
Portfolio 9	-0,00028	19,1%	1,49	0,0%	52%
Portfolio 10	-0,00060	1,0%	1,69	0,0%	53%

	F-test	P-value
GRS	1,02	42,05%

	Daily	Return annualized	T-stat
α	0,0328%	8,6%	2,13
λ_{EW}	-0,0037%	-0,9%	-0,16

Panel 2A

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00046	0,9%	0,55	0,0%	17%
Portfolio 2	0,00034	1,3%	0,58	0,0%	28%
Portfolio 3	0,00014	34,5%	0,73	0,0%	36%
Portfolio 4	0,00021	10,8%	0,74	0,0%	40%
Portfolio 5	0,00003	85,8%	0,89	0,0%	40%
Portfolio 6	-0,00006	67,7%	1,01	0,0%	50%
Portfolio 7	-0,00021	11,9%	1,10	0,0%	58%
Portfolio 8	-0,00032	3,4%	1,36	0,0%	63%
Portfolio 9	-0,00030	6,1%	1,49	0,0%	64%
Portfolio 10	-0,00039	21,7%	2,13	0,0%	49%

	F-test	P-value
GRS	2,19	1,56%

	Return		
	Daily	annualized	T-stat
α	0,0561%	15,2%	2,87
λ_{EW}	-0,0098%	-2,4%	-0,41

Panel 2B

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00022	16,4%	0,44	0,0%	15%
Portfolio 2	0,00003	83,3%	0,52	0,0%	23%
Portfolio 3	0,00000	98,6%	0,67	0,0%	37%
Portfolio 4	0,00005	70,9%	0,75	0,0%	38%
Portfolio 5	-0,00019	19,9%	0,84	0,0%	42%
Portfolio 6	-0,00028	12,9%	1,01	0,0%	40%
Portfolio 7	-0,00011	56,2%	1,13	0,0%	45%
Portfolio 8	-0,00023	21,5%	1,22	0,0%	48%
Portfolio 9	-0,00037	8,1%	1,50	0,0%	52%
Portfolio 10	-0,00061	1,0%	1,71	0,0%	53%

	F-test	P-value
GRS	1,15	32,25%

	Return		
	Daily	annualized	T-stat
α	0,0379%	10,0%	2,29
λ_{EW}	-0,0096%	-2,4%	-0,40

Panel 3A

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00093	0,3%	1,13	0,0%	22%
Portfolio 2	0,00023	23,5%	0,86	0,0%	30%
Portfolio 3	0,00012	39,7%	0,78	0,0%	37%
Portfolio 4	-0,00007	62,6%	0,84	0,0%	41%
Portfolio 5	-0,00028	2,5%	0,89	0,0%	52%
Portfolio 6	-0,00013	25,7%	0,96	0,0%	58%
Portfolio 7	-0,00010	36,0%	1,03	0,0%	63%
Portfolio 8	-0,00013	21,4%	1,01	0,0%	67%
Portfolio 9	-0,00026	2,2%	1,11	0,0%	68%
Portfolio 10	-0,00026	5,7%	1,34	0,0%	68%

	F-test	P-value
GRS	1,60	10,06%

	Return		
	Daily	annualized	T-stat
α	0,0034%	0,9%	0,10
λ_{EW}	0,0415%	11,0%	1,09

Panel 3B

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00004	86,1%	0,88	0,0%	23%
Portfolio 2	-0,00027	20,9%	0,88	0,0%	27%
Portfolio 3	-0,00021	16,2%	0,77	0,0%	36%
Portfolio 4	-0,00032	7,0%	0,82	0,0%	32%
Portfolio 5	-0,00040	0,3%	0,86	0,0%	48%
Portfolio 6	-0,00026	2,7%	0,94	0,0%	58%
Portfolio 7	-0,00004	76,2%	0,97	0,0%	60%
Portfolio 8	-0,00015	23,6%	1,01	0,0%	59%
Portfolio 9	-0,00030	0,6%	1,07	0,0%	67%
Portfolio 10	-0,00022	11,2%	1,19	0,0%	61%

	F-test	P-value
GRS	3,45	0,02%

	Return		
	Daily	annualized	T-stat
α	-0,0287%	-7,0%	-0,64
λ_{EW}	0,0523%	14,1%	1,07

Panel 4A

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	0,00010	58,4%	1,44	0,0%	55%
Portfolio 2	-0,00033	2,2%	1,28	0,0%	63%
Portfolio 3	-0,00002	89,2%	1,05	0,0%	58%
Portfolio 4	0,00008	52,3%	0,89	0,0%	51%
Portfolio 5	0,00008	52,5%	0,83	0,0%	51%
Portfolio 6	-0,00003	79,9%	0,77	0,0%	48%
Portfolio 7	0,00008	52,5%	0,78	0,0%	48%
Portfolio 8	0,00028	2,3%	0,74	0,0%	43%
Portfolio 9	-0,00010	47,1%	0,82	0,0%	41%
Portfolio 10	0,00003	93,2%	1,33	0,0%	29%

	F-test	P-value
GRS	1,32	21,54%

	Return		
	Daily	annualized	T-stat
α	0,0212%	5,5%	0,88
λ_{EW}	0,0247%	6,4%	0,87

Panel 4B

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00047	3,6%	1,54	0,0%	50%
Portfolio 2	-0,00056	0,4%	1,41	0,0%	52%
Portfolio 3	-0,00023	20,0%	1,18	0,0%	47%
Portfolio 4	-0,00007	67,7%	1,05	0,0%	43%
Portfolio 5	-0,00008	59,1%	0,89	0,0%	43%
Portfolio 6	-0,00005	81,2%	1,13	0,0%	43%
Portfolio 7	-0,00010	56,0%	0,99	0,0%	44%
Portfolio 8	-0,00015	36,1%	1,00	0,0%	45%
Portfolio 9	-0,00047	0,3%	0,97	0,0%	44%
Portfolio 10	-0,00060	0,1%	1,07	0,0%	44%

	F-test	P-value
GRS	2,86	0,15%

	Return		
	Daily	annualized	T-stat
α	0,0352%	9,3%	1,00
λ_{EW}	-0,0118%	-2,9%	-0,33

Panel 5A

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00021	52,9%	1,71	0,0%	36%
Portfolio 2	-0,00006	72,0%	1,02	0,0%	42%
Portfolio 3	-0,00013	37,6%	0,93	0,0%	45%
Portfolio 4	-0,00002	90,4%	0,94	0,0%	42%
Portfolio 5	-0,00001	91,8%	0,81	0,0%	50%
Portfolio 6	0,00021	5,9%	0,76	0,0%	50%
Portfolio 7	0,00023	3,7%	0,65	0,0%	44%
Portfolio 8	0,00009	41,4%	0,86	0,0%	56%
Portfolio 9	0,00013	27,6%	0,94	0,0%	56%
Portfolio 10	-0,00009	51,6%	1,23	0,0%	60%

	F-test	P-value
GRS	1,06	39,14%

	Return		
	Daily	annualized	T-stat
α	0,0392%	10,4%	1,22
λ_{EW}	0,0059%	1,5%	0,16

Panel 5B

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00093	0,2%	1,43	0,0%	33%
Portfolio 2	-0,00079	0,2%	1,34	0,0%	37%
Portfolio 3	-0,00084	0,0%	1,23	0,0%	40%
Portfolio 4	-0,00013	46,6%	1,17	0,0%	47%
Portfolio 5	-0,00011	53,2%	1,05	0,0%	45%
Portfolio 6	-0,00009	59,0%	0,98	0,0%	45%
Portfolio 7	0,00005	71,3%	0,85	0,0%	41%
Portfolio 8	-0,00034	3,8%	1,16	0,0%	52%
Portfolio 9	-0,00009	63,7%	1,22	0,0%	49%
Portfolio 10	-0,00015	48,9%	1,49	0,0%	49%

	F-test	P-value
GRS	3,35	0,02%

	Return		
	Daily	annualized	T-stat
α	0,0973%	27,8%	2,52
λ_{EW}	-0,0661%	-15,3%	-1,81

Panel 6A

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00046	0,8%	0,73	0,0%	27%
Portfolio 2	-0,00030	7,2%	0,77	0,0%	32%
Portfolio 3	0,00011	41,1%	0,76	0,0%	40%
Portfolio 4	0,00016	24,7%	0,78	0,0%	42%
Portfolio 5	0,00011	40,1%	0,81	0,0%	46%
Portfolio 6	0,00023	8,1%	0,90	0,0%	51%
Portfolio 7	0,00015	33,5%	1,00	0,0%	46%
Portfolio 8	-0,00003	79,5%	1,08	0,0%	60%
Portfolio 9	-0,00003	83,8%	1,28	0,0%	64%
Portfolio 10	0,00019	43,7%	1,72	0,0%	50%

	F-test	P-value
GRS	1,60	10,00%

	Return		
	Daily	annualized	T-stat
α	-0,0236%	-5,8%	-0,93
λ_{EW}	0,0697%	19,2%	2,35

Panel 6B

	Intecept	p-value	Beta	p-value	R^2
Portfolio 1	-0,00058	0,2%	0,62	0,0%	19%
Portfolio 2	-0,00058	0,1%	0,72	0,0%	28%
Portfolio 3	-0,00021	19,1%	0,95	0,0%	43%
Portfolio 4	-0,00019	21,5%	0,83	0,0%	38%
Portfolio 5	-0,00024	17,7%	0,99	0,0%	40%
Portfolio 6	-0,00004	83,4%	0,98	0,0%	40%
Portfolio 7	-0,00007	68,6%	1,05	0,0%	47%
Portfolio 8	-0,00033	6,9%	1,23	0,0%	50%
Portfolio 9	-0,00012	49,5%	1,27	0,0%	52%
Portfolio 10	-0,00029	11,1%	1,37	0,0%	55%

	F-test	P-value
GRS	2,78	0,20%

	Return		
	Daily	annualized	T-stat
α	-0,0672%	-15,6%	-2,55
λ_{EW}	0,0852%	23,9%	2,73

12.4 Appendix 4: 3-month, 2-year and 3-year momentum sort

Table 28: Return on portfolios sorted on momentum

All panel A's show ten portfolios daily and annualized return sorted based on each company's momentum. The portfolios are sorted in the order where portfolio 1 contains the assets with the lowest values and portfolio 10 will therefore have the assets with the highest values. In addition, the panels show the standard deviation and sharp ratio annualized based on daily returns. Panel B's shows the annualized return of each portfolio divided into four sub periods. The two first table show a 3-month momentum sorting, panel 3 and 4 show a 2-year momentum sorting and panel 5 and 6 show a 3-year momentum sorting.

Panel 1: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,02%	6%	37%	0,15	11	17	20
portfolio 2	0,01%	3%	26%	0,13	12	17	21
Portfolio 3	0,01%	1%	21%	0,07	12	17	20
Portfolio 4	0,05%	13%	21%	0,62	12	17	21
Portfolio 5	0,05%	14%	21%	0,66	12	17	21
Portfolio 6	0,04%	11%	20%	0,56	12	17	20
Portfolio 7	0,04%	12%	20%	0,60	12	17	21
Portfolio 8	0,08%	22%	40%	0,55	12	17	20
Portfolio 9	0,06%	18%	23%	0,77	12	17	21
Portfolio 10	0,09%	26%	31%	0,85	12	17	21

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	19%	5%	6%	-4%
portfolio 2	8%	19%	1%	-11%
Portfolio 3	15%	9%	-2%	-10%
Portfolio 4	11%	32%	6%	8%
Portfolio 5	13%	27%	9%	8%
Portfolio 6	13%	23%	5%	6%
Portfolio 7	11%	27%	5%	7%
Portfolio 8	21%	60%	8%	7%
Portfolio 9	13%	25%	8%	24%
Portfolio 10	37%	36%	8%	26%

Panel 2: Value Weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	-0,04%	-10%	38%	-0,27	11	17	20
portfolio 2	-0,02%	-4%	32%	-0,14	12	17	21
Portfolio 3	0,01%	3%	28%	0,12	12	17	20
Portfolio 4	0,04%	10%	29%	0,34	12	17	21
Portfolio 5	0,03%	9%	28%	0,32	12	17	21
Portfolio 6	0,04%	9%	28%	0,33	12	17	20
Portfolio 7	0,03%	9%	26%	0,33	12	17	21
Portfolio 8	0,03%	7%	28%	0,27	12	17	20
Portfolio 9	0,03%	9%	29%	0,32	12	17	21
Portfolio 10	0,06%	17%	35%	0,49	12	17	21

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-5%	-24%	6%	-14%
portfolio 2	0%	-11%	0%	-6%
Portfolio 3	26%	3%	1%	-10%
Portfolio 4	7%	30%	7%	-1%
Portfolio 5	12%	11%	1%	13%
Portfolio 6	9%	13%	5%	10%
Portfolio 7	0%	12%	15%	9%
Portfolio 8	14%	15%	-2%	3%
Portfolio 9	10%	15%	8%	6%
Portfolio 10	23%	36%	9%	7%

Panel 3: Equally weighted returns

	Mean		Annualized		Number of stocks		
A	Daily	Annualized	Std.dev	Sharp	Min	Median	Max
Portfolio 1	0,08%	23%	58%	0,39	10	14	18
portfolio 2	0,05%	13%	28%	0,47	10	15	19
Portfolio 3	0,03%	7%	23%	0,32	12	15	18
Portfolio 4	0,05%	12%	26%	0,47	11	16	19
Portfolio 5	0,04%	10%	21%	0,50	12	16	18
Portfolio 6	0,05%	14%	21%	0,69	11	16	19
Portfolio 7	0,05%	12%	20%	0,61	12	15	18
Portfolio 8	0,04%	10%	22%	0,46	11	15	19
Portfolio 9	0,04%	12%	22%	0,53	12	15	18
Portfolio 10	0,06%	17%	30%	0,56	11	16	19

	Annualized returns			
B	1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	21%	86%	-5%	1%
portfolio 2	3%	44%	-4%	12%
Portfolio 3	0%	21%	4%	4%
Portfolio 4	0%	30%	10%	7%
Portfolio 5	11%	16%	2%	15%
Portfolio 6	20%	33%	0%	7%
Portfolio 7	7%	19%	8%	15%
Portfolio 8	2%	27%	4%	6%
Portfolio 9	10%	19%	3%	16%
Portfolio 10	16%	34%	2%	16%

Panel 4: Value Weighted returns

A	Mean Daily	Mean Annualized	Annualized Std.dev	Annualized Sharp	Number of stocks Min	Number of stocks Median	Number of stocks Max
Portfolio 1	0,00%	1%	36%	0,02	10	14	18
portfolio 2	0,01%	1%	34%	0,04	10	15	19
Portfolio 3	-0,01%	-1%	29%	-0,05	12	15	18
Portfolio 4	0,04%	11%	32%	0,35	11	16	19
Portfolio 5	0,03%	9%	26%	0,33	12	16	18
Portfolio 6	0,03%	8%	26%	0,28	11	16	19
Portfolio 7	0,02%	6%	29%	0,20	12	15	18
Portfolio 8	0,03%	8%	28%	0,28	11	15	19
Portfolio 9	0,04%	10%	31%	0,31	12	15	18
Portfolio 10	0,06%	17%	39%	0,45	11	16	19

B	Annualized returns 1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-4%	26%	-8%	-12%
portfolio 2	3%	13%	0%	-12%
Portfolio 3	-2%	-4%	8%	-9%
Portfolio 4	2%	18%	11%	12%
Portfolio 5	1%	11%	4%	20%
Portfolio 6	6%	20%	-1%	5%
Portfolio 7	7%	13%	4%	-2%
Portfolio 8	-2%	22%	0%	11%
Portfolio 9	12%	6%	7%	15%
Portfolio 10	19%	39%	0%	15%

Panel 5: Equally weighted returns

A	Mean Daily	Mean Annualized	Annualized Std.dev	Annualized Sharp	Number of stocks Min	Number of stocks Median	Number of stocks Max
Portfolio 1	0,09%	24%	58%	0,42	9	13	18
portfolio 2	0,06%	16%	32%	0,48	9	14	19
Portfolio 3	0,04%	11%	21%	0,53	11	15	18
Portfolio 4	0,04%	11%	22%	0,49	11	15	19
Portfolio 5	0,01%	4%	21%	0,17	8	14	18
Portfolio 6	0,06%	16%	21%	0,79	8	14	19
Portfolio 7	0,04%	10%	20%	0,52	10	14	18
Portfolio 8	0,05%	12%	23%	0,53	9	14	19
Portfolio 9	0,03%	7%	24%	0,31	10	15	18
Portfolio 10	0,03%	9%	29%	0,31	12	15	19

B	Annualized returns 1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-4%	99%	-3%	21%
portfolio 2	2%	37%	7%	17%
Portfolio 3	6%	33%	-1%	8%
Portfolio 4	0%	29%	1%	14%
Portfolio 5	-1%	22%	3%	-11%
Portfolio 6	15%	33%	5%	14%
Portfolio 7	0%	20%	9%	12%
Portfolio 8	3%	29%	5%	11%
Portfolio 9	0%	21%	6%	1%
Portfolio 10	8%	19%	2%	9%

Panel 6: Value Weighted returns

A	Mean Daily	Mean Annualized	Annualized Std.dev	Annualized Sharp	Number of stocks Min	Number of stocks Median	Number of stocks Max
Portfolio 1	0,03%	7%	41%	0,17	9	13	18
portfolio 2	0,03%	7%	29%	0,23	9	14	19
Portfolio 3	0,04%	10%	27%	0,37	11	15	18
Portfolio 4	0,03%	7%	29%	0,26	11	15	19
Portfolio 5	0,03%	9%	29%	0,31	8	14	18
Portfolio 6	0,04%	12%	32%	0,37	8	14	19
Portfolio 7	0,02%	6%	24%	0,24	10	14	18
Portfolio 8	0,02%	5%	25%	0,21	9	14	19
Portfolio 9	0,04%	11%	40%	0,28	12	15	19
Portfolio 10	0,03%	9%	29%	0,31	12	15	19

B	Annualized returns 1997-2001	2001-2006	2006-2011	2011-2016
Portfolio 1	-10%	49%	-3%	-5%
portfolio 2	-5%	30%	-5%	9%
Portfolio 3	16%	18%	-1%	10%
Portfolio 4	1%	14%	-5%	23%
Portfolio 5	-7%	21%	7%	15%
Portfolio 6	9%	19%	13%	5%
Portfolio 7	3%	6%	6%	8%
Portfolio 8	1%	11%	-1%	10%
Portfolio 9	18%	26%	-1%	4%
Portfolio 10	8%	19%	2%	9%