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THE ARCTIC UNIVERSITY OF NORWAY

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# Testing Market Efficiency on Oslo Stock Exchange

*Can common abnormal return anomalies' predictive abilities create arbitrage opportunities?*

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# Abstract

This thesis studies the predictive abilities of the abnormal return anomalies of size, value and return momentum on Oslo Stock Exchange to determine possible forms of market inefficiency. Factor mimicking portfolios representing the anomalies are created for the sample period. The sample period is divided into two smaller sub-periods where the first sub-period is used to observe the anomalies, while sub-period 2 tests for market efficiency. Optimally weighted portfolios of the individual anomaly portfolios in sub-period 1 are constructed with and without restrictions of short-sale and gearing to compare performance to a benchmark market index. Using the portfolio weights obtained in the previous period, I analyse the portfolios' performance relative to the benchmark.

When assessing the overall sample period, the value anomaly yields statistically significant abnormal returns compared to the benchmark index. The statistics of the return momentum factor reports excess returns over the market index, but the results are not sufficiently significant to conclude the existence of abnormal returns related to return momentum. The results of the statistical analyses imply that there is no size effect apparent on Oslo Stock Exchange in the sample period.

Both the restricted and non-restricted optimally constructed portfolios of size, value and return momentum produces abnormal returns compared to the benchmark index. However, t-statistics of the portfolios determine that the returns are not significant at a 95% confidence interval as the portfolios reports p-values > 0,05. Based on the trading strategy proposed in this thesis, I cannot conclude that the efficient market hypothesis is violated.

The results of the thesis indicate that some arbitrage opportunities do exist based on the value anomaly, demonstrating a violation of the semi-strong efficiency. However, the return anomalies of size and return momentum seems to be weak or non-existing on Oslo Stock Exchange in the sample period.

Microsoft Excel are used to perform all quantitative analyses. All figures are created in Keynote.

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# 1 Introduction

## 1.1 Background

Market efficiency entails that asset prices fully reflect every aspect of available information in the market (Fama, 1970). Based on this assumption, all investors should have the same basis for making investment decisions. In an efficient market such as described, there are no obvious arbitrage opportunities for market participants. The empirical literature of market efficiency discusses three different adjustments to information that asset prices must reflect for there not to be any arbitrage opportunities (Fama, 1970). *Weak-form efficiency* is when the historical prices and returns of assets alone pose as the entire information adjustment for the current asset price. *Semi-strong efficiency* considers that prices may reflect other obvious publicly available information, such as earnings announcements, annual reports, etc. At last, *strong-form efficiency* concerns the idea that some individual in the market has monopolistic access to aspects that may be relevant for the asset price.

Although the efficient market model, which simply is the hypothesis that define market efficiency, seems to be quite accurate, there still is empirical evidence of abnormal returns due to public information available to all market participants. Fama and French (1992) explored the variation in expected stock returns in order to tie the returns to certain characteristics possessed by the different stocks. Contrary from popular assumptions such as the capital asset pricing model (CAPM), an asset's expected returns may be explained by more than the asset's exposure to the market return, $\beta$, and the risk-free interest rate.

In more recent history, the general assumption of the one-period capital asset pricing model presented by Sharpe (1964), Lintner (1965) and Black (1972) have met contradictions in the academic world. Asset pricing depending on only one single risk factor, being the market risk, gives a general understanding of market prices, although it is not very realistic. As an extension to the CAPM, Ross (1976) introduced a theory that explained asset prices as a linear function of several risk factors, not only the market risk. This theory, called the *arbitrage pricing theory*, offered a deeper understanding of an asset's expected return in terms of explaining different risk factors. The model also imposed fewer restrictions and assumptions, which made it more relevant for practical interpretation.

If the efficient market hypothesis is valid, there would not be possible for public information to indicate future price changes of an asset. A violation would mean that the information available in the market is not fully reflected in asset prices, and hence offer arbitrage opportunities for market participants.

Based on the arbitrage pricing theory, academics have proposed numerous possible risk factors to explain asset pricing. As well as doing a good job as explanatory variables in asset pricing models, multiple of these proposed factors have proven to yield abnormal returns when used in trading strategies. Some of the most prominent characteristics described as abnormal return factors are based on publicly available information and historical stock prices, obviously questioning the efficient market hypothesis.

## 1.2 Problem formulation

This thesis builds on earlier studies to test possible violations of the weak-form and semi-strong efficiency of asset pricing on Oslo Stock Exchange. By defining abnormal return factors and calculating factor mimicking portfolios, this paper tests the efficiency on Oslo Stock Exchange. Given that the market efficiency hypothesis holds, publicly available information should not offer arbitrage opportunities for market participants.

Market efficiency tests have been performed numerous times with numerous approaches. This paper develops a quantitative trading strategy based on constructed factor mimicking portfolios to further evaluate pricing efficiency on the Norwegian security market in the period 1996-2015. The research question of the thesis is:

*Can a trading strategy based on publicly available information yield abnormal returns on Oslo Stock Exchange?*

Return statistics of the trading strategy is compared to a benchmark market index to assess performance. To further study the possible arbitrage opportunities, the test is completed both with and without restrictions towards short-selling and gearing assets.

## 1.3 Scope of the thesis

This paper test whether obviously publicly available information can offer arbitrage opportunities, questioning especially the weak-form and semi-strong efficiency of asset pricing. Multiple abnormal return factors are highlighted to emphasize the academic scepticism toward the simplified assumption of market efficiency. Although many return anomalies are widely researched, this paper will just evaluate the performance of a few. Firm size, book-to-market equity and return momentum are among the most studied effects. These form the foundation for the trading strategy and a portfolio of the individual factor mimicking portfolios of these anomalies are tested for violation of the efficient market hypothesis on Oslo Stock Exchange. Computation of different characteristics' portfolios extend from Fama and French (1992) and Jegadeesh and Titman (1993).

## 1.4 Thesis structure

Chapter 2 presents previous studies on different return anomalies relevant to this paper. Evidence of the existence of different factor effects are introduced and possible explanations of the various factors are given. Furthermore, the reader will obtain insight in how the size, value and return momentum factors perform as explanatory variables in pricing models used on international stock returns. The theory behind central measures of performance are also included.

The paper then presents the methodology behind the analysis in chapter 3. Data collection is described and the data set is explained, as well as defining the sample period and sub-periods.

Chapter 4 contains statistics of the individual assets used in the analysis, in addition to the actual test of market efficiency. An evaluation of performance of the trading strategy in comparison to the benchmark index is also presented.

A thorough discussion of the results follow in chapter 5, in addition to possible test weaknesses posed by the paper, before concluding.

# 2 Theoretical framework

## 2.1 Evidence of return anomalies due to firm size and value

One of the theories that challenge the semi-strong efficiency of the market hypothesis discuss the opportunity that a firm's price-earnings ratio is an indicator of future performance. Basu (1977) attempts to determine the P/E ratio's effect on asset return. His findings point to a violation of the hypothesis in the matter that over the test period, portfolios consisting of low P/E stocks outperformed the portfolios with high P/E stocks both in terms of risk adjusted and absolute returns. This is contradicting the semi-strong efficiency as defined by the efficient market model, as the prices at any time obviously don't "fully reflect" other sources of public information (earnings announcements) rather than the historic asset price alone.

Firm size is another factor that has been empirically tested for implications on expected returns, in contradiction to efficient pricing following the CAPM (Banz, 1981). In his study, Banz found a significant relationship between a firm's market equity and its average risk adjusted return. Market equity refers to the size of a company, given by the sheer size of its market capital in terms of the number of shares in the market times the stock price. In general, small size firms on average yielded returns that were too high compared to their $\beta$, while the opposite was concluded for larger firms. Based on his findings, Banz could further explain what drives the average returns given by a firm's $\beta$. Another subject of interest is that these results point to a misspecification of the asset-pricing models previously mentioned, rather than a pure market inefficiency. As concluded by Ball (1978), market efficiency tests are often combined with a certain pricing equilibrium, and hence anomalies that have caused inefficiency in the market may just as well have been a result of model misspecification rather than a violation of the market efficiency hypothesis.

The anomaly of size is found by subtracting large firm returns from small firm returns (Fama & French, 1993). Hence, the name of this factor mimicking portfolio is SMB (small minus big). Portfolio construction of anomalies are further explained in chapter 3.2.

Reinganum (1981) discovered that the P/E anomaly seems to be related to the same set of factors as the size anomaly from Banz (1981). When tested separately it seems that both anomalies exist, but when controlled for each other the factors are more likely to be due to the effect of size than the P/E ratio.

Furthermore, the ratio of a firm's book values to its market equity has also shown to be strongly related to average returns (Stattman, 1980). The results show that companies with a high book-to-market equity ratio yield a higher average return than companies with lower book-to-market ratios. The high BE/ME firms are categorized as value stocks, while the firms with low BE/ME ratios are growth stocks. As with the size factor, value returns are found by constructing a simple portfolio of the companies rated as value stocks minus the growth stocks. Therefore, the value factor mimicking portfolio is called HML (high minus low).

Another important note to substantiate the size effect is the paper's reports about how the BE/ME effect disappears when controlled for firm size, although the size effect still is significant while controlled for the BE/ME ratio. This indicated that the BE/ME ratio proxied for the size effect, and not the opposite.

Rosenberg, Reid, and Lanstein (1985) also test for market inefficiency on the New York Stock Exchange, by implementing a book-to-market strategy that involves buying stocks with a high ratio of book value relative to market value and selling stock with a low such ratio. Their paper provided significant confirmation of the value anomaly. Out of the 141 months tested, 102 of these yielded a positive return on the book-to-market strategy, leading the authors to conclude that abnormal profits are possible, simply given the inefficiency of the asset pricing. This provided further evidence contradicting the market hypothesis, more specifically the semi-strong efficiency of market prices.

As the CAPM states, $\beta$ is the firm's exposure to the market return. Hence it poses as a risk measure in the sense that it is supposed to reflect the market's impact on the asset. As discussed previously, $\beta$ has been found to be an inadequate explanatory variable for expected return. As most economic theory agrees on, higher risk should lead to higher expected returns. The risk of a firm's equity can naturally be measured by its debt-to-equity ratio, or in other words the leverage of a firm. This ratio has proven to have a positive relationship to expected return, even when controlled for the $\beta$ and firm size (Bhandari, 1988). The results also entail that the premium of a high leverage is not just a consequence of an increased risk premium.

Later studies have found that these different explanatory factors in fact are all just scaled variants of a firm's actual stock price, in the matter that they extract information out of the price of a stock that are relevant in explaining the stocks expected return (Ball, 1978). In this regard, it is likely that some of these factors are redundant, as some of them are merely a proxy for another factor (Fama & French, 1992). This has already been established for the E/P anomaly and somewhat for the BE/ME ratio, which are captioned by the size factor. Fama and French tested the redundancy of size, E/P, leverage and BE/ME ratio to find that the size factor and the book-to-market equity together captured the variation in average stock returns related to all these four factors in addition to the market β. Even though BE/ME was described as a proxy for size by Stattman (1980), it seems that the size factor gives a more representative capturing of the variation in returns related to the market β when book-to-market equity is accounted for. Their study also revealed that market β, alone or when combined with other factors, has little explanatory power of average returns of stocks, in direct contradiction to previously popular asset pricing models where market β plays a central role.

The book-to-market anomaly was accepted by academics and in financial circles a long time ago, but the reasoning behind the abnormal returns were more uncertain. Lakonishok, Shleifer, and Vishny (1994) found that the strategy manipulates some suboptimal behaviour of investors. Their evidence therefore opposes the theory of abnormal returns due to increased risk, as proposed by Fama and French (1992).

During the 1968 to 1990 period, numerous trading strategies centred around value investment showed consistent positive returns for value stocks relative to growth stocks (Lakonishok et al., 1994). In their paper, the named investment strategies yielded returns of approximately 10% annually. Data mining may partly explain these results, although that discussion exceeds the scope of this paper. Furthermore, they test both the hypothesis of suboptimal behaviour as well as increased fundamental risk in their attempt to verify the value anomaly found.

Using traditional approaches to risk measurement, no significant difference was discovered in value stocks compared to growth stocks. Hence, the explanation of the abnormal returns was left to be described by the behaviour of market participants. Since growth stocks normally have high earnings multiples in the past, the market seems to overestimate the probability of future results to be equally good. When market expectations of growth stocks relative to value stocks are not satisfied, value stocks will outperform the growth stocks. Investors betting against these naive trading strategies therefore beat the market consistently (Lakonishok et al., 1994).

Based on the studies above, it is fair to say that some size and value anomaly does exist, but it is still somewhat unclear just why it is so. All interpretation of factor effects should therefore be carefully implemented, due to the possibility of underlying causes which is still to be discovered.

### 2.1.1 Size and book-to-market equity effects on earnings

As discussed in Fama and French (1992) the size and BE/ME factors proxy for some unknown economic risk factor in average returns. The tests in that exact paper, however, does not help explain why these factors offers arbitrage opportunities.

Evidence points to the effect being a result of the fact that size and BE/ME are closely related to profitability (Fama & French, 1995). A rational market should not let asset prices be affected by variations in profitability over a shorter period. This also entails that the book-to-market equity is not influenced by short-term variations in profitability. Fama and French found that firms characterised with a high BE/ME have sustained low earnings to book values ratios. Controversially, the firms with a low BE/ME proved consistently stronger profitability.

When the BE/ME effect in profitability is tested for size, the results show that bigger stocks on average are more profitable. This is closely connected to the recession in the 1980s. Their data showed that following the recession, a persistent earnings depression affected smaller stocks. This depression was most likely a result of some unexplained risk-factor relating to firm size.

Although there is proof of common book-to-market and size factors in earnings and profitability as there are in returns, we cannot directly see responding effects. Both the market and size factors related to earnings seems to do a good job capturing the effects these two factors have on returns, but when assessing the book-to-market factor in earnings, it has little explanatory power of the responding return effect. There may be multiple reasons why the book-to-market factor in returns are not explained by its effect on earnings, but most likely this is due to measurement error caused by noise in shocks to expected earnings (Fama & French, 1995).

Even though the results only showed partially connections in the factors effects in the relation between returns and earnings, these results can help explain the underlying reason of the factors arbitrary effects on returns, especially for the market and size factors.

### 2.2 Market factor

As discussed above, the market factor has explanatory power when comparing the average returns of the stock market to that of the risk-free asset. The market factor is simply the excess return of the market to that of the risk-free asset, $RM(t) – RF(t)$. When pricing an asset based on the CAPM, the excess return of the market, or the market premium, is an important measure. As previously mentioned, the CAPM calculate expected return of an asset as the asset's sensitivity to systematic risk. Assets with $\beta$ equal to 1 is expected to yield a return equal to the market.

### 2.3 The predictive power of return anomalies

In an attempt to respond to preceding findings regarding the explanatory variables of average returns, Fama and French (1993) attempts to identify and test the common risk factors in average returns of stocks and bonds. The stock market factors used in their model extends from Fama and French (1992), and includes both size and book-to-market equity as risk factors. Both have, as previously determined, shown to be significantly descriptive of the variation in average returns when tested alone as well as in combination with other factors. The results also offer important evidence that the former one-factor model used in performance evaluation of stock portfolios has little relevance in comparison.

Since their paper builds on the precondition of rational asset pricing, all variables related to average returns is required to proxy for the sensitivity to the returns risk factors. By implementing time-series regression on the data, they could determine whether the identified risk factors explained the common difference in returns. Moreover, the time-series regression used excess returns of the stock returns compared to the treasury bill rate as the dependent variable of the model. Although the common risk factors capture the variation in returns, and therefore proves their proxy for sensitivity to the returns risk factors as explanatory variables, they cannot describe the excess return over the treasury bills. To solve this complication, Fama and French introduce a market factor to mimic the risk premium of the market, and link the average returns on stocks together with that of the T-bills. Their model, including SMB, HML and the market factor, is:

$$R_i(t) - RF(t) = \alpha_i + b_i[RM(t) - RF(t)] + s_i SMB(t)$$
$$+h_i HML(t) + e_i(t),$$

where:
- *Ri(t)* is the return on asset *i* for month *t*,
- *RF(t)* is the risk-free rate,
- *RM(t)* is the market return,
- *SMB(t)* is the difference between the returns on diversified portfolios of small stocks and big stocks,
- *HML(t)* is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks.

All model notations are from Fama and French (1993). The market factor in the model does a good job of imitating the excess market return, but it has little to no explanation of the differences in cross-sectional average returns and the corresponding volatilities (Fama & French, 1993). The variety of different stock performance is left to be explained by the size factor and book-to-market equity. With their ability to determine differences in cross-sectional average returns and their volatility, beyond the general risk premium covered by the market factor, these factors can be used as tools for defining portfolio performance.

## 2.4 Future returns explained by past return's performance

Fama (1970) introduced the efficient market hypothesis, stating that it is not possible to outperform the market, as prices at all time should reflect the information available. This implies that only new information can cause changes in asset prices. Historical prices and returns should therefore not have any predictive ability of a stocks future returns and price changes. Judging by the definition of weak-form efficiency specified earlier in the paper, the possibility of abnormal future returns based solely on past return's performance clearly would not be achievable. However, many economists have studied the tie between past and future performance of stocks.

De Bondt and Thaler (1985, 1987) were among the first to test the relationship between previous returns and future performance of stocks, based on Bayes' rule that most people tend to overreact to information. The tests unveiled that stock returns seemed to have a contradicting evolution over time. Results showed that a strategy consisting of buying past losing stocks over the previous 3 to 5 years and selling past winning stocks over the same period would yield an abnormal return. A portfolio consisting of the past losers would achieve a higher return compared to the past winners over a period of 3 to 5 years. This research has, however, received a lot of debate due to its results. Arguments against the results are that other factors such as size effect can explain some of the returns described. Also, the systematic risk of the portfolios may cause some return effect. This in turn led to several related studies with contradicting results.

We know from (Jegadeesh, 1990) and (Lehmann, 1990) that market inefficiency leads to a short-time reversal of stock returns due to corrections in the bid-ask spreads. More recent studies have shown that there is a clear relationship between past performance of a stock and returns over the next 3- to 12-month period (Jegadeesh & Titman, 1993). When assessing returns over longer periods, we can see a positive correlation between past and future returns up to 12 months forward. Jegadeesh and Titman analyzed stocks from NYSE and AMEX in a sample period from 1965 to 1989, to provide evidence of the relative strength strategies in a 3- to 12-month perspective. When evaluating the results of the tests, Jegadeesh and Titman found that the stocks yielded a significant return over the period of 3 to 12 months. The most tested trading strategy selected stocks based on returns over the previous 6 months and held the stocks for another 6 months before selling. Over the entire test period of 24 years, the strategy yielded an annual return of 12.01% on average. However, the positive returns seemed to decrease over the next 24 months following. This is consistent with the abnormal returns discovered by De Bondt and Thaler (1985, 1987) at a longer time perspective, due to overreaction to price information.

The evidence of relative strength strategies suggests that past winners achieve superior future returns compared to past losers (Jegadeesh & Titman, 1993). However, they find that this interpretation is likely to be a simplified solution to the fact that the market seems to underreact to information. Their paper attempts to explain this relationship by two alternative hypotheses. One possibility is that price changes are a result of investors buying winning stocks and selling losing stocks, causing the prices briefly to shift from the long-term values and cause an overreaction in the market. This theory was first studied by DeLong, Shleifer, Summers and Waldman (1990) in their paper about how market reacts to “positive feedback traders”. The other option is that there is a skewed relationship between how information is interpreted in the market. This entails that the market underreacts to information of shorter-term prospects while overreacting to long-term prospects.

Despite the uncertainty related to the underlying reason, the analysis provided important proof that the delayed price reactions to information was related to the specific firm, and showed that future returns on the well-performing stocks in the portfolio were not explained by systematic risk. This is important because it proves the very existence of the momentum factor of future expected stock returns in a 3- to 12-month period.

A momentum based trading strategy as tested by Jegadeesh and Titman (1993) have shown to consistently give abnormal returns over a longer period. As with the size and value factor, the momentum factor mimicking portfolio consist of stocks fulfilling the threshold of past winners minus the stocks rated as past losers. Further in the thesis, the momentum factor portfolio will be referred to as WML (winners minus losers).

The average return of the most representative portfolio was, as mentioned above, over 12% per year. Comparing this to the return of the market index, it is obvious that some anomaly is causing these arbitrage opportunities in the market. Exactly what underlying phenomenon it is that are triggering these abnormal returns, are yet to be determined, although there are some hypotheses. However, the effect of the momentum factor is still significant in describing positive returns in the market.

The abnormal returns yielded from the momentum strategy presented by Jegadeesh and Titman (1993) has been widely accepted by economists. Despite of this, many still argue the reasoning behind these results. Some of the criticism points out the possibility of risk compensation or data mining. To test the basis of the criticism regarding data mining, another momentum based trading strategy like the 1993 edition was performed nine years later. With nine additional years of data, similar results were found (Jegadeesh & Titman, 2001). As with the previous period, also the 1990 to 1998 period showed proof of a highly profitable strategy, with returns of approximately the same extent. Jegadeesh and Titman (2001) therefore answers the criticism of data mining, ruling this out as an alternative explanation.

This further statue the approval of relative strength strategies. In contrast, other well documented factor effects have not shown similar results when retested and compared to the original studies (Jegadeesh & Titman, 2001). Amongst these anomalies, we can find the small firm effect originally documented by Banz (1981). Even though Banz found a significant relationship between firm size and average returns, this effect has not been persistently documented after the sample periods of the first study.

The fact that the momentum effect of stock returns seems consistent over time increases the importance of determining the underlying cause to this anomaly. Jegadeesh and Titman (2001) proposes two main hypotheses in their renewed effort to explain the effect, whereas one of them seem to be consistent with the results of the tests. This is the theory of, amongst other, Barberis, Shleifer, and Vishny (1998) Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). These authors present possible behavioural models explaining how the momentum profits appear based on investors biased interpretation of stock information. The main idea behind these models are connected to investors overreacting to information. Because of this delayed overreaction, prices of stocks with positive (negative) returns gets pushed over (under) their long-term values. This in turn leads to a reversal of stock prices, causing previous losers to yield higher returns than previous winners. This is somewhat consistent with the theory presented by DeLong, Shleifer, Summers and Waldman (1990) explained in Jegadeesh and Titman (1993).

However, the explanation based on behavioural models should be interpreted carefully. Even though the models do a good job explaining the performance of momentum portfolios, the results of the test show that the models only partly describe the full effect of the momentum anomaly (Jegadeesh & Titman, 2001). The persistency of momentum based returns, nevertheless, points to an obvious violation of the weak-form efficiency.

## 2.5 Size, value and return momentum in international stock returns

Given the works of especially Banz (1981), DeBondt and Thaler (1985), Fama and French (1992), Lakonishok, Shleifer and Vishny (1994) and Jegadeesh and Titman (1993) the factor effects of size, value and momentum have been exposed. Attempts of explaining cross-sectional patterns in average returns based on both SMB and HML, as well as the market factor as explanatory variables have not been complete, although these three-factor models are successful compared to more primitive asset pricing models such as the CAPM (Fama & French, 1993). Carhart (1997) proposes a four-factor model to also capture the momentum effect on returns proven by Jegadeesh and Titman (1993):

$$R_i(t) - RF(t) = \alpha_i + b_i[RM(t) - RF(t)] + s_i SMB(t)$$
$$+h_i HML(t) + w_i WML + e_i(t),$$

which denotes exactly the same as Fama and French (1993), as well as supplementing *WML(t)* as the momentum factor, describing “the difference between the month *t* returns on diversified portfolios of the winners and losers of the past year” (Fama & French, 2012, p. 458).

As mentioned, Carhart proposes his four-factor model based on Fama and French’s three-factor model (1993). His paper includes the three-factor model and the CAPM for comparative reasons and the tests find that neither the CAPM or the three-factor model can compare to the more representative four-factor model in terms of performance. Also, he finds that the factors show a low degree of cross-correlations, meaning they do not proxy for each other.

Fama and French (2012) adds to the extent of the four-factor model by implementing it on international returns. As earlier empirical research entails, the average returns of value stocks outperform the returns of growth stocks in all regions observed. Except for Japan, also momentum returns are consistent with the evidence presented above. Furthermore, Fama and French (2012) provides important proof regarding the variance in returns in relation to firm size. Both value premiums in returns and momentum effects are larger for small stocks, and the effect spreads decrease as firm size increases. The only exception here is Japan, which shows no obvious trace of momentum effects in average returns. Size factor therefore plays an important role in describing returns in both the value and momentum factor portfolios.

Contrary to earlier studies, the paper finds no conclusive evidence of the existence of SMB returns. In all regions tested, the SMB portfolio averages a return close to zero.

### 2.6 Measure of performance

Based on earlier studies we can establish that the abnormal returns related to size, value and momentum are not due to increased risk taking. Rather, evidence points towards investor's expectations and behaviour being the plausible reasons behind the factor’s effects on returns.

Measuring portfolio performance can be done in multiple fashions. Performance can be related to two aspects, namely the ability to increase the return of an investment or decrease the volatility, or risk, through successful diversification. Theoretically, the CAPM states that a portfolio with a higher level of risk will yield higher returns. However, the abnormal factor returns cannot be attributed to higher risk. Hence, measuring the performance of factor mimicking portfolios must include a risk adjusted evaluation for it to have any practical implication. There are several computations for measuring risk adjusted performance, considering both a portfolio’s returns and standard deviations to assess performance.

#### 2.6.1 Sharpe-ratio

In terms of risk adjusted portfolio performance measure, the most common method is to calculate the Sharpe-ratio of a portfolio. The ratio poses as a reward-to-variability measure and is derived mathematically as the excess return of an asset to the return of a risk-free security divided by the asset’s standard deviation (Sharpe, 1964):

$$SR = \frac{E(r_i) - R_f}{\sigma_i},$$

where $E(r_i) - R_f$ is the excess return of the asset and $\sigma_i$ is the asset’s standard deviation.

From the mathematical derivation of the Sharpe-ratio it is clear to see that investors prefer to maximize their reward-to-variability ratio to get the highest risk premium per unit of risk imposed by the portfolio. As the Sharpe-ratio uses the portfolio’s total risk as risk measure, it is suited for computing the risk-adjusted performance of well diversified portfolios (Sharpe, 1964). Including the total portfolio risk, the model assumes that the asset's return is normally distributed. Complex financial assets that are not diversified does not always follow such a distribution, and interpretation of the ratio's result may therefore be misleading. For performance measuring purposes, the Sharpe-ratio should be used as information input for investment options rather than an absolute trading rule.

Sharpe (1964) explains the linear relationship between risk and return for an investor considering a portfolio consisting of a risky asset as well as a risk-free asset, referred to as the capital allocation line (CAL). Along the CAL are all possible weighted combinations of the risky and risk-free assets, with different compositions of expected return and standard deviation for the portfolios. Higher returns following the CAL are only possible by enquiring a riskier portfolio profile. Given that there are almost infinite risky assets available of different natures, every one of these assets combined with a risk-free asset forms their own separate CAL.

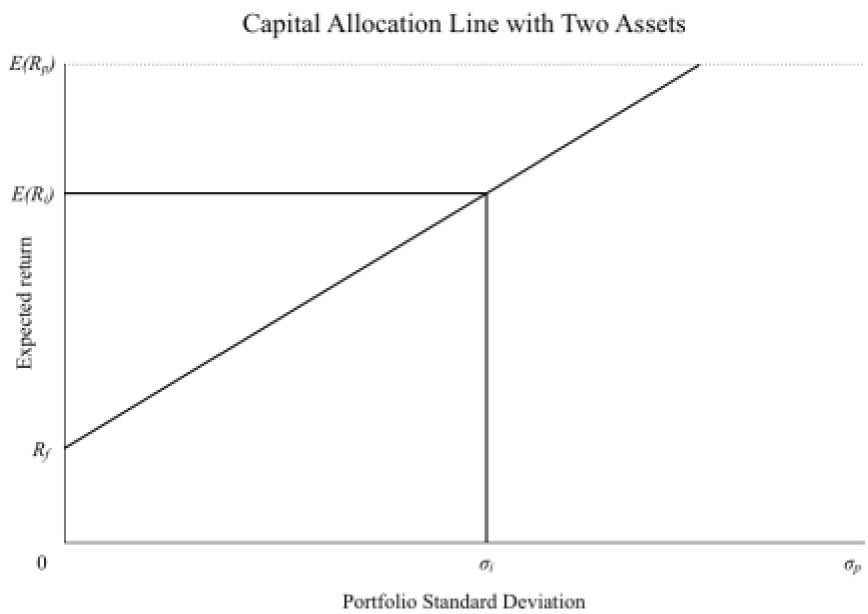

*Figure 1: Capital allocation line with two assets.*

Markowitz (1952) introduced the framework of modern portfolio theory, including the efficient frontier. All portfolios of risky assets representing superior return and risk compositions form the efficient frontier. In other words, the frontier consists of the portfolios with the highest returns at a given level of standard deviation.

Introducing a risk-free asset to the efficient frontier expands the set of opportunities, considering that the risk-free asset yield a given return without any risk parameter involved. Optimizing a portfolio consisting of the risk-free asset as well as a risky asset on the efficient frontier results in the portfolio combination yielding the highest possible return at any level of risk. By drawing a straight line from the return intercept of the risk-free asset that tangent to the efficient frontier of risky assets, we obtain the best possible risk-return relationship possible.

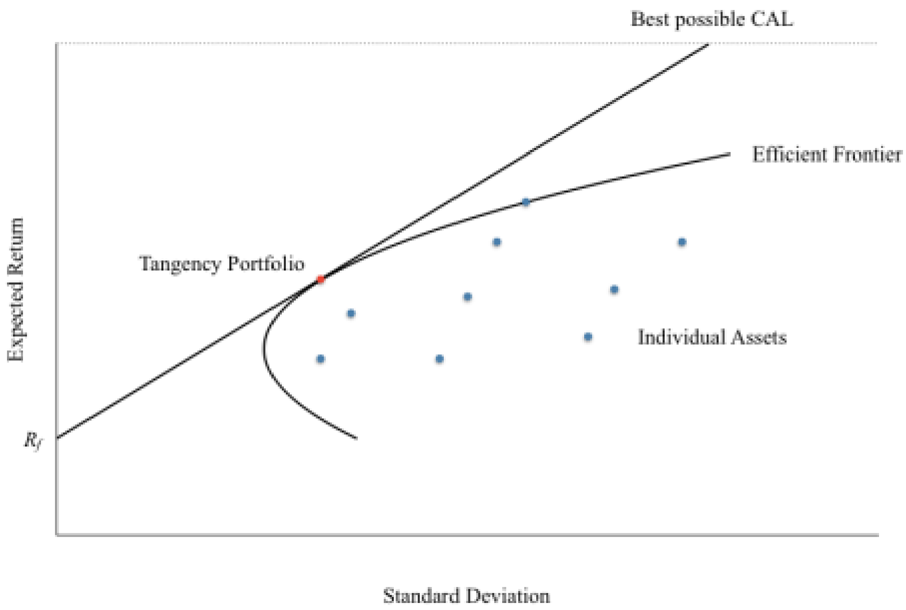


*Figure 2: The efficient frontier.*

A combination of the risk-free asset and the tangency portfolio thus provide the highest CAL, meaning the greatest return compensation per extra unit of risk acquired. This shows why the Sharpe-ratio is a preferable measure of portfolio performance, as maximizing it ensures the optimal portfolio weights of risky and risk-free assets.

Another measure of performance similar to the Sharpe-ratio is the Treynor rate. Although it is comparable to the Sharpe-ratio, the Treynor rate expresses portfolios performance in relation to the systematic risk of the asset, or in other words its β (Treynor, 1965). The two performance ratios contain different definitions of portfolio risk. Because of this the rating of a given set of portfolios may vary from the methods. Investors should therefore be thoughtful of this when interpreting results from the ratios.

### 2.6.2 Student's t-test

Asset performance in terms of the Sharpe-ratio is useful as a comparative measure of multiple assets. Determining statistical significance of variables can add to the evaluation of performance. A t-test can be helpful in judging whether multiple return variables are statistically different from one another. The test got its name from the English statistician William Sealy Gosset in 1908, when he anonymously submitted his statistical findings in a journal of economics under the pen name "Student". Assuming returns follow a normal distribution, the t-test will report if the returns are statistically different from each other, or if the difference is likely to be explained by a random distribution.

Hypothesis testing form the foundation for the t-test. Based on a null hypothesis stating that there is no significant difference between the variables, the t-test determine if the statistical significance of the variables violate the null hypothesis or if it is valid. Generally, a 95% confidence interval is used as a threshold for statistical difference. At this confidence level, statistics state that there is less than a 0,05 chance that the assets' excess returns are due to a random distribution.

### 2.6.3 Jensen's alpha

Both the Sharpe-ratio and the Treynor rate allows investors to measure a portfolio's excess return relative to its risk, and therefore help quantify investment decisions in terms of a reward-to-variability ratio. Neither of the measures focuses on a portfolio manager's ability to predict fluctuations. Jensen (1968) problematize the lack of attention to portfolio manager's performance, and develop a model to evaluate their predictive ability. Portfolio managers' capability of earning returns higher than the returns expected given the portfolio's level of risk are used to determine the level of success. Jensen debated the need of an absolute performance measure, contrary to the relative measures of Sharpe and Treynor, amongst others.

One of the main problems with the performance measures of Sharpe and Treynor is that the varying definitions of riskiness may cause troubles for investors when interpreting results. Ranking of performance become a result of defining performance variables instead of pure performance.

Jensen's alpha is a measure of the difference in actual returns compared to the expected return given the capital market line. Any portfolio yielding a higher (lower) return than estimated by the portfolio's riskiness, will have a positive (negative) alpha. Consequently, alpha is a measure of risk adjusted performance suited to rate absolute performance. The higher the alpha, the bigger the difference between actual and expected return of a portfolio, and vice versa. Jensen's alpha is formulated as:

$$\alpha_i = R_i - \left[R_f + \beta_i\left(R_m - R_f\right)\right]$$

where $R_i$ is the actual return of a portfolio, $R_f$ is the risk-free rate, $\beta_i$ is the systematic risk of the portfolio and $R_m - R_f$ is the excess return of the market. The expression in the brackets indicate the capital market line of the portfolio.

# 3 Methodology

## 3.1 Data collection

Quantitative analyses require large data sets to be representative and significant. This paper uses daily historical stock price data from Oslo Stock Exchange from January 1996 to December 2015. Stock prices are used to calculate daily logarithmic returns. In total, 5018 observations of data are included, which should be sufficient for the analysis. The data includes all companies that have been listed on Oslo Stock Exchange during the sample period. In addition, accounting data of all firms are used to compute the necessary fundamental key figures for calculating the factor mimicking portfolios of SMB and HML. All stock price and accounting data are acquired from the financial database TITLON. TITLON is developed as a collaboration between several institutions in Norway.

The specific sample period is chosen because of available accounting data. Being that all companies listed in the period are included in the data material, the paper is not object of data selection biases. However, it is worth noticing that Oslo Stock Exchange is a relatively small market, and the total trading volume is rather small and may vary a lot in different stocks. This leads to different sensitivities to trading volume, which may affect short time price changes.

The benchmark market index used to assess portfolio performance and to compute the market factor is the OSEBX. The preferred benchmark portfolio that holds a representative selection of all listed stocks on Oslo Stock Exchange, ensuring that it reflects the actual market as best as possible. Historical prices of the benchmark index from the sample period are obtained from Oslo Stock Exchange.

### 3.1.1 Risk-free rate

The risk-free rate included in the model are estimated forward looking overnight borrowing rate from January 1996 to December 2015. Daily interest rate estimates are obtained from Ødegaard (2017).

Despite of the interest rate being relatively small, it is an important aspect of the pricing model, as a measure of market and portfolio excess return.

### 3.1.2 Accounting data

Stock price data from Oslo Stock Exchange were available for downloading from TITLON and included fully adjusted prices. However, the accounting data for all companies listed in the sample period was not aggregated with a usable interface. By merging all accounting data into preconditioned definitions for the different sectors and time periods, I could compose factor-mimicking portfolios of size and value by accessing important key figures.

The TITLON database now includes both the momentum factor portfolio, as well as the benchmark portfolios of size and value required to obtain the factor mimicking portfolios for the factor effects. Accounting data for every firm listed on Oslo Stock Exchange in the sample period are also available.

## 3.2 Constructing portfolios representing return anomalies

### 3.2.1 Calculating the size and value factor

The size and book-to-market factors presented by Fama and French (1993) are created from different size and book-to-market benchmark portfolios. Various portfolios are created by using pre-set breakpoints for both size and BE/ME. Two size portfolios, describing the buy scope of small and big portfolios, are formed around the median market equity. All stocks under the median are included in the small portfolio, while the stocks over the median are put in the big portfolio.

Book-to-market portfolios are constructed in three levels, parted by the $30^{th}$ percentile and the $70^{th}$ percentile. This gives a high, medium and low portfolio of stocks rated by their BE/ME. Fama and French categorizes high BE/ME stocks as value stocks, medium BE/ME stocks as neutral stocks and low BE/ME stocks as growth stocks. Combined with the two size portfolios, the result is six portfolios of different size and book-to-market ranges of stocks (French, 2017).

| | Median ME | |
|---|---|---|
| | Small Value | Big Value |
| 70th BE/ME percentile | | |
| | Small Neutral | Big Neutral |
| 30th BE/ME percentile | | |
| | Small Growth | Big Growth |

*Figure 3: Benchmark portfolios of size and book-to-market equity.*

The size factor is represented by the average returns of the three small portfolios minus the average returns of the three big portfolios.

$$SMB = \frac{1}{2}(SMALL_{VALUE} + SMALL_{NEUTRAL} + SMALL_{GROWTH}) \\ - \frac{1}{2}(BIG_{VALUE} + BIG_{NEUTRAL} + BIG_{GROWTH})$$

The book-to-market factor is constructed similarly to the size factor, except the fact that only the value stocks and growth stocks are represented. Stocks with neutral BE/ME are taken out of the equation, as an approach to explain the effect. By calculating the difference in average returns of the two value portfolios minus the two growth portfolios we get the book-to-market factor.

$$HML = \frac{1}{2}(SMALL_{VALUE} + BIG_{VALUE}) - \frac{1}{2}(SMALL_{GROWTH} + BIG_{GROWTH})$$

Neither of the six benchmark portfolios take hold ranges into account. Transaction costs are not included either.

### 3.2.2 Calculating the return momentum factor

Fama and French (1993) computes the momentum factor by accounting for firm size and previous 2- to 12-month returns. By using six value weight portfolios, where two are formed on size and three are formed on previous returns, the intersections of these portfolios form different portfolios with different size and return attributes (French, 2017).

| | Median ME | |
|---|---|---|
| | Small High | Big High |
| 70th return percentile | | |
| | Small Neutral | Big Neutral |
| 30th return percentile | | |
| | Small Low | Big Low |

*Figure 4: Benchmark portfolios of size and previous returns.*

The size factor is measured using a firm's market equity. Firms are thereafter divided in three categories ranking their recent previous returns. The top 30% will form the high return portfolio, while the bottom 30% form the low return portfolio. To measure the spread of momentum returns, the medium returns portfolio is cancelled out. Finally, the portfolio representing the momentum factor is constructed as the average of the two high return portfolios minus the average of the low return portfolios. In other words, the portfolio display the average returns of past winners minus past losers.

$$WML = \frac{1}{2}(HIGH_{BIG} + HIGH_{LOW}) - \frac{1}{2}(LOW_{BIG} + LOW_{SMALL})$$

## 3.3 Trading strategy

To test the efficiency of Oslo Stock Exchange regarding the anomalies of size, value and momentum, this paper evaluates the performance of an optimal portfolio of the factor mimicking portfolios compared to the performance of the benchmark index of the market. The sample period is divided into smaller sub-periods to further verify the consistency of the factor effects. Since the entire data set consist of 20 years of daily stock notations, the sub-periods will be divided into 10 years each. Sub-period 1 will include data from 02.01.96 – 30.12.05. In total, there are 2508 observations in sub-period 1. Sub-period 2 consists of data from 02.01.06 – 30.12.15, with a total of 2510 observations. The slight difference in total observations is explained by the number of trading days on Oslo Stock Exchange in the two periods.

The weights of the optimal portfolio of the anomalies will be based on the first sub-period variance-covariance matrix and average returns. The portfolio in the subsequent period will be weighted equally as the first period optimal portfolio to study the stability of the factor effects. Comparing the weights of the composed second sub-period portfolio performance to the weights of the optimal portfolio in the same sub-period will shed some light on the persistency of the performance of the different factor effects.

Following the Markowitz (1952) framework, the efficient frontier of the factor mimicking portfolios is calculated by composing different weighted portfolios of the factor effects and maximizing their Sharpe-ratio.

# 4 Data analysis and results

This chapter will discuss the performance of the above anomalies of size, value and momentum on Oslo Stock Exchange. An evaluation of the trading rule presented in chapter 3.2 will follow, with descriptive statistics of the different assets. A review of some basic statistics will be presented for the sample period overall, as well as for the sub-periods. This helps evaluate the consistency of the factor effects. To determine the statistical significance of the results, a t-test is performed.

## 4.1 Factor independency

The correlation coefficient describes the statistical dependency of numerical variables. The coefficient can range from -1 to 1. A correlation coefficient of 1 entail that the variables movements resemble each other perfectly, while -1 expresses a perfectly negative relationship between the variables. This means that when one variable increase by one unit, the other variable will decrease by the same amount. Statistically, a correlation coefficient close to zero illustrate that there is no apparent relationship between the variables, expressing that the variables move independent of one another.

Mathematically the correlation coefficient is stated as:

$$\rho_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y},$$

where *cov(x,y)* is the covariance of asset x and y and $\sigma_x \sigma_y$ are the assets standard deviations.

The daily returns correlation coefficients of the factors are:

*Table 1: Correlation coefficient of daily factor returns.*

| | SMB | HML | WML |
|---|---|---|---|
| **SMB** | 1, | | |
| **HML** | -0,07758 | 1, | |
| **WML** | 0,00791 | 0,22576 | 1, |

When tested for factor correlation, no coefficients express a strong relationship, although the

HML and WML portfolios indicate a positive relation of approximately 0,22. Size and value also report a negative correlation. Although not significant, this is highlighted in the variation from sub-period 1 to sub-period 2. These statistics emphasize the factors independency, according with the theory presented earlier in this paper. The evidence therefore points to the fact that return effects of size, value and momentum on Oslo Stock Exchange are all explained by different risk factors.

### 4.1.1 Factor correlation's sensitivity to periodic changes

The correlation coefficients of portfolios' daily returns suggest very low correlation between the different factors. By altering the period of the returns to express weekly or monthly summed returns, the correlation coefficients may change as well. Larger periods will not be as affected by extreme values that may occur on daily returns, as larger periods mainly demonstrate the periodic tendency of the returns. Because of this, correlation coefficients should increase. The below tables report factor correlation of weekly and monthly summed returns:

*Table 2: Correlation coefficient of weekly factor returns.*

| | SMB | HML | WML |
|---|---|---|---|
| **SMB** | 1, | | |
| **HML** | 0,00894 | 1, | |
| **WML** | -0,03667 | 0,32873 | 1, |

Weekly return correlation illustrates how the relationship between factors adjust to periodic changes. There is no definite change that affect all factors. The correlation between HML and WML has increased to approximately 0,33, which indicate a weakly significant relationship. The relationship between SMB and HML is now marginally positive, despite being negatively related when assessing daily returns. Weekly correlation of SMB and WML has a negative value, compared to a positive value when calculating daily returns. Both the relationship between SMB and HML, as well as SMB and WML report insignificant values, representing that the factors have no impact on each other.

*Table 3: Correlation coefficient of monthly factor returns.*

| | SMB | HML | WML |
|---|---|---|---|
| **SMB** | 1, | | |
| **HML** | 0,00577 | 1, | |
| **WML** | -0,15311 | 0,2603 | 1, |

Assessing monthly correlation coefficients, results demonstrate similar modifications as weekly correlation, when compared to daily correlation coefficients. Although factor correlation demonstrates a stronger relationship when assessing weekly or monthly returns, daily returns offers a more accurate representation of the data.

## 4.2 Sample period summary statistics

Summary statistics for the sample period is presented in the table below. This simple analysis includes average returns, variances and standard deviations for the benchmark index, the risk-free asset and the size, value and momentum factors. All values are calculated at daily rates.

*Table 4: Sample period overall summary statistics.*

| | OSEBX | RF | SMB | HML | WML |
|---|---|---|---|---|---|
| Average return | 0,000360445 | 0,000154387 | 0,000094003 | 0,000774928 | 0,000436541 |
| Variance | 0,000209444 | 7,81923E-09 | 0,000101671 | 0,00013545 | 0,000157032 |
| Standard deviation | 0,014472194 | 0,0000884264 | 0,010083213 | 0,011638313 | 0,012531249 |

We clearly see that the value and momentum portfolio has yielded superior average returns in the sample period when compared with the OSEBX benchmark index. The size effect also has positive mean returns in the sample period, although lower than the market index. Portfolio standard deviations of all three factors have lower mean values than that of the index. This entails that there is a relatively small variation in the returns of the portfolios.

The portfolio capturing the value effect seems to be statistically superior to the other portfolios and the market index both when assessing average returns and standard deviation. HML has an average daily return of almost 0,0008 in the sample period. The lowest average daily return yielded comes from SMB, with approximately 0,0001. Over the entire sample period, the size effect actually has lower average daily return than the risk-free asset. As discussed above, traditional economic theory states that increased returns should come at the cost of a relative increase in risk taken by the investor. The summary statistics from the factors indicate that this simple risk-reward view on returns obviously does not hold. Only the SMB portfolio has a lower standard deviation than HML, while HML significantly outperforms all the assets evaluated in terms of average returns. Even though the size portfolio report a lower standard deviation than the value portfolio, the relationship between risk and return is considerably stronger for the value effect.

When judging factor portfolio based on these simple statistics, there is a need for a risk-adjusted measure of performance, as discussed in chapter 2.6. Calculating the Sharpe-ratio of the assets give a clear indication of their performance relative to their respective risk levels and adjusted for the risk-free rate.

*Table 5: Sample period individual sharpe-ratios.*

| | **OSEBX** | **SMB** | **HML** | **WML** |
|---|---|---|---|---|
| Sharpe-ratio | 0,01424 | -0,00599 | 0,05332 | 0,02252 |

Results of the Sharpe-ratio calculation clearly reveal the superior performance of the value portfolio. Per extra unit of risk, the expected return is almost four times as high as OSEBX. The Sharpe-ratio of the size portfolio is negative because the portfolio's average return in the sample period is negative when adjusting for the risk-free rate.

The t-test of the individual factor portfolios evaluate if there is a significant difference between the anomalies and the excess return of the market. Anomalies are tested at a 95% confidence interval, requiring a p-value < 0,05 for results to be significant. Results are reported in table 6.

*Table 6: Sample period t-test results of individual anomaly portfolios to excess market return.*

| | **SMB** | **HML** | **WML** |
|---|---|---|---|
| P-value | 0,32640 | 0,01504 | 0,19694 |

As implied by the summary statistics from the sample period, the value anomaly stands out as the only factor effect significantly different from the excess return of the market. With a p-value < 0,05 it is well within the threshold of significance in the 95% confidence interval. Neither the size or momentum effect are statistically different from the excess market return in the overall sample period.

### 4.2.1 Sub-period 1 summary statistics

As with the sample period overall, summary statistics from the smaller sub-periods includes some interesting statistical inferences. The sub-periodic statistics for sub-period 1 and sub-period 2 will mainly express some of the variety in average returns. This is because factors show stronger/weaker effects from one period to another.

*Table 7: Sub-period 1 summary statistics.*

| | **OSEBX 1** | **RF** | **SMB** | **HML** | **WML** |
|---|---|---|---|---|---|
| Average return | 0,000479065 | 0,000205391 | 0,000243608 | 0,000600709 | 0,000028686 |
| Variance | 0,000143559 | 6,66252E-09 | 0,0000960898 | 0,000173565 | 0,000162546 |
| Standard deviation | 0,011981624 | 0,0000816243 | 0,009802538 | 0,013174389 | 0,012749369 |

As with the sample period overall, the value portfolio has the highest average daily returns in sub-period 1, with a mean value of 0,0006. Contrary to the statistics of the sample period, the momentum portfolio has the lowest average return of the portfolios measured. As the size portfolio in the sample period overall, the momentum portfolio yields a return much lower than the risk-free asset in the first sub-period. The benchmark index outperforms both the size and momentum portfolio in sub-period 1 in terms of average return.

Regarding the standard deviations, HML report the highest variability in returns. OSEBX has a lower risk than WML, in addition to yielding higher average returns.

*Table 8: Sub-period 1 individual sharpe-ratios.*

| | **OSEBX 1** | **SMB** | **HML** | **WML** |
|---|---|---|---|---|
| Sharpe-ratio | 0,022841138 | 0,003898648 | 0,030006536 | -0,01385993 |

Judging by the sub-period 1 Sharpe-ratio of the assets, the same conclusion can be drawn. The value portfolio beats the other factor effects, as well as the market index when assessing risk-adjusted returns in sub-period 1.

*Table 9: T-test results for indivudual anomaly portfolios in sub-period 1.*

| | SMB | HML | WML |
|---|---|---|---|
| P-value | 0,47361 | 0,17604 | 0,25171 |

The t-statistics for sub-period 1 indicate that neither of the individual anomalies are statistically significant. Interpreting results based on statistics therefore imply the anomalies' returns in the sub-period are due to random distribution.

#### 4.2.2 Sub-period 2 summary statistics

*Table 10: Sub-period 2 summary statistics.*

| | OSEBX 2 | RF | SMB | HML | WML |
|---|---|---|---|---|---|
| Average return | 0,000241919 | 0,000103424 | -0,000055483 | 0,000949009 | 0,000844071 |
| Variance | 0,000275249 | 3,77842E-09 | 0,000107203 | 0,0000973059 | 0,00015119 |
| Standard deviation | 0,016590626 | 0,0000614689 | 0,010353911 | 0,009864374 | 0,012295939 |

Sub-period 2 statistics also manifest the value portfolio as superior compared to the other effects and the market index. Yielding an average return of 0,00095 with a standard deviation marginally under 0,01, no other asset comes close to the risk adjusted returns of the HML portfolio. Summary statistics of the momentum portfolio express a drastic increase in the difference in momentum returns from the first sub-period to the second. The risk measured by its standard deviation is approximately equal to the first sub-period, but the average return of the portfolio has increased remarkably to 0,00084.

OSEBX statistics indicate a lower average return compared to sub-period 1 with a higher risk. This may be caused by the financial crisis of 2007, that strongly affected the Norwegian security market, especially in 2008.

*Table 11: Sub-period 2 individual sharpe-ratios.*

| | OSEBX 2 | SMB | HML | WML |
|---|---|---|---|---|
| Sharpe-ratio | 0,008347796 | -0,015347573 | 0,085721061 | 0,060235063 |

The calculated Sharpe-ratios for sub-period 2 essentially report the difference in performance between the sample period overall and the first sub-period. It is interesting to see, however, that the value portfolio seems to perform well in both sub-periods. Over the 20 years tested, the Norwegian security market have experienced both bull and bear markets, financial crises of different magnitudes etc. It is quite clear how this has affected both the market index and the momentum portfolio, but the value effect seems to be somewhat consistent.

*Table 12: T-test results for individual anomaly portfolios in sub-period 2.*

| | SMB | HML | WML |
|---|---|---|---|
| P-value | 0,30969 | 0,01776 | 0,04355 |

In contrast to sub-period 1, where none of the factor effects where significantly different from the excess market return, both the value and return momentum anomalies are statistically significant at a 0,05 level in sub-period 2. The size effect shows no indication of statistical significance in either of the two sub-periods or in the overall sample period.

## 4.3 Results

As explained in chapter 3.2, the test on market efficiency will consist of comparing the performance of the factor effects to the performance of the benchmark index. Based on the covariance matrix of the factor portfolios in the first sub-period, the optimal weights of the assets were calculated in order to obtain the optimal portfolio consisting of SMB, HML and WML in sub-period 1 (hereafter known as $p_1^*$). The weights of $p_1^*$ will be the foundation of the portfolio constructed in sub-period 2, and the results of the portfolio will be compared to the benchmark index. When assessing performance, the Sharpe-ratio is the preferred measure.

### 4.3.1 Sample period optimal portfolio of SMB, HML and WML

I have calculated the efficient frontier of the factor portfolios in the sample period following the Markowitz framework for portfolio optimization. The front represents the best returns possible at any given level of risk by combining the portfolios of size, value and momentum. The individual assets are plotted as well, in addition to the benchmark index and the risk-free rate.

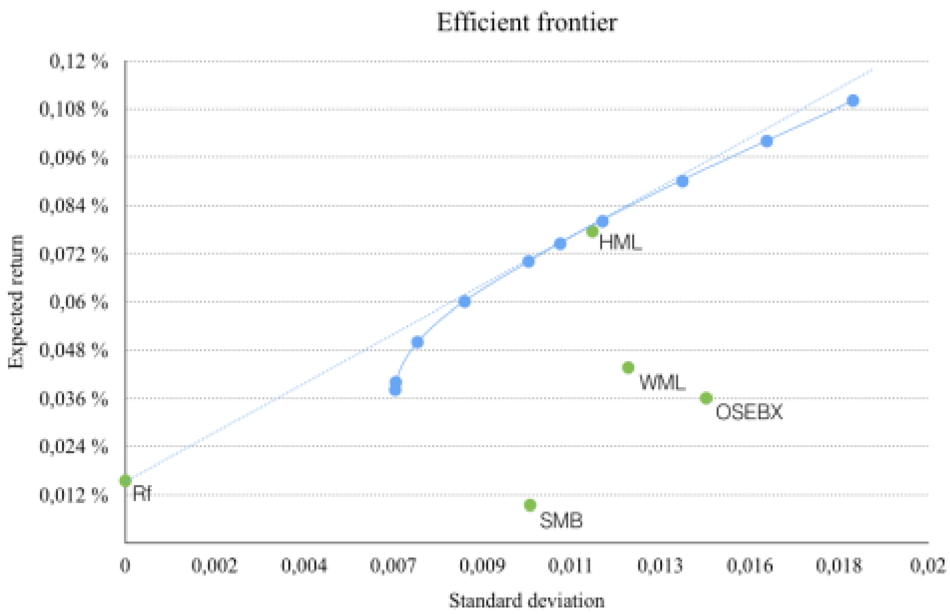


*Figure 5: Summary statistics and the efficient frontier of SMB, HML and WML.*

The frontier clearly picture the potential excess return over the market index. Given the standard deviation of the benchmark index, the expected return is more than doubled for the best portfolio constructed of size, value and momentum. At the same time, we can reduce the risk substantially at the same level of return, compared to the market index.

The optimal portfolio for the sample period overall is the tangency portfolio of the risk-free rate and the efficient frontier. With a Sharpe-ratio of 0,0544, the sample period optimal portfolio clearly outperforms the benchmark index, whose Sharpe-ratio is 0,0142.

However, calculating the efficient frontier of a set of assets and comparing to the benchmark index will have limited performance measuring effects. The assets in the front are dynamic, and the front may therefore change from one period to another. Another important note is that the front is based on historic data. To obtain an excess return of the magnitude the front entails in the sample period, investors must obtain and hold a perfectly weighted portfolio prior to the period, which obviously is not realistic.

Investors may however obtain the optimal weights of a portfolio from the past period and construct a portfolio to hold in the coming period. If the factor effects are consistent, the portfolio statistics should vary minimally from one period to another. From the summary statistics of the two sub-periods we see that the factor effects change, but the variation in size and value effect seems to be negatively related. This counteracting effect may contribute to stabile results.

### 4.3.2 Sub-period 1 optimal portfolio

Based on the data from sub-period 1, the sub-period 1 optimal portfolio ($p_1^*$) of size, value and momentum is calculated. The test is completed twice, with one major modification, being a short-sale constraint. By adding this constraint, the portfolio is limited to hold only long positions in any of the three factor portfolios. When constructing $p_1^*$ without the short-sale constraint, individual asset weights may be negative. This allows investors to potentially profit from negative periodic returns of an asset. Short-selling may also be a method of lowering the total risk of a portfolio.

As the liquidity of the assets proposed in this thesis is uncertain, it will be speculative to assume there is a fully efficient market for short selling these assets. The assumption of short selling may however offer a more comprehensive overview of the potential returns of the factor effects in the Norwegian security market and is therefore included.

#### 4.3.2.1 Imposed short-selling and gearing constraint

Maximizing the Sharpe-ratio of the portfolio with the constraints that $\sum w_i = 1$ and that $w_i >= 0$, where $w_i$ is the asset weight, gives $p_1^*$ with short-selling and gearing constraints. The weights of $p_1^*$ given these restrictions are:

*Table 13: Restricted sub-period 1 optimal portfolio weights.*

| *Portfolio weights of $p_1^*$* | |
|---|---|
| SMB | 0,2457 |
| HML | 0,7543 |
| WML | 0,0000 |

Assuming a short-selling constraint, the momentum portfolio is not included in the optimal factor portfolio. The value factor make up 75,43% of the portfolio, making it the dominant asset of $p_1^*$.

The statistics of $p_1^*$ is reported below, with a comparison to the benchmark index of sub-period 1. Key figures from sub-period 1 indicates that there is a rather modest difference in performance, although the benchmark is slightly weaker than $p_1^*$.

*Table 14: Sub-period 1 restricted optimal portfolio and benchmark statistics.*

| | **$P_1^*$** | **OSEBX 1** |
|---|---|---|
| Average return | 0,000512 | 0,000479 |
| Standard deviation | 0,009950 | 0,011982 |
| Sharpe-ratio | 0,030913 | 0,022841 |

Daily averages illustrate that $p_1^*$ is expected to generate a return of 0,00051, compared to the market return of 0,00048. The risk level, in terms of standard deviation, is also marginally lower for $p_1^*$ as opposed to the market benchmark.

#### 4.3.2.2 Allowed short-selling and gearing

Assuming a fully efficient market with the possibility of short-selling as well as increasing the gearing of certain assets, the weights of $p_1^*$ drastically change. The weights are given in the table below:

*Table 15: Non-restricted sub-period 1 optimal portfolio weights.*

| *Portfolio weights of $p_1^*$* | |
|---|---|
| SMB | 0,3966 |
| HML | 1,4785 |
| WML | -0,8751 |

As the value effect is the most prominent in sub-period 1, this portfolio is heavily geared in $p_1^*$ without short-selling and gearing restrictions. At the same time, we observe that the momentum portfolio is weighted negatively, implying a short position. This geared and shorted position allows investors to increase (decrease) their exposure to assets that are expected to perform well (bad), and therefore increase their return margins.

*Table 16: Sub-period 1 non-restricted optimal portfolio and benchmark statistics.*

| | **$P_1^*$** | **OSEBX 1** |
|---|---|---|
| Average return | 0,000960 | 0,000479 |
| Standard deviation | 0,020686 | 0,011982 |
| Sharpe-ratio | 0,036463 | 0,022841 |

Imposing the constraints obviously affect the risk and return aspects of $p_1^*$. As discussed above, gearing of the value factor increases investors exposure to the abnormal return effect of the value anomaly in sub-period 1. This in turn leads to a higher average return of $p_1^*$ compared to the benchmark index of the market. We can see that the daily average return of $p_1^*$ without short-sale and gearing restrictions is 0,00096, as opposed to 0,00051 with the restrictions. The risk of the portfolio has increased to 0,02. Geared portfolios often lead to an increase in portfolio risk, as the increased leverage generally comes from lending. However, the Sharpe-ratio of $p_1^*$ without constraints is 0,036, which is an increase from the Sharpe-ratio of $p_1^*$ with constraints. This is an indicator that investors will get higher risk-adjusted returns by utilizing the short-selling and gearing opportunities.

#### 4.3.2.3 Optimal portfolios in sub-period 1

From chapter 4.2.2.1 and 4.2.2.2 we can conclude that the optimal portfolio of sub-period 1 deviates depending on different constraints. When allowing the possibility of short positions as well as gearing, the potential profits increase. For a visual comparison of the two optimal portfolios, figure 6 illustrate the risk-return relationship of the optimal portfolios as well as the individual factor effects and the benchmark index for sub-period 1.

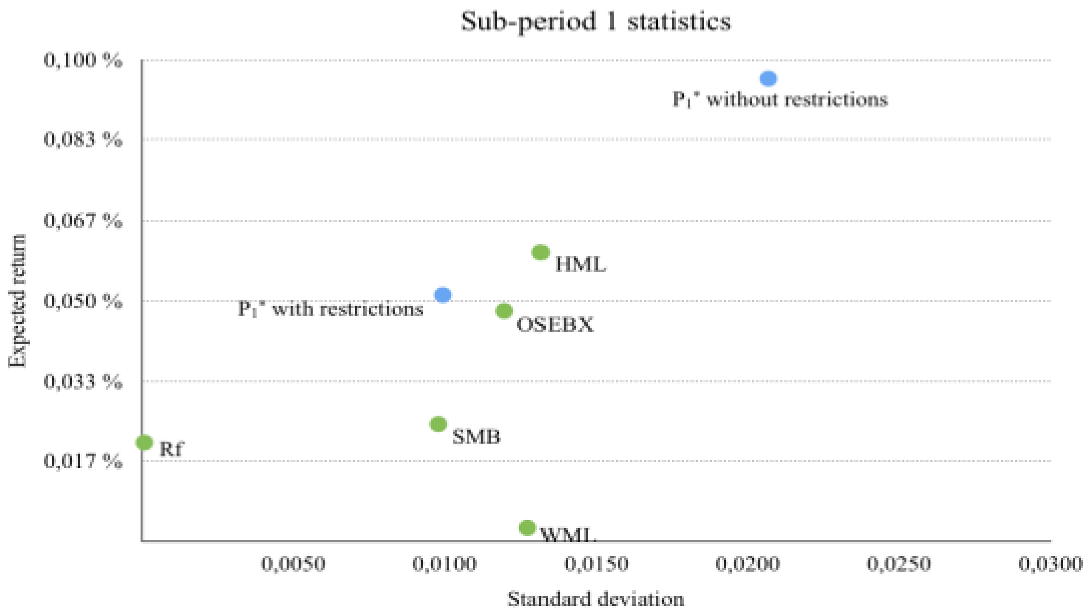


*Figure 6: Sub-period 1 return statistics.*

### 4.3.3 Implementing sub-period 1 optimal portfolios in sub-period 2

Market efficiency will be tested based on the optimal portfolios constructed from sub-period 1. By applying sub-period 1 optimal weights of the restricted and non-restricted portfolio in sub-period 2, we will be able to test the performance of the optimal portfolios in the following sub-period.

#### 4.3.3.1 Restricted optimal portfolio

The weights of the restricted optimal portfolio are given in table 13. By constructing a portfolio using the given weights, I will test the hypothesis that the returns of the restricted $p_1^*$ yield significantly higher returns than the benchmark index of the market in the second sub-period. The statistics of the restricted $p_1^*$ in sub-period 2 is given in the below table:

*Table 17: Sub-period 1 restricted optimal portfolio and sub-period 2 benchmark statistics.*

| | **Restricted $p_1^*$** | **OSEBX 2** |
|---|---|---|
| Average return | 0,000702211 | 0,000241919 |
| Std dev portfolio | 0,007788543 | 0,016590626 |
| Sharpe-ratio | 0,076880422 | 0,008347796 |

The constructed portfolio report a daily average return of 0,0007, compared to the benchmark index's return of 0,00024. Average returns' standard deviation for the portfolio also has a lower value than that of the benchmark. When adjusted for the sub-period 2 average risk-free rate, the portfolio noticeably outperforms the market benchmark in the sub-period.

#### 4.3.3.2 Non-restricted optimal portfolio

The optimal portfolio allowing for short-selling and gearing were notably different weighted than the restricted portfolio. Individual asset weights can be found in table 15 Statistics from the non-restricted $p_1^*$ are reported in the table below, in addition to the benchmark statistics in sub-period 2:

*Table 18: Sub-period 1 non-restricted optimal portfolio and sub-period 2 benchmark statistics.*

| | **Non-restricted $P_1^*$** | **OSEBX 2** |
|---|---|---|
| Average return | 0,000642436 | 0,000241919 |
| Std dev portfolio | 0,009567761 | 0,016590626 |
| Sharpe ratio | 0,056336233 | 0,008347796 |

Daily average return of the non-restricted optimal portfolio in sub-period 2 is 0,00064. In comparison to the benchmark, the non-restricted $p_1^*$ is superior both when assessing risk and return. The risk-adjusted performance of the portfolio is considerably higher than the benchmark for the sub-period.

### 4.3.4 Evaluation of performance

Figure 7 visually describes the risk-return relationship of the two optimal portfolios constructed from sub-period 1 compared to sub-period 2 statistics of the factor effects, benchmark and efficient frontier of SMB, HML and WML.

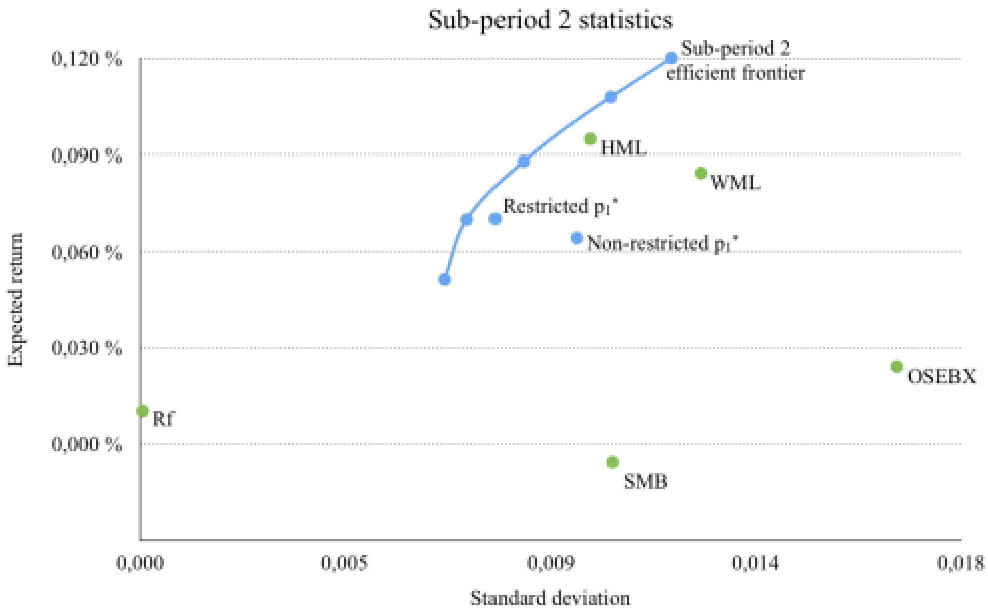


*Figure 7: Sub-period 2 return statistics.*

The chart clearly illustrates how both the created portfolios outperform the benchmark in terms of risk and returns. The restricted $p_1^*$ is close to the efficient frontier for sub-period 2, demonstrating that there are few combinations of HML, SMB and WML that are superior. Furthermore, the benefits of diversification have noticeably affected the risk-return relationship of the restricted $p_1^*$. Although the created portfolio is simply a combination of HML and SMB, figure 7 shows that the portfolio's standard deviation is distinctively lower than the standard deviations of the individual assets.

The reward-to-variability ratio of the two optimal portfolios constructed is greater than that of the index in sub-period 2.

*Table 19: Optimal portfolios' sharpe-ratios in sub-period 2.*

| | **OSEBX 2** | **Restricted $P_1^*$** | **Non-restricted $P_1^*$** |
|---|---|---|---|
| Sharpe-ratio | 0,008347796 | 0,076880422 | 0,056336233 |

Evaluating performance solely based on risk-adjusted returns, both constructed portfolios beat the market index in sub-period 2. Results of the Sharpe-ratios describe the expected increase in return per extra unit of risk for the individual asset.

However superior these risk-adjusted measures of performance may seem, it is vital to test their statistical significance. A simple t-test will determine the significance of the optimal portfolios' excess return over the benchmark index of the market. The results will highlight the probability of obtaining results statistically different the benchmark index.

*$H_0$: There is no significant difference between the returns of the optimal portfolios and the return of the benchmark index in sub-period 2.*

*$H_A$: There is a significant difference between the returns of the optimal portfolios and the return of the benchmark index in sub-period 2.*

Daily returns of both portfolios as well as the benchmark index are the basis of the t-test. The test is performed at a 95% confidence level. This entails that the t-test must have a p-value < 0,05 for the null hypothesis to be rejected. Results of the t-test are reported below:

*Table 20: T-test results of optimal portfolios in sub-period 2.*

| | **Restricted $P_1^*$** | **Non-restricted $P_1^*$** |
|---|---|---|
| P-value | 0,104241904 | 0,189262035 |

Both the restricted or the non-restricted optimal factor portfolios report p-values > 0,05. At this level of confidence, the null hypothesis is accepted, meaning that the abnormal excess returns of the two portfolios is not significantly different to the return of the benchmark index.

Performance in terms of the risk-to-variability ratio is far superior for both constructed portfolios when compared to the market benchmark. The statistical significance of these results, however, is not satisfactory at the given level of confidence. Results of the t-test suggests that the portfolios' excess returns are due to a random distribution. The p-values state that there is a 10,4% and 18,9% probability of results to be explained by a random distribution of the benchmark index for the restricted and non-restricted portfolio respectively. There is no significant difference between the portfolios' returns and the returns of the benchmark index.

# 5 Discussion and conclusion

## 5.1 Discussion

This paper has studied the effects of well-established return anomalies on Oslo Stock Exchange in the period 1996-2015. Following the methods introduced in Fama and French (1993) and Jegadeesh and Titman (1993) portfolios representing the size, value and return momentum factors have been computed to further analyse their ability to predict abnormal future returns. The sample period was then divided into two equally small sub-periods, where sub-period 1 were used to observe the effects and sub-period 2 was the test period. Results of the first sub-period laid the foundation for the trading rule on which the test of efficiency was built on.

All tests and analyses are performed on daily logarithmic return variables. An issue that may occur when working with daily data is that some extreme observations potentially may lead to the appearance of noise in the data set. This can consequently corrupt the data set and cause misleading test results. I have not corrected for potential outliers in the data set to ensure the analyses are performed as accurately as possible, with no data manipulation.

Based on the individual factor portfolios in sub-period 1, the optimal portfolio of SMB, HML and WML were found. To add to the explanation of possible arbitrage opportunities due to factor effects, the optimal factor portfolio is constructed both with and without restrictions of short-selling and gearing. In theory, short-selling and gearing may increase possible returns margins and lower the portfolio's risk if done properly. Implementing the sub-period 1 optimal weights in sub-period 2 allowed me to test the persistency of factor effects, as well as defining an easily repeatable strategy for comparison to a benchmark index. The return statistics of the constructed portfolios were compared to the benchmark and a test for statistical significance were performed.

Return statistics of the sample period demonstrates the abnormal returns offered by the anomalies. Both the HML and WML portfolios report daily average returns far superior to the benchmark index of the market over the 20-year period. Assessing the risk-adjusted performance of these factors relative to the benchmark further proves their dominance. However, the SMB portfolio reported returns closer to zero. When tested for significance, SMB reported p-values far above the threshold level in both sub-periods as well as the overall sample period. This is consistent with the results of Fama and French (2012), who finds no apparent size effect on returns in international stocks. The fact that there are no apparent size effect present is not too surprising, given that many academics have had difficulties obtaining the same size related return results as the original study by Banz (1981). When sorting HML and WML portfolios after size, I found a negative relationship between firm size and returns. Although not significant, these results are consistent with Fama and French (2012). However, I cannot say with certainty that there is a size effect in HML and WML returns for the sample period tested.

The sample period reported t-statistics for the individual anomalies determining their statistical significance. Although both the HML and WML portfolios outperform the market index in a risk and return perspective, only the HML is significant at a 0,05 level. Consequently, this paper cannot confirm abnormal return momentum effects in the sample period. The value anomaly, however, is significantly apparent in the overall sample period.

When assessing the statistics of the two sub-periods individually, differences in average returns emphasizes the variability in WML and SMB. WML report a return close to zero in sub-period 1, while yielding notably higher returns in sub-period 2. SMB has the opposite evolution, from a positive daily average return in sample-period 1 of 0,0002 to a negative return in sample period 2. Only HML seems to consistently yield positive excess returns compared to the market index. The t-test for the two sub-periods indicates that none of the anomalies are present in sub-period 1, while both the value and return momentum factor are significant in sub-period 2.

Both the restricted and non-restricted optimal portfolio are heavily invested in HML, which is the main source of the abnormal returns yielded in sub-period 2. The restricted portfolio yields a higher return than the non-restricted portfolio and the benchmark index, even though it reports a lower standard deviation. The non-restricted portfolio also outperforms the benchmark index both in a risk and return perspective, given the assumption of short-selling and gearing individual assets in the portfolio. Calculating the efficient frontier of the factor effects in sub-period 2 gave a visual evaluation of how well the constructed portfolios performed compared to the maximum potential.

Because of the rather modest scope of this paper, a simplified test had to be used. It would have been interesting to see how a similar trading strategy would have performed if the sub-periods were smaller. With the somewhat large sub-periods defined in this paper, factor effects of SMB and WML showed a relatively big variability.

Due to the weak return momentum performance in sub-period 1, neither of the constructed portfolios include long positions in WML. The non-restricted portfolio has a large short-sell position in WML, representing 87% of the total investment. As mentioned above, short-selling and increased gearing of individual assets representing return anomalies in this degree is not realistic in a practical matter. However, assuming fully efficient market places for these trades allows greater margins of returns at potentially lower risk levels. Although WML performs well in sub-period 2, the short-position allows investors to gear the long position in HML, explaining the high portfolio returns. The restricted portfolio would probably perform better including WML in sub-period 2 because of the great return reversal displayed. However, as we can see from figure 7, the risk-return relationship of the restricted portfolio is close to the efficient frontier, implying a nearly optimal composition of assets.

The WML return reversal from sub-period 1 to sub-period 2 displays a potential weakness of the trading strategy proposed in this thesis. Although anomaly effects are well documented, the variability may cause unpredicted fluctuations affecting future returns. This has implications on the chosen trading strategy in the matter that the optimal portfolio from a certain period can change depending on how the factor effects are represented in the following period.

Despite the high returns and low risk measures of the portfolio compared to the benchmark index, the statistical analysis revealed that the results were not statistically significant. This entails that there is an insufficient probability for results to be explained by abnormal factor returns, rather than a random distribution of market returns. The threshold for the t-test was a p-value $< 0,05$. Although neither the restricted or non-restricted portfolio reported p-values under the critical values, the p-value of the restricted portfolio is somewhat close at 0,10. It is fair to assume that smaller sub-periods would lead to less variability in factor, possibly increasing the statistical significance of the results.

This thesis uses relative measures of performance as it studies the predictive abilities of return anomalies compared to a benchmark index. Because of the levels of volatility in the underlying assets of the portfolios, the portfolios' alpha would be very small, making it hard to achieve results significantly different from zero. Using an absolute measure of performance such as Jensen's alpha will therefore not be suitable.

Basing the test on daily returns may consequently lead to extreme values affecting the results. However, daily returns give a more correct impression of the actual variation than summed weekly or monthly returns. The daily return correlation coefficients also emphasize the independency of the anomalies. When assessing weekly and monthly returns, the anomalies' dependency of each other increase, contradicting the theoretical foundation stating that the return anomalies represent different risk factors. Fluctuations in one anomaly should not affect the other.

## 5.2 Conclusion

The anomalies of value and return momentum seems to possess some predictive abilities based on the abnormal returns reported in the sample period. Particularly the value anomaly represented by HML achieves abnormal returns on a consistent basis throughout the period in addition to reporting t-test results indicating significance at a 0,05 level in the overall sample period. A relative strength strategy posed by the return momentum of WML also showed abilities to yield significant returns, although not as consistently as HML. T-statistics for the return momentum effect seems to be less significant than the value anomaly, as it is only significant in sub-period 2. The size factor reported returns consistently lower than the market index. When tested for significance, the t-test determined that the size effect is not statistically different from the excess market return. The results of this thesis suggest that there are no apparent abnormal returns related to size effect on Oslo Stock Exchange in the sample period.

The consistent abnormal returns of HML suggest a violation of the semi-strong efficiency on the Norwegian security market. This is substantiated by the test of significance for the overall sample period as well as sub-period 2. A company's book-to-market equity ratio is calculated entirely from publicly available information. This information obviously has some predictive abilities of future returns, implying non-efficient pricing in the period.

The weak-form efficiency is not clearly violated. Although WML reported significant abnormal returns in sub-period 2, sub-period 1 and the overall sample period WML returns were not significantly different from the excess market return. I therefore cannot say with certainty that previous prices have predictive abilities of future returns.

Testing market efficiency using the Sharpe-ratio as a relative measure of performance entails that both the constructed portfolios outperform the benchmark market index. Results of the statistical significance analysis, however, offered an ambiguous conclusion. Even though the constructed portfolios based on abnormal return anomalies are superior to the benchmark index, the statistical analysis determined that the returns are not significantly different from the returns of the market index. Market inefficiency cannot be concluded at a 95% confidence level, as the probability of returns being a result of random distribution cannot be excluded. I believe a similar trading strategy performed on smaller sub-periods may have the possibility to prove market inefficiency in some extent based on the amomalies of size, value and return momentum.

This thesis concludes that there definitely are abnormal returns related to some anomalies from the traditional capital asset pricing model. The test provided here does, however, not provide a conclusive answer to whether these anomalies violate the market efficiency on Oslo Stock Exchange in the chosen sample period.

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