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Portfolio construction on profitability

A performance analysis of the Norwegian stock market

Konstruering av porteføljer med fokus på bedrifters lønnsomhet

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Preface

This master thesis is the final product of the master degree in Economics and Business Administration at NTNU Business school. The thesis is written within the field of Finance and investment spring 2019. I would like to thank my supervisor Michael Kisser for constructive feedback and guidance through this thesis. He has provided valuable insights in the field of quantitative finance and investment.

The author takes full responsibility for the content of this thesis.

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Abstract

This thesis presents an analysis of how different asset pricing models explain average returns in the Norwegian stock market. The analysis covers the time period from 1990 to 2018 for firms listed at Oslo Stock Exchange. The focus will be on profitability, as measured by the ratio of a firm's gross profit to its assets, inspired by Novy-Marx (2013). The first part of this thesis investigates whether gross profitability scaled by book assets can generate abnormal return in the Norwegian stock market using different asset pricing models. Estimation is done through Fama and MacBeth (1973) regression and the results report, surprisingly, negative alpha values. Similar to what Novy-Marx (2013) finds, I find that the most profitable firms are growth firms, however the results report that high gross profits-to-assets stocks do not outperform the Norwegian stock market. Second part of this thesis test the prediction of Novy-Marx (2013), who argues that gross profitability portfolios exhibit better performance when they are combined with book-to-market. In order to test this prediction, the thesis conduct a double sorting on gross profitability and book-to-market. The results from the regression show that when controlling for gross profitability within book-to-market improve the performance, which is in line with what Novy-Marx (2013) finds. Third part of this thesis performs a robustness test with different asset pricing models on portfolios sorted on gross profitability. These tests also report a negative alpha value for the high profitable firms and confirm what I find in the three-factor model, that high gross profits-to-assets stocks do not outperform the Norwegian stock market. In order to compare the results, an alternative measure of profitability, operating profitability, is used. According to what Ball, Gerakos, Linnainmaa and Nikolaev (2015) find, operating profitability is a better measure of profitability and should outperform the gross profitability. The last part of this thesis tests this expectation by constructing portfolios sorted on operating profitability, using the same method as applied with gross profitability. The results from the regression report negative alpha values for all portfolios, except for portfolios with the most profitable firms. More specifically, this thesis finds that the most profitable firms, measured by operating profitability, outperform gross profitability. This is in line with what Ball, Gerakos, Linnainmaa and Nikolaev (2015) find.

Sammendrag

I denne masteroppgaven blir det gjort en empirisk analyse av hvordan forskjellige prisingsmodeller beskriver det norske aksjemarkedet i perioden fra 1990 til 2018. Oppgaven er inspirert av Novy-Marx (2013) og fokuserer på bedrifters lønnsomhet, som er målt ved en gross profit ratio. Formålet med oppgaven er å konstruere porteføljer fra lav til høy lønnsomhet og deretter undersøke hvordan gjennomsnittlige avkastning endres fra hver portefølje. Porteføljene prises ved hjelp av ulike prisingsmodeller og blir estimert gjennom Fama and MacBeth (1973) regresjon. I motsetning til Novy-Marx (2013), finner denne oppgaven negative alpha verdier. Videre tar oppgaven for seg en dobbel sortering, inspirert av Novy-Marx (2013), hvor resultatene viser at lønnsomme bedrifter gir en bedre lønnsomhet når de er kombinert med book-to-market. For å sammenligne resultatene, konstrueres det også porteføljer basert på lønnsomhet, målt med operating profit. Porteføljene konstrueres også her fra lav til høy, og resultatene viser negative alpha verdier, for utenom de mest lønnsomme firmaene som genererer en positiv alpha verdi.

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1 Introduction

The Capital Asset Pricing Theory (CAPM) of Sharpe (1964) and Lintner (1965) builds on the model of portfolio choice (Markowitz, 1952). By now it is well known that the model shows poor empirical results. For example, Black, Jensen and Scholes (1972), and Fama and MacBeth (1973) find evidence that the relation between average return and market beta is flatter than predicted by CAPM. Other empirical studies find evidence that the beta in CAPM does not seem to explain the cross-section of average stock returns[1] (see Banz (1981), Basu (1983), Stattman (1980) and Rosenberg, Reid and Lanstein (1985)). Common for these findings are that stock returns pattern cannot be explained by a simple linear relationship as the CAPM assume.

These findings were also supported by Fama and French (1992) where they reject the market beta associated with the CAPM. In the study, Fama and French (1992) find that size and book-to-market better capture the cross-section of average stock returns. Right after, they published their three-factor model (Fama and French, 1993) where they included size (Banz, 1981) and book-to-market (Basu, 1983) in their model. Further, empirical research started to challenge the three-factor model of Fama and French (1993). Novy-Marx (2013), Titman, Wei and Xie (2004), and others, argues that the three-factor model miss much of the variation in average returns related to profitability and investment. Novy-Marx (2013) finds that profitability has roughly the same power as book-to-market (B/M) when predicting the cross-section of average returns. Asness, Frazzini and Pedersen (2018) also find that profitability predicts cross-section stock returns on a significant level.

As both Novy-Marx (2013) and Asness, Frazzini and Pedersen (2018) find that profitability predicts stock returns on a significant level for U.S. stocks, it is interesting to investigate how profitability can predict the cross-section of returns in the Norwegian stock market. Inspired by Novy-Marx (2013) this thesis will focus on whether gross profitability, as measured by the ratio of a firm's gross profit to its assets, can generate abnormal returns in the Norwegian stock market.

[1] Studying the cross-section average of stock returns means one would look at how average returns changes across different stock or portfolios. This means one would investigate why for example one stock or portfolio earn a higher (or lower) return than another stock or portfolio.

The research question for this thesis is therefore:

Do profitable firms have higher return than less profitable firms in the Norwegian stock market?

In order to answer this research question, portfolios will be constructed on gross profitability, and Fama and MacBeth (1973) cross-sectional regression will be conducted on all stocks listed at Oslo Stock Exchange (OSE). The time period for this analysis covers the entire period from January 1990 to December 2018.

As this thesis follows the methodology of Novy-Marx (2013), I start sorting firms into portfolios sorted from low to high based on their gross profitability, using a quintile sort that are rebalanced each year. From this, I create the quintile cut-off points and assign firms into one of the five groups, sorted from low to high profitability. The results from the regression on portfolios sorted on gross profitability, surprisingly, report negative alpha values, however not all are statistically significant from zero. Further, the portfolio characteristics show the same relationship as what Novy-Marx (2013) finds, that is, high profitability firms are typical growth firms. However, I do not find that the profitability firms outperform low profitability firms. The zero-cost, high minus low portfolio, generates an alpha value of 0.69% using Fama and French (1993) three-factor model. Consistent with Novy-Marx (2013), the high minus low portfolio generate a negative loading in market factor and value factor, while the positive loading in the size factor differ from what Novy-Marx (2013) finds.

Novy-Marx (2013) argues that when controlling for profitability it will improve the performance of value strategies and when controlling for book-to-market it will improve the performance of profitability strategies. In other words, he finds that double sorted portfolios on gross profitability and book-to-market yields a better performance when they are combined. Based on this, second part of the thesis tests this prediction by analysing the performance of portfolios double sorted on gross profitability and book-to-market. Portfolio are formed by independently and conditionally quintile sorting on the two variables, which results in ten different high minus low portfolios for both sorts. The results show that when controlling for gross profitability within book-to-market improves the performance.

Third part of this thesis do a robustness test on portfolios sorted on gross profitability, regressed against Carhart (1997) four-factor model and Pastor and Stambaugh (2003) four-factor model. The results from the regression are similar to what the three-factor model of Fama and French (1993) finds, that is, negative alpha value for the most profitable firms. Once again, I find that high profitability firms do not outperform low profitability firms.

In the last section, I sort firms into portfolios sorted on operating profitability in order to get a comparison of the gross profitability sort. Portfolios are constructed using the same method as applied with gross profitability. The results from the regression on portfolios sorted on operating profitability report negative alpha values for all portfolios except for the most profitable firms with an alpha value of 0.68%. This is in line with what Ball, Gerakos, Linnainmaa and Nikolaev (2015) find, which is that operating profitability outperform gross profitability. Further, the zero-cost, high minus low portfolio, generate an alpha value of 1.28% which is higher than what I find in the high minus low portfolio sorted on gross profitability. Once again, this confirm that operating profitability outperforms gross profitability.

1.1 Sequence of this thesis

The remaining chapters of this paper is structured as follows; chapter 2 gives a brief introduction to asset pricing theory and empirical evidence, while chapter 3 presents data selection and description. Chapter 4 presents the methodology behind this analysis. Chapter 5 presents the regression results and analysis. Lastly, chapter 6 summarise and discuss the findings and give a conclusion on the research problem.

2 Literature Review

The following section will give a short introduction to asset pricing models and empirical evidence. Section 2.1 gives a brief introduction to asset pricing theory, while section 2.2 covers empirical evidence on asset pricing theories. Lastly, section 2.3 present more empirical evidence from recent time.

2.1 Asset pricing theory

The Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964) and Lintner (1965) and builds on the model of portfolio choice (Markowitz, 1952). As the model of portfolio choice focus on the mean-variance efficient portfolio[2], the CAPM is an attempt to give a theoretical explanation for risk premiums. The CAPM assume there is a linear relationship between asset returns and market risk and can therefore be expressed by the following formula:

$$E(R_i) = R_f + \beta[E(R_m) - R_f]$$

where $E(R_i)$ is the expected return on asset i, R_f is the risk-free rate and $E(R_m)$ is the expected market return. Hence, $E(R_m) - R_f$ is the expected excess return of the market portfolio beyond the risk-free rate, also called the equity risk premium. β express the market beta and is calculated by the covariance of asset i and the market divided by the variance of the market return, given by the following formula:

$$\beta = \frac{COV(R_i, R_m)}{\sigma^2(R_m)}$$

However, the theoretical assumption of CAPM has been widely criticised because they do not seem to hold in practice. The CAPM is often called an "empirical failure" (Fama and French, 2004) as several empirical studies find evidence that stock return patterns, also known as anomaly, cannot be explained by a simple linear relationship as the CAPM assume.

[2] That is, a portfolio that maximise the expected return for a given level of risk. Or the opposite, minimise the variance given a certain expected return.

Other theoretical approaches, such as the intertemporal CAPM (ICAPM) and the consumption CAPM (CCAPM), has been an attempt to overcome some of the limitation of the CAPM. The ICAPM, developed by Merton (1973), is trying to capture the multi-period aspect of investments opportunities. The CCAPM, developed by Rubinstein (1976), Lucas (1978), and Breeden (1979), focus on a consumption beta instead of a market beta to explain expected return premiums over the risk-free rate.

Furthermore, Ross (1976) proposed the Arbitrage Pricing Theory (APT) as an alternative asset pricing model to the CAPM. APT is a multi-factor asset pricing model, that can forecast an asset's return by using linear relationship between a financial asset expected return and its risk. The theory allows for the possibility that markets sometimes misprice securities. This implies that the APT propose that there is an opportunity that arbitrage exist. Meaning investors are able to use a trading strategy to gain profit by differences in the prices of similar or identical assets. The APT looks at several macroeconomic factors that determine the risk and return on a specific asset. Further, the model assumes investors diversify their portfolios and choose their own individual portfolio based on the risk of the macroeconomic factors. This implies that some investors would exploit the differences in expected return and real return by using arbitrage.

An asset or a portfolio's return in the APT model, follow a factor intensity structure if the returns could be expressed as:

$$E(R_i) = R_f + \beta_{i1}\lambda_1 + \beta_{i2}\lambda_2 + ... + \beta_{ij}\lambda_n$$

where $E(R_i)$ is the expected return on asset i, R_f is the risk-free rate, β_{ij} represents the sensitivity of asset i's return to risk factor j, λ_n is the risk premium for factor j, and n is the number of explanatory risk factors.

A significant difference between the CAPM and APT, is that the CAPM generate one factor and one beta, while the APT has a multiple factor that include non-company factors. However, the APT does not tell you which factors should be included. Meaning users of the APT model must analytically determine relevant factors that might affect the assets returns. Another important difference is that the CAPM assume that markets are perfectly efficient. Conversely, the APT allows individual stocks to be mispriced. Overall, the APT has been an important response to the CAPM because this extension has led to a multi-factor asset pricing model. However, the CAPM is simpler to use than the APT, if investors want to determine the expected theoretical appropriate rate of return.

2.2 Empirical evidence on asset pricing theories

The most basic prediction of the CAPM is that average stock returns are positively related to the market beta. Black, Jensen and Scholes (1972), and Fama and MacBeth (1973) find evidence that support this prediction during the pre-1969 period. Further, they also find evidence that show that the relation between average return and market beta is flatter than predicted by CAPM. Several other contradictions of CAPM occur in the U.S. market during the late 1970, and one of the first was Basu (1977). He discovered that common stocks sorted on price-earnings (P/E) ratios yield higher returns for stocks with low P/E ratio than stocks with high P/E ratio.

Banz (1981) was the first to discover the size effect by using U.S. data from 1936 to 1975. He shows that market equity for a stock, helped explain the cross-section of average returns provided by market beta. Banz (1981) find a strong negative relation between average return and firm size, meaning that average returns on small stocks was higher than predicted by the CAPM. Basu (1983) also find a significant size effect. Since the size effect was discovered, similar studies discovered the same findings in several other countries (Næs, Skjeltorp and Ødegaard, 2009).

Another anomaly, documented by Stattman (1980) and Rosenberg, Reid and Lanstein (1985), is that stocks with high book-to-market equity ratios have higher average returns that are not captured by their betas. Meaning they find a positive relation between average return and book-to-market equity for U.S. stocks. This evidence was also confirmed by Chan, Hamao and Lakonishok (1991), who find a strong relation between book-to-market equity and average return for Japanese stocks. Further, Bhandari (1988) discovered the value effect. He finds that average return was positively related to leverage. Research by Basu (1983) find a positive relation between average return and earnings-price ratios. He shows that earnings-price ratios helped explain the cross-section of average returns on U.S. stocks. Research continued to find contradictions to CAPM, for example some show that average stock return can be explained by long-term reversal (DeBondt and Thaler, 1985), leverage (Bhandari, 1988) and momentum (Jegadeesh, 1990).

Fama and French (1992) find that the simple relation between beta and average return, discovered by Black, Jensen and Scholes (1972), and Fama and MacBeth (1973), disappears in the period 1963 to 1990. They argue that size, earnings-to-price, leverage, and book-to-market equity are all different variations of scaling stock prices. Therefore, they evaluate the joint roles of these variables in the cross-section of returns on NYSE, AMEX and NASDAQ stocks. They find that average stock returns are negatively related to market betas. However, using cross-sectional regression approach of Fama and MacBeth (1973) they find that size and book-to-market equity capture the cross-sectional variation in average stock returns associated with size, E/P, book-to-market equity and leverage. Fama and French (1993) find that their three-factor model capture many of the contradictions of CAPM. They conclude that the three-factor model explains the cross-section of stock returns by using a value-weighted market portfolio (MKT), a size factor (SMB) and a book-to-market equity factor (HML).

Furthermore, Jegadeesh and Titman (1993) discover the momentum strategy. The strategy is defined as buying winners and selling losers and receive a risk-adjusted excess return. Jegadeesh and Titman (1993) argues that it is possible to rank stocks after their past performance over the last 3 to 12 months return and predict relative returns for the next 3 to 12 months. The strategy is based on the statement that winners will continue to be winners, and losers will continue to be losers. Asness (1997) confirmed this evidence and find that after 12 months the performance of momentum profitability disappeared. This evidence was also confirmed by Rouwenhorst (1998) who was able to document the momentum strategy in the European stock market between the period 1980 to 1995. Chan, Hameed and Tong (2000) also documented the momentum strategies in Asian, European, North-American and South-African. In the late 1990s, Carhart (1997) argues that buying top performing funds, and selling bottom performing funds yields a return of 8% per year. He also argues that the spread difference between the market value and momentum of stocks can be explained with 4.6%. Carhart (1997) expanded the three-factor model of Fama and French (1993) by adding the momentum factor to their model.

2.3 More empirical evidence

Fama and French (2006) connect the dividend discount model of Miller and Modigliani (1961) to contradictions of CAPM. The dividend discount model shows that the market value of a firm's stock at time t, are expressed as:

$$M_t = \sum_{\tau=1}^{\infty} \frac{Y_{\tau+1} - dB_{t+\tau}}{(1+r)^{\tau}} \tag{1}$$

where M_t is the stock price at time t, $Y_{\tau+1}$ is equity in the period $\tau + 1$, $dB_{t+\tau}$ is the change in book equity, and r is the internal rate of return on expected cash-flows to shareholders. Further, Miller and Modigliani (1961) show that dividing the equation with book equity at time t, gives:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t} \tag{2}$$

The equation now shows that by dividing on book equity, an increase in the book-to-market equity will be positive correlated with expected earnings. This implies that we can expect a higher return. In addition, an increase in expected growth book equity implies a lower expected return.

Fama and French (2006) find that current earnings has explanatory power in Fama and MacBeth (1973) cross-section regressions. Hence, they use current earnings as a proxy for future profitability. When Fama and French (2006) test the expected relation between profitability and expected return using the equation (2) they find mixed results. Firstly, their cross-sectional regression show that earnings are related to average return. Secondly, their portfolio test suggest that profitability adds little or nothing to the prediction of returns provided by size and book-to-market.

Novy-Marx (2013) further investigates the connection between profitability and stock returns. He claims that the gross profitability is a better proxy than what Fama and French (2006) suggest and argues that current earnings are reduced by investments that are treated as expenses without increasing book equity. Since earnings in the equation (2) represent *a firm's true economic profitability* they should be measured before investments are expenses. Novy-Marx (2013) finds a strong relationship between gross profitability and stock returns, and a negative correlation between book-to-market and size. He shows that profitable firms generate significantly higher returns than non-profitable firms. Furthermore, Novy-Marx (2013) perform a trading strategy between 1963 and 2010 that yields a positive abnormal excess return. The trading strategy involves of buying profitable stocks with high gross profitability and selling stocks with low gross profitability. Moreover, Hou, Xue and Zang (2015) find that high profitability stocks are associated with higher return with portfolio sorted on return on equity.

Fama and French (2015a) extended their model by using Novy-Marx (2013) findings and introduced profitability and investment as additional factors in their five-factor model. Fama and French (2015a) find patterns in average returns related to size, B/M, profitability and investment. These patterns are rejected by the GRS-test, developed by Gibbons, Ross and Shanken (1989). However, they estimate the model to explain between 71% and 94% of the cross-sectional variance of expected returns for size, value, operating profit and investment factor in portfolios. Further, they show that HML is a redundant factor for describing average returns for U.S. data in the period 1963 to 2013. Thus, they conclude that if the sole interest is to evaluate abnormal returns, the four-factor model performs as well as the five-factor model. However, the five-factor model is a better choice if the interest is to estimate factor loading's to size, value, operating profitability and investment premiums. As a concession to these findings Fama and French (2015a) suggest that an alternative method is to substitute the factor HML with HMLO [3] (orthogonal HML) in the five-factor model.

Further, Fama and French (2015b) dissect anomalies with a five-factor model. The study uses data sample from July 1963 to December 2014 of NYSE, AMEX and NASDAQ stock where they investigate implications of anomalies on the five-factor model. Their main findings show that the list of anomalies shrink in the five-factor model, but the five-factor model fails to completely capture the average returns.

[3] defined as the sum of the intercept and residual from the regression of HML on $R_m - R_f$, SMB, RMW and CMA (Fama and French, 2015a, p. 12)

In recent history there is a new generation of factor pricing models that has emerged in the cross-section of expected returns (Hou, Mo, Xue and Zang, 2019). This include Hou, Xue and Zang (2015) four-factor q model, Hou, Mo and Xue (2018) five-factor q^5 model, Fama and French (2015a) and Fama and French (2018) five- and six-factor models, Stambaugh and Yuan (2017) four-factor model (SY), Barillas and Shanken (2018) six-factor model (BS), and Daniel, Hirshleifer and Sun (2019) three-factor model (DHS).

Hou, Mo, Xue and Zang (2019) compare this new factor models and find that the q- and q^5 models largely subsume the Fama and French models. They find that the alpha values, investment, profitability, and momentum factors in the Fama and French models relative to the q-model are small and statistically insignificant. However, the investment and profitability factors have large alpha values when they are regressed in Fama and French model and are strongly significant. Even though, the q-model has significant explanatory power relative to the Fama and French models.

Furthermore, the Stambaugh and Yuan (2017) four-factor model and the Daniel, Hirshleifer and Sun (2019) three-factor model both have significant alpha values relative to the q-model. At the same time the q-model have alpha values relative to the SY model and the investment factor in the q-model are also relative to the DHS model. Lastly, they find that Barillas and Shanken (2018) six-factor model also have alpha values relative to the q-model.

3 Data Selection and Description

The following section describes the data set used to construct portfolios. Section 3.1 explains how the data was retrieved and introduce different filtering methods applied in order to clean up the sample. Section 3.2 describes the combined data set. Section 3.3 - 3.5 describe simple calculations that are necessary in order to conduct the analysis.

3.1 The sample

The data and analysis of this thesis covers the period from January 1990 to December 2018. Monthly stock data are retrieved from Amadeus 2.0[4] where the following variables are extracted: *TradeDate, SecurityID, Symbol, ISIN, SecurityName, SecurityType, IsStock, Last (Price), AdjLast (Price) and ShareIssued.* Annual accounting data for Norwegian firms listed at OSE are retrieved from Compustat Global database through Wharton Research Data Services[5]. The collected accounting data are shown in table 3.2. Monthly NIBOR rate are used as a proxy for the risk-free rate and are retrieved from Ødegaards database. Market return and the Fama French factors for the Norwegian market as well as momentum and liquidity factors are also retrieved from Ødegaards database.

3.1.1 Filtering the stock data

The initial sample consist of firms traded on OSE, but not all stocks should be included in this analysis (Ødegaard, 2019). In order to make the sample applicable for this analysis, different filtering methods will be used. First, all other security types than ordinary common stocks are excluded from the sample. Second, all observations where firms have zero shares issued are removed. Third, any observation with missing variables in the data set are also excluded from the sample. Further, I follow the example of Ødegaard (2019) and remove low value stocks. Low value stocks are known as "penny stocks" and could be problematic as they might have extreme returns. Ødegaard (2019) define penny stocks as a stock with price less than 10 NOK. In this case, I set the limit of a stock to have a price above 1 NOK. This is done to keep more observations in the sample and increases

[4]Amadeus 2.0 is *Børsprosjektet* at NHH and provide financial data from OSE through information at Oslo Børs.

[5]https://wrds-web.wharton.upenn.edu/wrds/

the sample with 31%. This is also in line with the delisting rules from OSE (Børs, 2018). Lastly, a similar requirement by Ødegaard that considers an equity market value above 1 mill NOK. This means that all firms with a lower limit of total value outstanding (market capitalisation[6]) than 1 mill NOK are removed from the sample.

3.1.2 Filtering the accounting data

Total accounting data contains accounting data for firms listed at OSE and extracted variables are shown in table 3.2. As this thesis follows the methodology of Novy-Marx (2013), financial firms (i.e. those with a standard industrial classification (SIC) code between 6000 and 7000) are excluded from the sample. This is because the profitability of financial firms differ from industrial corporations and joint analysis could be difficult to interpret. Furthermore, in order to reduce survivorship bias all returns on shares of firms that are active, inactive or delisting are included in the sample. Lastly, to assure that the sample only consist of firms that are listed at OSE, all firms that do not have the OSE code 228 and 229 are excluded.

3.2 Combining the data

In order to sort portfolios on gross profits-to-assets, the stock data and accounting data are combined into one data set. This is done by matching accounting data from December year t, with return data starting in July year $t + 1$. When combining the return data and accounting data into one data set there are certain criteria that needs to be followed. First, all observations need to have both return and accounting data to be included in the sample. This means that all financial firms are excluded from the sample. Second, there must be non-missing variables of equity, book-to-market, gross profits and current month return (Fama and MacBeth, 1973).

[6]Market capitalisation is defined as last stock price times total shares issued.

As a result of this combining, the final data set contains 18 448 observations of 274 unique firms over the time period January 1990 to December 2018. Table 3.1 provides a description of number of observations and firms from the original file to the final data set. Further, the combining process and portfolio construction, presented in chapter 4, are illustrated in appendix A1.

Table 3.1: The table provides a description of number of observations and firms from the original file to the final data set. The filtering process is described in section 3.1. As mention, the sample includes data from the time period 1990 to 2018 from firms listed at the OSE. It is worth mentioning that stock data is given monthly and accounting data is given annually.

Panel A: Stock Data		
	Observations	Firms
Original file	126 301	6 951
Filtered	46 294	643
Panel B: Accounting Data		
	Observations	Firms
Original file	4 864	412
Filtered	4 126	359
Panel C: Merged file		
	Observations	Firms
Final sample	18 448	274

Table 3.2: Accounting data retrieved from Compustat Global database.

Variable	Description
Identification variables	
datedate	Date
comn	Company Name
gvkey	Global Company Name
fic	Incorporation Country Code
sic	Standard Industrial Classification Code
ISIN	International Securities Identification Number
Accounting variables	
cured	Currency Code
fyear	Fiscal Year
at	Total Assets
cogs	Cost of Goods Sold
lt	Total Liabilities
opprft	Operating Profit
pstk	Total Preferred Stock (Capital)
pstkr	Preferred Stock Redeemable
revt	Total Revenue
seq	Stockholders' Equity
txdb	Deferred Taxes (Balance Sheet)
txditc	Deferred Taxes and Investment Tax Credit
xopro	Total Operating Expenses
xsga	Selling, General and Administrative Expense

3.3 Return calculations

As the retrieved stock data only contain *adjusted last price* and *last price*, the stock return is calculated. In order to calculate the stock return, the following formula are used on a monthly basis using the adjusted last price:

$$r_t^i = \frac{AdjLast_t^i - AdjLast_{t-1}^i}{AdjLast_{t-1}^i}$$

Adjusted last price is adjusted for dividends, stocks split and other corporate events. This makes it more preferable than last price, because it is a more accurate reflection of the true value of the stock compared to last price.

3.4 Gross profits-to-assets and operating profits-to-assets

Gross profit are defined as total revenues minus cost of goods sold[7] (Novy-Marx, 2013).

$$GrossProfit = Revenues - COGS$$

Following the methodology of Novy-Marx (2013), profitability is measured by the ratio of a firm's gross profits-to-assets [(REVT-COGS)/AT]. The variables are found in Compustat Global database under REVT, COGS and AT. As a consequence of Compustat being less comprehensive on Norwegian data, it is missing values regarding cost of goods sold. By excluding firms with zero value of cost of goods sold reduces the final sample from 359 unique firms to 274 unique firms.

[7] where "COGS represent all expenses directly related to production, including the cost of materials and direct labour, amortisation of software and capital with a useful life of less than two years, license fees, lease payments, maintenance and repairs, taxes other than income taxes, and expenses related to distribution and warehousing, heat, lights, and power" (Novy-Marx, 2013, p. 3)

Operating profitability (OP) is an alternative measure of profitability, which better matches current expenses with current revenue (Ball, Gerakos, Linnainmaa and Nikolaev, 2015). Operating profitability is defined as gross profitability (Revenue minus COGS) minus selling, general, and administrative expenses (XSGA).

$$OperatingProfit = GrossProfit - XSGA$$

Operating profitability (Gross profits - XSGA) scaled by assets (AT), is found in Compustat Global database under REVT, GOGS, XSGA and AT. As a consequence of missing values regarding selling, general and administrative expense (XSGA), I use total revenue (REVT) minus total operating expenses (XOPRO) as a proxy for operating profit when XSGA is not available. This is done in order to not loose more data from the sample.

3.5 Book-to-market ratio

Book-to-market (B/M) is book equity scaled by market equity, where book equity is defined as stockholder's equity, plus deferred taxes, minus preferred stock (Novy-Marx, 2013). The variables are found in Compustat Global database under SEQ, TXDITC and PSTKR. Market equity is defined as total shares issued times last stock price. In order to calculate the book-to-market ratio the following equation are used:

$$B/M_t = \frac{SE + DET - PS}{ME_{t12}}$$

Similar to Novy-Marx (2013), I use stockholder's equity if available, or else total assets minus total liabilities (AT - LT). Deferred taxes and investment tax credits (TXDITC) are used if available, or else deferred taxes (TXDB) are used. Preferred stock redemption value (PSTKR) is used if available, or else total preferred stock (PSTK) is used instead. As a consequence of missing some values regarding deferred taxes and preferred stock, stockholder's equity will be used as a proxy for book equity.

Following the methodology of Novy-Marx (2013) also mean using Fama and MacBeth (1973) regression. The regression of Fama and MacBeth (1973) require non negative or zero book value of equities in the sample, which means they need to be excluded from the sample. However, this is not done in order to keep the sample as representative as possible. Moreover, Fama and French (1992) also report in their study that firms with a negative book value of equity yields a high return.

4 Methodology

In this chapter, I will present the theoretical background for the methodology used in the thesis. Section 4.1 presents different asset pricing models, and section 4.2 give a short introduction on cross-sectional regression of Fama and MacBeth (1973). Section 4.3 describes the portfolio sorting process.

4.1 Portfolio analysis of asset pricing models

4.1.1 Fama and French three-factor model

The three-factor model of Fama and French (1993) was developed by adding size (Banz, 1981) and value (Bhandari, 1988) to their model. The two factors are now well known as SMB and HML. The size (SMB) factor represent the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks (Small minus Big), while the value (HML) factor is the difference between the returns on diversified portfolios of high and low B/M stocks (High minus Low). By including these two factors, the purpose of the model is to capture the relation between average return and size, and the relation between average return and price ratios like B/M (Fama and French, 2015a). The following equation (3) represents the three-factor model used in the analysis to estimate abnormal returns:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + e_{it} \tag{3}$$

where R_{it} is the return on asset i for period t, R_{ft} is the risk-free return, $R_{Mt} - R_{ft}$ is the excess market return, SMB_t is the *size* factor and HML_t is the *value* factor. The coefficients β_i, s_i and h_i capture all variation in expected returns, α_i is the intercept and e_{it} is the error term at time t.

4.1.2 Carhart four-factor model

The four-factor model of Carhart (1997) was developed by adding the momentum factor from Jegadeesh and Titman (1993) to the three-factor model of Fama and French (1993). The momentum factor represents the tendency of stock prices to continue rising if it is going up and to continue declining if it is going down. Carhart (1997) find significant evidence for momentum in stock returns with the four-factor model. The following equation (4) represents the four-factor model used in this analysis to estimate abnormal returns:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + p_i PR1YR_t + e_{it} \tag{4}$$

where $PR1YR_t$ is the difference between the month t returns on diversified portfolios of the winners and losers of the past year. The other variables are presented in equation (3) from section 4.1.1.

4.1.3 Pastor and Stambaugh four-factor model

The four-factor model of Pastor and Stambaugh (2003) also improved the three-factor model of Fama and French (1993) by adding a liquidity factor to their model. In their study they find that market-wide liquidity is important for pricing common stocks. Furthermore, they find that stock that are sensitive to aggregate liquidity have substantially higher expected returns, even when controlling for size, value and momentum. Their model include liquidity as an additional factor. The following equation (5) represents the four-factor model used in this analysis to estimate abnormal returns:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + l_i LIQ_t + e_{it} \tag{5}$$

where LIQ_t is the difference between the month t on portfolios formed on stocks with high predicted sensitivities to liquidity and stocks with low predicted sensitivities to liquidity. The other variables are presented in equation (3) from section 4.1.1.

4.1.4 Fama and French five-factor model

The five-factor model of Fama and French (2015a) is an extension of their original three-factor model of Fama and French (1993), where they add profitability and investment as additional factors. This choice was based on other empirical evidence that argued that the three-factor model of Fama and French (1993) missed much of the variation in average returns related to profitability and investment. The two factors are known as RMA and CMA. The profitability (RMA) factor represent the difference between returns on diversified portfolios of stocks with robust and weak profitability (Robust minus Aggressive), while the investment (CMA) factor represent the difference between the returns on diversified portfolios of the stocks of low and high investment firms (Conservative minus Aggressive). Fama and French (2015a) show that the five-factor model explain the cross-section of returns better than the three-factor model. The following equation (6) represents the five-factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RML_t + c_i CMA_t + e_{it} \qquad (6)$$

where RML_t is the profitability factor and CMA_t is the investment factor and the other variables are presented in equation (3) from section 4.1.1.

4.2 Cross-sectional regression of Fama MacBeth

Asset pricing theories use "risk factors", such as macroeconomics and financial factors, to explain asset returns. Fama MacBeth created a two-step regression in order to test how these factors describe portfolio or asset returns. In the first step, Fama MacBeth regression determine the factor exposure for each factor. This means that one would estimate betas for each factor and then regress each portfolio against one or more factor time series. The following formula represents a regression example for a general case:

$$R_{n,t} = \alpha_n + \beta_n(R_m) + e_{n,t}$$

where the subscript n denotes test assets that are regressed on the model factors in n regressions.

The second step in Fama MacBeth regression, is to estimate the cross-section of portfolio returns and regress against the factor exposures, at each time period. This is done by estimating the risk premiums by running T cross-sectional regression of the returns on n estimates of the betas calculated from the first step, on form:

$$R_{i,T} = \lambda_{T,0} + \lambda_{n,1}\hat{\beta}_{i,f_i} + e_{i,t}$$

However, this thesis wants to investigate whether the average beta across the cross-section is positive or negative. This implies that the analysis only need to run the first step in Fama and MacBeth (1973) regression. This enables me to run an ordinary least squares (OLS) regression in order to estimate betas. This is done through Python, using the libraries pandas, numpy and statsmodels. The regression code is shown in appendix A2.

4.3 Portfolio construction

First, I start sorting portfolios on gross profitability scaled by assets that are rebalanced each year. I use the GP/A value from June that are based on reported December data, for each firm in that year. From this, I create the quintile cut-off points and assign firms into one of the five groups. This results in five independent data frames, where each quintile represents different portfolios containing equally weighted monthly returns. For a firm to be included in the portfolio construction, I require that each year need at least five firms with 12 months of return data. This is done in order to keep the same number of observations in each quintile. This requirement means the sample now covers the time period from 1996 to 2018, and number of unique firms is reduced from 274 to 186 firms.

After sorting gross profits-to-assets into quintiles, the next step is to merge the risk-free rate and the Fama and French factors as well as the momentum and liquidity factors to each portfolio. This is done by matching the risk-free rate and the factors with date using monthly data. The resulting portfolios are now the CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997) and the four-factor model of Pastor and Stambaugh (2003). Each portfolio now contains all necessary information in order to conduct the analysis.

Additionally, I create the high minus low gross profits-to-assets portfolios by subtracting the return of the highest quintile with the return from the lowest quintile. The resulting portfolios and all quintiles are now regressed against the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997) and the four-factor model of Pastor and Stambaugh (2003). Furthermore, in order to get a comparison, I sort portfolios on operating profitability using the same method as applied above.

This thesis also conducts a double sorting on portfolios sorted on gross profits-to-assets and book-to-market ratio. This is done by first independently double sort on the two variables and then do a conditional double sort on the two variables. The double sorted portfolios are further regressed against the three-factor model of Fama and French (1993).

5 Empirical Results and Analysis

In this chapter, I sort the data set into different portfolios and regress them against different asset pricing models, explained in chapter 4. Section 5.1 sort portfolios on gross profitability, while section 5.2 conduct a double sorting on gross profitability and book-to-market. Section 5.3 performs a robustness test and section 5.4 sort portfolios on operating profitability.

5.1 Portfolios sorted on gross profitability

In this section, portfolios are sorted on gross profitability (REVT minus COGS) scaled by assets (AT). The entire data sample covers the period from January 1996 to December 2018 for firms listed at OSE. Table 5.1 provides descriptive evidence on returns of portfolios sorted on gross profits-to-assets.

I observe from table 5.1 a positive monthly equally weighted average return for all five portfolios. There are no clear patterns between average return and rising gross profitability. The bottom portfolio achieves an average return of 0.55%, while the top portfolio achieves an average return of 1.30%. The high minus low portfolio generate the spread between these two with an average return of 0.74%. This implies that the most profitable firms earn 0.74% higher average returns than the least profitable firms per month. The portfolio also has a standard deviation of 12.67%, resulting in a Sharpe ratio of 5.84%. Observing Sharpe ratio for all portfolios, the high portfolio gives the best performance. Further, I observe that Q3 is the most volatile portfolio. The returns measured by gross profitability exhibit positive skewness for all portfolios, except for portfolio Q3 and for the high minus low portfolio. All portfolios have a positive kurtosis, which implies they have significant fat tails. Furthermore, the Jarqe-Bera test rejects the null hypothesis for normal distribution for all portfolio returns measured by gross profitability.

Table 5.1: This table shows descriptive statistics on monthly average returns of the gross profits-to-assets portfolios. The H-L portfolio is a result of the highest quintile minus the lowest quintile.

	GP/A Quintiles					
	Low	Q2	Q3	Q4	High	H-L
Mean	0.0055	0.0006	0.0163	0.0086	0.0130	0.0074
Std	0.1170	0.1109	0.1531	0.1203	0.1005	0.1267
Min	-0.3686	-0.4150	-0.8070	-0.5327	-0.3396	-0.8435
25%	-0.0511	-0.0544	-0.0336	-0.0426	-0.0298	-0.0430
50%	0.0016	0.0031	0.0154	0.0102	0.0120	0.0100
75%	0.0562	0.0563	0.0694	0.0548	0.0560	0.0615
Max	0.7866	0.5484	0.8359	0.6842	0.4808	0.4282
Sharpe Ratio	0.0470	0.0054	0.1065	0.0715	0.1294	0.0584
Skewness	2.192	0.707	-0.160	1.215	1.151	-1.178
Kurtosis	17.792	10.030	12.960	12.303	9.364	12.361
Jarque-Bera	2618	565	1034	1017	504	1025

Table 5.2: This table shows result of portfolios sorted on gross profits-to-assets regressed against the Fama French three-factor model. The six portfolios displayed in the table are quintiles sorted from low to high. The high minus low portfolio is a result of the highest quintile minus the lowest quintile. The table also shows average portfolio characteristics [portfolio gross profits-to-assets (GP/A), book-to-market (B/M), average firm size (ME, in million NOK), number of observations (N) and number of firms (n)]. Additionally, test-statistics are shown in square brackets.

Panel A					*Panel B*				
	Alphas and three-factor loadings				Portfolio characteristics				
	α	MktRf	SMB	HML	GP/A	B/M	ME	N	n
Low	-0.0084	1.4539	-0.4359	-0.1677	0.0372	0.9896	4 660	264	83
	[-1.44]	[11.66]	[-2.96]	[-1.27]					
Q2	-0.0171	1.6367	-0.0936	0.1280	0.1536	0.8970	12 373	264	79
	[-3.27]	[14.67]	[-0.71]	[1.08]					
Q3	-0.0010	1.7083	-0.2991	0.0969	0.2605	0.8814	19 307	264	75
	[-0.12]	[9.53]	[-1.41	[0.51]					
Q4	-0.0063	1.2535	-0.0111	-0.6843	0.3888	0.6775	34 769	264	75
	[-1.00]	[9.37]	[-0.07]	[-4.83]					
High	-0.0015	1.2787	-0.0297	-0.1867	0.6677	0.3699	82 627	264	60
	[-0.29]	[11.72]	[-0.23]	[-1.62]					372
High - Low	0.0069	-0.1752	0.4062	-0.0191					
	[0.85]	[-1.01]	[1.98]	[-0.10]					

Table 5.2 reports equally weighted return on portfolios regressed against Fama and French (1993) three-factor model. The table also include average portfolio characteristics. As noted, the sample excludes financial firms (those with a standard industrial classification (SIC) code between 6000 and 7000) and covers the time period from 1996 to 2018. Panel A provides regression results from high minus low portfolio and five individual portfolios of the gross profitability sort. Further, panel B provides descriptive statistics of portfolio characteristics that includes average of portfolio gross profits-to-assets (GP/A), book-to-market (B/M), average market capitalisation (ME), number of observations and firms in each portfolio. Number of firms in the five portfolios are added up to be 372. As noted in section 4.3, there is only 186 unique firms in the time period 1996 to 2018. This

implies that some firms can be both low and high profit within this time period. Panel B, shows that there is a positive relationship between gross profitability and rising portfolios, but there is a negative relationship between rising portfolios and book-to-market ratio. Further, there is a positive relationship between average firm size and rising portfolios. These findings are in line with what Novy-Marx (2013) finds.

Surprisingly, the results from the regression in table 5.2 report negative alpha values for all portfolios. However, not all are statistically significant different from zero. As noted, there are no clear patterns between gross profits-to-assets portfolios average returns and increasing profitability. However, the highest portfolio reports a higher average return than the lowest portfolio, shown in table 5.1. This is in line with what Novy-Marx (2013) finds. Further, I observe that the market factor has a positive and statistically significant average monthly returns for all portfolios. Additionally, there is a negative loading in SMB factor for all portfolios, however not all are statistically significant from zero.

Focusing on the highest portfolio minus the lowest portfolio, I observe a positive alpha value of 0.69% with test-statistics of 0.85. The portfolio has a negative market factor, while the SMB factor is positive and significant. The positive loading in the SMB factor, implies that diversified portfolios of small stocks outperform diversified portfolios of large stocks. Additionally, I observe a negative loading in the HML factor with a coefficient of -0.0191 and test-statistics of -0.10. This is also consistent with the correlation test shown in appendix A1. An interesting observation is that the most profitable firms have negative loading in their HML factor with a coefficient of -0.1867, while the second least profitable firms (Q2) have a positive loading in their HML factor with a coefficient of 0.1280. This is in line with what Novy-Marx (2013) finds, but he also find a positive loading in the HML factor for the least profitable firms. Panel B shows that the most profitable firms tend to be growth firms in the sense of having low book-to-markets and unprofitable firms tend to be value firms, with high book-to-markets.

Novy-Marx (2013) finds that high gross profits-to-assets stocks resemble typical growth firms in both characteristics and covariances (with low B/M and negative HML loadings), but they are distinctly dissimilar in terms of expected returns. That is, while they appear to be typical growth firms, under standard definitions, they are good growth firms because they outperform the market despite their low book-to-markets (Novy-Marx, 2013). As this thesis also find that high gross profits-to-assets stocks are resemble typical growth firms, I do not find that they outperform the market. The results, therefore, indicate that the gross profitability portfolios fail to generate abnormal returns in the Norwegian stock market.

5.2 Portfolio double sorts on profitability and book-to-market

The negative correlation between profitability and book-to-market observed in section 5.1 suggests that the performance of value strategies can be improved by controlling for profitability, and the performance of profitability strategies can be improved by controlling for book-to-market (Novy-Marx, 2013). According to Novy-Marx (2013) a univariate sort on book-to-market yields a value portfolio with unprofitable stocks, and a gross profitability portfolio yields a portfolio with expensive stocks. This implies that a profitability strategy that avoids holding stocks that are profitable but ”fully priced”, and avoids selling stocks that are unprofitable but ”cheap”, should outperform conventional profitability strategies (Novy-Marx, 2013).

This section tests these predictions by first analysing the performance of portfolios that are independently double sorted on gross profits-to-assets and book-to-market, and then analysing the performance of portfolios that are conditionally double sorted on gross profits-to-assets and book-to-market.

5.2.1 Independent double sorts

In this section, I double sort portfolios on gross profitability and book-to-market for firms listed at OSE. This is done by first sorting the sample independently on gross profits-to-assets and then sort the sample independently on book-to-market. From this, I combine both of the samples, meaning the sample are sorted on two different variables. This results in 25 combinations of equally weighted average returns to portfolios double sorted and 10 different high minus low portfolios. The sample excludes financial firms (those with a standard industrial classification (SIC) code between 6000 and 7000) and covers the time period from 1996 to 2018.

Table 5.3 report descriptive statistics of portfolio characteristics from the independent double sorting. This include the number of average firms in each portfolio. It is worth mentioning that each GP/A qunitiles and each B/M quintiles consist of 186 unique firms, as shown in the table. Further, the table shows average firm size, as well as average gross profits-to-assets (GP/A) and book-to-market (B/M). The table shows little variation in average GP/A and B/M. Further, I observe that more profitable growth firms tend to be smaller than less profitable growth firms. This is opposite of what Novy-Marx (2013) finds, however, more profitable value firms tend to be smaller than less profitable value firms. This is similar to what Novy-Marx (2013) finds.

Table 5.3: This table shows number of average firms within each portfolio and average firm size (in million NOK), including average gross profits-to-assets and book-to-markets within each portfolio. The table also show that each GP/A quintile and each B/M quintile represent 186 unique firms.

		GP/A Quintiles						GP/A Quintiles				
		L	2	3	4	H		L	2	3	4	H
		Average of firms						Average firm size				
B/M Quintiles	L	63	65	68	76	114	186	3 498	4 827	7 927	14 904	5 961
	2	24	21	20	26	71	186	13 493	7 023	6 569	3 550	12 404
	3	21	20	13	16	62	186	4 243	3 811	2 955	8 831	7 666
	4	16	19	12	14	61	186	4 595	3 289	5 403	3 221	7 324
	H	14	17	14	21	68	186	2 413	2 727	4 853	5 820	6 983
		186	186	186	186	186						
		Average GP/A						Average B/M				
B/M Quintiles	L	0.1801	0.2405	0.2926	0.3550	0.4921		0.5059	0.4481	0.4394	0.3412	0.1928
	2	0.1495	0.2107	0.2641	0.3283	0.4692		0.5932	0.5362	0.5276	0.4265	0.2734
	3	0.1850	0.2473	0.3010	0.3652	0.5062		0.6763	0.6213	0.6129	0.5113	0.3573
	4	0.1753	0.2373	0.2908	0.3549	0.4956		0.8136	0.7625	0.7544	0.6528	0.4980
	H	0.1395	0.2000	0.2531	0.3168	0.4568		1.8095	1.7856	1.7801	1.6767	1.5156

Table 5.4: This table shows 25 combinations of equally weighted average returns to portfolios independently double sorted on gross profits-to-assets and book-to-market, including 10 different results of regressions of both sorts' high minus low portfolio returns on the Fama French factors (the market, size and value factors). r^e is the monthly equally weighted average return of the portfolios. Additionally, test-statistics are shown in square brackets.

		GP/A					Profitability Strategies				
		L	2	3	4	H	r^e	α	β_{mkt}	β_{smb}	β_{hml}
B/M	L	0.0177	0.0169	0.0230	0.0195	0.0220	0.0043	0.0041	-0.0855	0.1946	-0.0431
								[1.12]	[-1.10]	[2.12]	[-0.52]
	2	0.0134	0.0121	0.0187	0.0161	0.0173	0.0039	0.0034	-0.0764	0.2268	-0.0229
								[0.77]	[-0.81]	[2.05]	[-0.23]
	3	0.0071	0.0047	0.0125	0.0076	0.0103	0.0033	0.0028	-0.0883	0.2464	0.0024
								[0.59]	[-0.88]	[2.07]	[0.02]
	4	0.0033	0.0008	0.0078	0.0048	0.0068	0.0035	0.0032	-0.0962	0.2341	0.0157
								[0.69]	[-0.97]	[1.99]	[0.15]
	H	-0.0055	-0.0093	-0.0022	-0.0058	-0.0027	0.0028	0.0026	-0.1034	0.2145	-0.0191
								[0.63]	[-1.15]	[2.02]	[-0.20]
Value Strategies	r^e	-0.0231	-0.0262	-0.0252	-0.0253	-0.0247					
	α	-0.0241	-0.0273	-0.0261	-0.0261	-0.0255					
		[-5.13]	[-5.28]	[-5.09]	[-5.04]	[-5.13]					
	β_{mkt}	0.0630	0.0672	0.0458	0.0435	0.0451					
		[0.63]	[0.61]	[0.42]	[0.39]	[0.43]					
	β_{smb}	0.0602	0.0805	0.0885	0.0721	0.0801					
		[0.51]	[0.62]	[0.68]	[0.55]	[0.64					
	β_{hml}	0.1262	0.1757	0.1223	0.1039	0.1502					
		[1.19]	[1.51]	[1.06]	[0.89]	[1.34]					

Table 5.4 report regression results from the independent double sorted portfolios average returns, and the average returns of both sorts high minus low portfolio returns regressed against Fama and French (1993) three-factor model. The results from table 5.4 report positive average return and alpha value for all portfolios in the profitability strategy. I observe a higher average return and alpha value for typical growth firms than for typical value firms. However, both high and low portfolio has increasing returns when controlling for profitability. This confirms that when controlling for profitability within book-to-market improves the performance of profitability strategies. The results from the regression do not show the same pattern with increasing average return and alpha values for value strategies, with increasing profitability sorted on book-to-market within profitability. This is due to the return spread between high and low portfolios that show there is no increase within profitability.

Focusing on the profitability strategies, I observe that the market factor has a negative loading for all portfolios. However, it is not statistically significant from zero. Further, I observe a positive and a significant SMB factor, while the HML factor report both negative and positive loadings. The significant coefficient of the SMB factor implies that the optimal strategy is buying small stocks and selling large stocks. Overall, the results from the regression show that when controlling for gross profitability within book-to-market improve the performance. This is in line with what Novy-Marx (2013) finds.

5.2.2 Conditional double sorts

In this section, I double sort portfolios on gross profitability and book-to-market for firms listed at OSE. Portfolios are formed by conditional quintile sorting on the two variables. This means that I start sorting portfolio on gross profits-to-assets using the same method applied in section 5.1. From this I sort each GP/A quintiles into five new quintiles based on normal distribution on book-to-markets ratio. This results in 25 combinations of equally weighted average returns and 10 different high minus low portfolios. The sample excludes financial firms (those with a standard industrial classification (SIC) code between 6000 and 7000) and covers the time period from 1996 to 2018.

Table 5.5: This table shows number of average firms within each portfolio and unique firms for each quintile, including average firm size (in million NOK), average gross profits-to-assets and book-to-markets in each portfolio.

		GP/A Quintiles					GP/A Quintiles				
		L	2	3	4	H	L	2	3	4	H
		Number of firms					Average firm size				
B/M Quintiles	L	31	28	26	29	21	7 328	20 726	9 498	7 200	4 864
	2	29	21	27	25	22	7 322	12 747	13 275	42 352	4 686
	3	28	27	25	28	25	4 303	7 269	26 023	53 734	5 538
	4	28	28	22	25	21	2 636	6 688	27 017	36 772	7 558
	H	28	24	20	22	18	1 704	14 306	20 927	34 018	18 748
		Unique number of firms									
		83	79	75	75	60					
		Average GP/A					Average B/M				
B/M Quintiles	L	0.0556	0.1548	0.2638	0.4225	0.7030	-0.0789	0.0468	0.0426	0.0238	0.0203
	2	0.0588	0.1470	0.2543	0.4310	0.6702	0.1015	0.1566	0.2089	0.2357	0.1203
	3	0.0433	0.1478	0.2793	0.3860	0.6634	0.2287	0.2827	0.4491	0.3984	0.2376
	4	-0.0003	0.1541	0.2554	0.3596	0.6616	0.5365	0.6103	0.7799	0.6775	0.3823
	H	0.0288	0.1641	0.2496	0.3454	0.6398	4.1424	3.3634	2.8973	2.0414	1.0977

Table 5.5 report descriptive statistics of portfolio characteristics. This include the number of average firms in each portfolio and unique number of firms within each GP/A quintile. The table shows that unique firms are added up to be the same as what I find in section 5.1. However, the reason why number of firms in each B/M quintile is summed up to be higher than number of unique firms, is because a firm can be in more than one of the B/M quintile for that conditional GP/A quintile. Further, the table shows average firm size, as well as average gross profits-to-assets (GP/A) and book-to-market (B/M). The table shows little variation in average GP/A and B/M, however I observe that more profitable growth firms tend to be smaller than less profitable growth firms, and more profitable value firms tend to be larger than less profitable value firms. This is opposite of what Novy-Marx (2013) finds.

Table 5.6 report regression results from the conditional double sorted portfolios average returns, and the average returns of both sorts high minus low portfolio returns regressed against Fama and French (1993) three-factor model. Focusing on profitability strategies, I observe no pattern in average return and alpha values. I observe a higher average return and alpha value for typical value firms than for typical growth firms. This is opposite of what I find in the independent double sorting. However, there is positive alpha values from profitability strategies for all quntiles except for one with a coefficient of -0.0158. Focusing on the value strategies, there is no clear pattern between average return and alpha values, and the results show negative values. This implies that the performance of value strategies does not improve the performance by controlling for profitability, due to negative alpha values.

Table 5.6: This table shows 25 combinations of equally weighted average returns to portfolios double sorted on gross profits-to-assets and book-to-market, including 10 different results of regressions of both sorts' high minus low portfolio returns on the Fama French factors (the market, size and value factors). r^e is the monthly equally weighted average return of the portfolios. Additionally, test-statistics are shown in square brackets.

		GP/A quintiles					Profitability Strategies				
		L	2	3	4	H	r^e	α	β_{mkt}	β_{smb}	β_{hml}
B/M quintiles	L	0.0304	0.0233	0.0195	0.0215	0.0252	0.0103	0.0001	0.9125	-0.3756	-0.0243
								[0.01]	[2.81]	[-1.01]	[-0.07]
	2	0.0401	0.0148	0.0217	0.0158	0.0152	-0.0124	-0.0158	-0.2616	0.7813	-0.5433
								[-1.07]	[-0.82]	[2.37]	[-1.62]
	3	-0.0086	0.0074	0.0106	0.0027	0.0085	0.0146	0.0152	-0.2459	0.3091	-0.4241
								[1.49]	[-0.92]	[1.09]	[-1.57]
	4	-0.0099	-0.0216	0.0089	-0.0086	0.0124	0.0221	0.0244	-0.5445	-0.5935	0.2918
								[2.21]	[-1.70]	[1.71]	[-0.12]
	H	-0.0478	-0.0317	-0.0193	-0.0048	-0.0246	0.0174	0.0221	-0.4938	0.5069	-0.0368
								[1.91]	[-1.75]	[-0.52]	[-0.92]
Value Strategies	r^e	-0.0549	-0.0412	-0.0246	-0.0218	-0.0437					
	α	-0.0748	-0.0389	-0.0299	-0.0245	-0.0396					
		[-4.53]	[-2.67]	[-2.82]	[-2.41]	[-3.33]					
	β_{mkt}	1.7050	-0.5597	0.4780	0.0368	-0.3017					
		[3.05]	[-1.52]	[1.69]	[0.14]	[-0.86]					
	β_{smb}	-0.1586	0.4740	0.6734	0.4404	0.5280					
		[-0.33]	[1.23]	[2.33]	[1.61]	[1.50]					
	β_{hml}	0.2283	0.4822	0.3020	-0.4798	0.3106					
		[0.49]	[1.23]	[1.02]	[-1.69]	[0.95]					

5.3 Robustness Tests

In this section, I use the same return sample as in section 5.1 to do a robustness test with two different four-factor models. Note that descriptive evidence on returns of portfolios sorted on gross profits-to-assets are presented in table 5.1. Section 5.3.1 test the four-factor model of Carhart (1997), while section 5.3.2 test the four-factor model of Pastor and Stambaugh (2003). As noted, the sample excludes financial firms (those with a standard industrial classification (SIC) code between 6000 and 7000) and covers the time period from 1996 to 2018.

5.3.1 Carhart four-factor model

Table 5.7 report monthly equally weighted return to portfolios sorted on gross profits-to-assets [(REVT-COGS)/AT] regressed against Carhart (1997) four-factor model.

Table 5.7: This table shows result of portfolios sorted on gross profitability scaled by assets regressed against Carhart four-factor model. The six portfolios displayed in the table are quintiles sorted from low to high. The high minus low portfolio is a result of the highest quintile minus the lowest quintile. Additionally, test-statistics are shown in square brackets.

	Alphas and four-factor loadings				
Portfolio	α	MktRf	SMB	HML	PR1YR
Low	-0.0042	1.3855	-0.3867	-0.1914	-0.3630
	[-0.71]	[11.07]	[-2.64]	[-1.47]	[-2.91]
Q2	-0.0128	1.5654	-0.0424	0.1033	-0.3781
	[-2.42]	[14.06]	[-0.33]	[0.89]	[-3.41]
Q3	0.0020	1.6591	-0.2637	0.0798	-0.2612
	[0.23]	[9.11]	[-1.24]	[0.42]	[-1.44]
Q4	-0.0030	1.1987	0.0283	-0.7033	-0.2908
	[-0.46]	[8.86]	[0.18]	[-4.99]	[-2.16]
High	-0.0007	1.2656	-0.0203	-0.1913	-0.0695
	[-0.13]	[11.38]	[-0.16]	[-1.65]	[-0.63]
High - Low	0.0035	-0.1199	0.3664	0.0001	0.2935
	[0.42]	[-0.68]	[1.78]	[0.00]	[1.67]

The results from the regression in table 5.7 report negative alpha value for all portfolios, except for portfolio Q3 with an alpha value of 0.20% and test-statistics 0.23. Even though there are negative alpha values, not all are statistically significant from zero. Further, I observe no clear pattern between increasing alpha and increasing profitability, but the reported alpha value from the most profitable firms is closer to zero than the reported alpha value from the least profitable firms. The table shows a positive and statistically significant market factor for all portfolios, while the SMB factor reports negative loadings for all portfolios, except for portfolio Q3. Further, the HML factor report positive and negative loadings.

The high minus low portfolio generate an alpha with a coefficient of 0.35%, which is 0.34% lower than the three-factor model of Fama and French (1993). This is due to when controlling for more factors, in this case the momentum factor, the abnormal return for the highest portfolio is more affected than the abnormal return of the lowest portfolio. As mention in section 4.1.2, the momentum factor represents the tendency of stock prices to continue rising if it is going up and to continue declining if it is going down. This is consistent with the positive loading of PR1YR value of 0.2935 with test-statistics of 1.67 for the high minus low portfolio.

5.3.2 Pastor and Stambaugh four-factor model

Lastly, I test Pastor and Stambaugh (2003) four-factor model with the same sample of return data as above. Table 5.8 report monthly equally weighted return to portfolios sorted on gross profits-to-assets [(REVT-COGS)/AT] regressed against Pastor and Stambaugh (2003) four-factor model.

The results from the regression in table 5.8 report negative alpha value for all portfolios, however not all are statistically significant from zero. There is no clear pattern between increasing alpha and increasing profitability, but the reported alpha value from the most profitable firms is closer to zero than the reported alpha value from the least profitable firms. The table shows positive and statistically significant market factor for all portfolios. I observe a negative loading in the SMB factor for the lowest and the highest portfolio, which is also significant, while there is a positive loading in the SMB factor between portfolio Q2 and Q4, however they are not significant. The

HML factor report negative and positive loadings, similar to the findings in section 5.1. The LIQ factor generates a positive loading for the least profitable firms, while all other portfolios generate a negative loading in the LIQ factor.

Focusing on the highest portfolio minus the lowest portfolio, I observe a positive alpha value of 0.68% with test-statistics of 0.83. This alpha value is 0.01% lower than the three-factor model of Fama and French (1993). Further, I observe a negative market factor, while the SMB factor is positive with a coefficient of 0.4619 and both HML and LIQ factor are negative.

Table 5.8: This table shows result of portfolios sorted on gross profitability scaled by assets regressed against Pastor and Stambaugh four-factor model. The six portfolios displayed in the table are quintiles sorted from low to high. The high minus low portfolio is a result of the highest quintile minus the lowest quintile. Additionally, test-statistics are shown in square brackets.

	Alphas and four-factor loadings				
Portfolio	α	MktRf	SMB	HML	LIQ
Low	-0.0083	1.4820	-0.4657	-0.1727	0.0599
	[-1.42]	[9.49]	[-2.61]	[-1.29]	[0.30]
Q2	-0.0175	1.4644	0.0895	0.1585	-0.3674
	[-3.36]	[10.56]	[0.57]	[1.34]	[-2.07]
Q3	-0.0018	1.3244	0.1089	0.1648	-0.8186
	[-0.22]	[5.99]	[0.43]	[0.87]	[-2.89]
Q4	-0.0069	0.9924	0.2663	-0.6380	-0.5566
	[-1.30]	[6.00]	[1.41]	[-4.52]	[-2.63]
High	-0.0015	1.2543	-0.0038	-0.1824	-0.0520
	[-0.30]	[9.17]	[-0.02]	[-1.56]	[-0.30]
High - Low	0.0068	-0.2277	0.4619	-0.0098	-0.1119
	[0.83]	[-1.05]	[1.86]	[-0.05]	[-0.40]

5.4 Portfolios sorted on operating profitability

According to Ball, Gerakos, Linnainmaa and Nikolaev (2015) a profitability measure that subtracts both expenses from revenue would be expected to outperform gross profitability in asset pricing tests. In this section, I test this prediction by sorting portfolios on operating profitability (gross profit minus XSGA) scaled by assets (AT). As noted, the sample excludes financial firms (those with a standard industrial classification (SIC) code between 6000 and 7000) and covers the time period from 1996 to 2018 for firms listed at OSE. Table 5.9 provide descriptive evidence on returns of portfolios sorted on operating profits-to-assets.

Table 5.9: This table shows descriptive statistics on monthly average returns of the operating profits-to-assets portfolios.

	Portfolios sorted on OP/A					
	Low	Q2	Q3	Q4	High	H-L
Mean	0.0093	-0.0002	0.0077	0.0045	0.0207	0.0114
Std	0.1412	0.1066	0.1116	0.1412	0.0908	0.1422
Min	-0.3497	-0.4150	-0.5356	-0.8070	-0.2750	-1.1261
25%	-0.0596	-0.0528	-0.0389	-0.0405	-0.0176	-0.0454
50%	0.0112	0.0006	0.0103	0.0003	0.0152	0.0097
75%	0.0623	0.0564	0.0512	0.0550	0.0600	0.0746
Max	1.0692	0.4706	0.4583	0.8359	0.4808	0.4549
Sharpe Ratio	0.0659	-0.0019	0.0690	0.0319	0.2280	0.0802
Skewness	2.840	-0.290	-0.958	0.088	0.916	-2.074
Kurtosis	24.372	8.424	8.701	16.034	6.015	19.982
Jarque-Bera	5380	327	398	1869	137	3361

I observe from table 5.9 a positive monthly equally weighted average return for all five portfolios, except for portfolio Q2 with a negative return value. There are no clear patterns between average return and rising operating profitability. The bottom portfolio achieves an average return of 0.93%, while the top portfolio achieves an average return of 2.07%. The high minus low portfolio generate the spread between these two with an average return of 1.14%. This implies that the most profitable firms earn 1.14% higher average returns than the least profitable firms per month. The portfolio also has a standard deviation of 14.22%, resulting in a Sharpe ratio of 8.02%. Observing Sharpe ratio for all portfolios, the high portfolio gives the best performance. Further, I observe that portfolio low and Q4 are the most volatile portfolios. The returns measured by operating profitability exhibit positive skewness for portfolio low, Q4 and high, while the other portfolios report a negative skewness. All portfolios have a positive kurtosis, which implies they have significant fat tails. Furthermore, the Jarqe-Bera test rejects the null hypothesis for normal distribution for all portfolio returns measured by operating profitability.

Table 5.10 report equally weighted return on portfolios regressed against Fama and French (1993) three-factor model. The table also include average portfolio characteristics. Panel A provides regression results from high minus low portfolio and five individual portfolios of the operating profitability sort. Further, panel B provides descriptive statistics of portfolio characteristics that includes average of portfolio operating profits-to-assets (OP/A), book-to-market (B/M), average market capitalisation (ME), number of observations and firms in each portfolio. Number of firms in the five portfolios are added up to be higher than 186. This implies that a firm can be in both low and high portfolio within this time period. However, the number of unique firms in this time period is equal to 186. Further, panel B shows that there is a positive relationship between operating profitability and rising portfolios, while there is a negative relationship between rising portfolios and book-to-market ratio (except for Q2 that exhibit a higher B/M than the other portfolios). Further, there is a positive relationship between average firm size and rising portfolios. This is in line with what I find in section 5.1.

Table 5.10: This table shows result of portfolios sorted on operating profitability scaled by assets regressed against the Fama French three-factor model. The six portfolios displayed in the table are quintiles sorted from low to high. The high minus low portfolio is a result of the highest quintile minus the lowest quintile. Additionally, test-statistics are shown in square brackets. The table also show average portfolio characteristics [portfolio operating profits-to-assets (OP/A), book-to-market (B/M), average firm size (ME, in million NOK), number of observations (N), and number of firms (n)].

Panel A					*Panel B*				
	Alphas and three-factor loadings				Portfolio characteristics				
	α	MktRf	SMB	HML	OP/A	B/M	ME	N	n
Low	-0.0060	1.5403	-0.4162	-0.4005	-0.0702	0.6566	3 071	264	82
	[-0.80]	[9.67]	[-2.21]	[-2.37]					
Q2	-0.0161	1.4642	-0.0752	0.1000	0.0862	1.3172	7 935	264	96
	[-3.03]	[12.91]	[-0.56]	[0.83]					
Q3	-0.0069	1.4532	-0.2768	0.0933	0.1468	0.8702	16 358	264	85
	[-1.22]	[12.06]	[-1.94]	[0.73]					
Q4	-0.0119	1.5887	-0.2400	0.0605	0.2224	0.6495	17 022	264	86
	[-1.54]	[9.63]	[-1.23]	[0.35]					
High	0.0068	1.1839	0.0158	-0.3905	0.4016	0.3404	34 667	264	63
	[1.58]	[12.81]	[0.14]	[-3.99]					
High - Low	0.0128	-0.3564	0.4320	0.0100					
	[1.41]	[-1.84]	[1.88]	[0.05]					

The results from the regression report negative alpha value for all portfolios, except for the highest portfolio that generates an alpha with a coefficient of 0.68% and test-statistics of 1.58. As noted, there is no clear patterns between operating profits-to-assets portfolios average return and increasing profitability. However, the highest portfolio reports a higher average return than the lowest portfolio, shown in table 5.9. Further, I observe that the market factor has a positive and statistically significant average monthly returns for all portfolios. Additionally, there is a negative loading in SMB factor for all portfolios, however not all are statistically significant from zero.

Focusing on the highest portfolio minus the lowest portfolio, I observe a positive alpha value of 1.28% with test-statistics of 1.41. The portfolio has a negative market factor, while the SMB factor and the HML factor is positive. Similar to the findings in section 5.1, I observe that the most profitable firms have a negative loading in their HML factor with a significant coefficient of -0.3905, while the second least profitable firms (Q2) have a positive loading in their HML factor with a coefficient of 0.1. Panel B shows that the most profitable firms tend to be growth firms in the sense of having low book-to-markets and unprofitable firms tend to be value firms, with high book-to-markets.

As mentioned, profitability as measured by operating profitability, expect to outperform gross profitability (Ball, Gerakos, Linnainmaa and Nikolaev, 2015). I find that the high minus low portfolio sorted on operating profitability generate an average return on 1.14%, while the high minus low portfolio sorted on gross profitability generate an average return on 0.74%. Ball, Gerakos, Linnainmaa and Nikolaev (2015) find that the high minus low portfolio for operating profitability is 29 basis points per month (t-value = 1.95) compared with 36 basis points per month (t-value = 2.64) for gross profitability. This means that I find a higher average return for the high minus low portfolio sorted on operating profitability, than what Ball, Gerakos, Linnainmaa and Nikolaev (2015) find.

Further, Ball, Gerakos, Linnainmaa and Nikolaev (2015) argue that when they compare the alpha values from the three-factor model, operating profitability significantly outperforms gross profitability. More specifically, Ball, Gerakos, Linnainmaa and Nikolaev (2015) find that the high minus low portfolio sorted on operating profitability generate a higher value of alpha value of 74 basis points per month (t-value = 6.25) than the high minus low portfolio sorted on gross profitability with an alpha value of 55 basis points per month (t-value = 4.18). Compared to Ball, Gerakos, Linnainmaa and Nikolaev (2015), I find that the high minus low portfolio sorted on operating profits-to-assets generate an alpha value of 1.28% with test-statistics of 1.41, while the high minus low portfolio sorted on gross profits-to-assets generate an alpha value of 0.69% with test-statistics of 0.85. This is in line with the expectation that profitability, measured by operating profitability, outperform gross profitability in asset pricing testing (Ball, Gerakos, Linnainmaa and Nikolaev, 2015).

As this thesis find that the high operating profitability generate a positive alpha value of 0.68% with test-statistics of 1.58, it implies that operating profitability outperforms gross profitability. A robustness test with Carhart (1997) four-factor model and Pastor and Stambaugh (2003) four-factor model, shown in appendix A2, confirm this by also reporting a positive alpha value for the highest portfolio. The results, therefore, indicate that operating profitability outperform the gross profitability, and can generate abnormal returns in the Norwegian stock market.

6 Conclusion

In this thesis, I look at the relationship between return and profitability for the Norwegian stock market in the time period 1990 to 2018. I use stock data and accounting data for firms listed at OSE to estimate profitability and stock return. More specifically, I define profitability as measured by gross profits-to-assets and operating profits-to-assets. Based on estimates of profitability, I sort firms into portfolios using a quintile sort that are rebalanced each year. From this, I create the quintile cut-off points and assign firms into one of the five groups, sorted from low to high profitability. This results in five independent quintiles where each quintile represent a portfolio and contain equally weighted return. Moreover, I construct the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997) and the four-factor model of Pastor and Stambaugh (2003). This enables me to estimate alpha and beta values through Fama and MacBeth (1973) regression.

The first part of this thesis, sort portfolios on gross profitability scaled by assets and regress the return on Fama and French factors. The results from the regression, surprisingly, report negative alpha value for all portfolios. Novy-Marx (2013) finds that the gross profits-to-assets portfolio average returns generally increase with profitability, while this study finds that there is no pattern between gross profits-to-assets portfolio and increasing profitability. However, consistent with Novy-Marx (2013) the most profitable firms report a higher average return than the least profitable firms. The portfolio characteristics shows that there is a positive relationship between gross profitability and rising portfolios, and a negative relationship between rising portfolios and book-to-market ratio. This implies that the most profitable firms are typical growth firms in the sense of having low book-to-markets, while the least profitable firms are value firms with high book-to-markets. These findings are in line with Novy-Marx (2013), however the high gross profits-to-assets stocks do not outperform the Norwegian stock market, due to negative alpha value. This is opposite of what Novy-Marx (2013) finds, who finds that profitable firms generate significantly higher average returns than unprofitable firms, despite having, on average, lower book-to-markets and higher market capitalisation. The results of this thesis, therefore, imply that gross profitability portfolios fail to generate abnormal returns in the Norwegian stock market.

Second part of this thesis, double sort portfolios on gross profitability and book-to-market. Portfolios are formed by independently and conditionally quintile sorting on the two variables. This results in 25 combinations of equally weighted average returns and 10 different high minus low portfolios. The results from the independent double sorting regression find that average return and alpha values increase when controlling for profitability within book-to-market. The positive alpha values from profitability strategy are all significant at 5% level confidence and implies that the performance of profitability can be improved by controlling for book-to-markets. Further, the value strategies do not report a clear pattern in average return and alpha values. The results also report negative alpha values, which indicates that the performance of value strategies does not improve the performance by controlling for profitability in this case. Focusing on the conditional double sorting, I find positive average return and alpha values from the profitability strategy (except for portfolio Q2). I also observe a higher average return and alpha value for typical growth firms than for typical value firms. Overall, the results from the regression show that when controlling for gross profitability within book-to-market improve the performance, which is in line with what Novy-Marx (2013) finds.

Third part of this thesis, performs a robustness test with portfolios sorted on gross profitability scaled by assets. Gross profitability portfolios are regressed against the four-factor model of Carhart (1997) and the four-factor model Pastor and Stambaugh (2003). The four-factor model of Carhart (1997) find that the high minus low portfolio generate 0.34% lower average return than the three-factor model of Fama and French (1993), while the four-factor model of Pastor and Stambaugh (2003) generate 0.01% lower average return than the three-factor model of Fama and French (1993). Looking at the number of significant alpha values in the three-factor model of Fama and French (1993), four-factor model of Carhart (1997) and four-factor model of Pastor and Stambaugh (2003) at the 5% level confidence, the models perform poorly.

The last part of this thesis, sort portfolios on operating profitability scaled by assets and regress the return on Fama and French factors. Similar to portfolios sorted on gross profitability, there is no pattern between operating profits-to-assets portfolios and increasing profitability, but the most profitable firms generate a higher average return than the least profitable firms. Further, I find that operating profitability increase with rising profitability. The most profitable firms are typical growth firms in the sense of having low book-to-markets, while the least profitable firms are value firms with high book-to-markets. This is consistent with portfolios sorted on gross profitability and what Novy-Marx (2013) finds. However, the results from the regression from portfolios sorted on operating profitability report negative alpha value for all portfolios, except for the most profitable firms that generate an alpha value of 0.68%. The high operating profits-to-assets portfolio, therefore, outperform gross profitability. These findings are in line with the expectations that operating profitability outperforms gross profitability (Ball, Gerakos, Linnainmaa and Nikolaev, 2015). Further, I find that the high minus low portfolio sorted on operating profitability generate a higher alpha value (1.28%) than the high minus low portfolio sorted on gross profitability (0.69%), which is similar to what Ball, Gerakos, Linnainmaa and Nikolaev (2015) find.

Summarised, this thesis find that portfolios sorted on gross profitability scaled by assets do not generate significant alpha values in the three-factor model of Fama and French (1993), four-factor model of Carhart (1997) and the four-factor model of Pastor and Stambaugh (2003). This means that profitable firms do not have higher return than less profitable firms in the Norwegian stock market. These findings are not consistent with what Novy-Marx (2013) finds. However, this thesis find that portfolios sorted on operating profitability scaled by assets outperform the gross profitability. These findings are in line with what Ball, Gerakos, Linnainmaa and Nikolaev (2015) find.

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Appendices

Table A1: Spearman Correlation Matrix between factor returns.

	GP	Mkt.Rf	SMB	HML
GP	1	-0.0848	0.1352	0.0037
Mkt.Rf	-0.0848	1	-0.7140	-0.2343
SMB	0.1352	-0.7140	1	-0.0396
HML	0.0037	-0.2343	-0.0396	1

Table A2: This table shows result of portfolios sorts on operating profitability scaled by assets regressed against Carhart (1997) four-factor model and Pastor and Stambaugh (2003) four-factor model. The six portfolios displayed in the table are quintiles sorted from low to high. The high minus low portfolio is a result of the highest quintile minus the lowest quintile. Additionally, test-statistics are shown in square brackets.

	Carhart four-factor model					Pastor Stambaugh four-factor model				
	α	MktRf	SMB	HML	PR1YR	α	MktRf	SMB	HML	LIQ
Low	0.0015	1.4173	-0.3280	-0.4430	-0.6519	-0.0063	1.3909	-0.2576	-0.3740	-0.3184
	[0.20]	[9.01]	[-1.78]	[-2.70]	[-4.16]	[-0.85]	[6.99]	[-1.14]	[-2.20]	[-1.25]
Q2	-0.0148	1.4429	-0.0598	0.0926	-0.1132	-0.0164	1.3118	0.0868	0.1270	-0.3250
	[-2.71]	[12.50]	[-0.44]	[0.77]	[-0.98]	[-3.11]	[9.29]	[0.54]	[1.05]	]-1.80]
Q3	-0.0006	1.3504	-0.2030	0.0577	-0.5453	-0.0071	1.3454	-0.1622	0.1124	-0.2300
	[-0.11]	[11.43]	[-1.47]	[0.47]	[-4.63]	[-1.26]	[8.93]	[-0.94]	[0.87]	[-1.19]
Q4	-0.0098	1.5542	-0.2153	0.0486	-0.1828	-0.0127	1.2344	0.1365	0.1232	-0.7554
	[-1.23]	[9.26]	[-1.10]	[0.28]	[-1.09]	[-1.66]	[6.07]	[0.59]	[0.71]	[-2.90]
High	0.0040	1.2307	-0.0179	-0.3742	0.2485	0.0069	1.2343	-0.0378	-0.3994	0.1075
	[0.90]	[13.24]	[-0.16]	[-3.86]	[2.68]	[1.60]	[-0.65]	[0.80]	[-0.12]	[1.37]
High - Low	0.0025	-0.1866	0.3101	0.0688	0.9004	0.0133	-0.1567	0.2198	-0.0254	0.4259
	[0.28]	[-0.98]	[1.40]	[0.35]	[4.76]	[1.46]	[-0.65]	[0.80]	[-0.12]	[1.37]

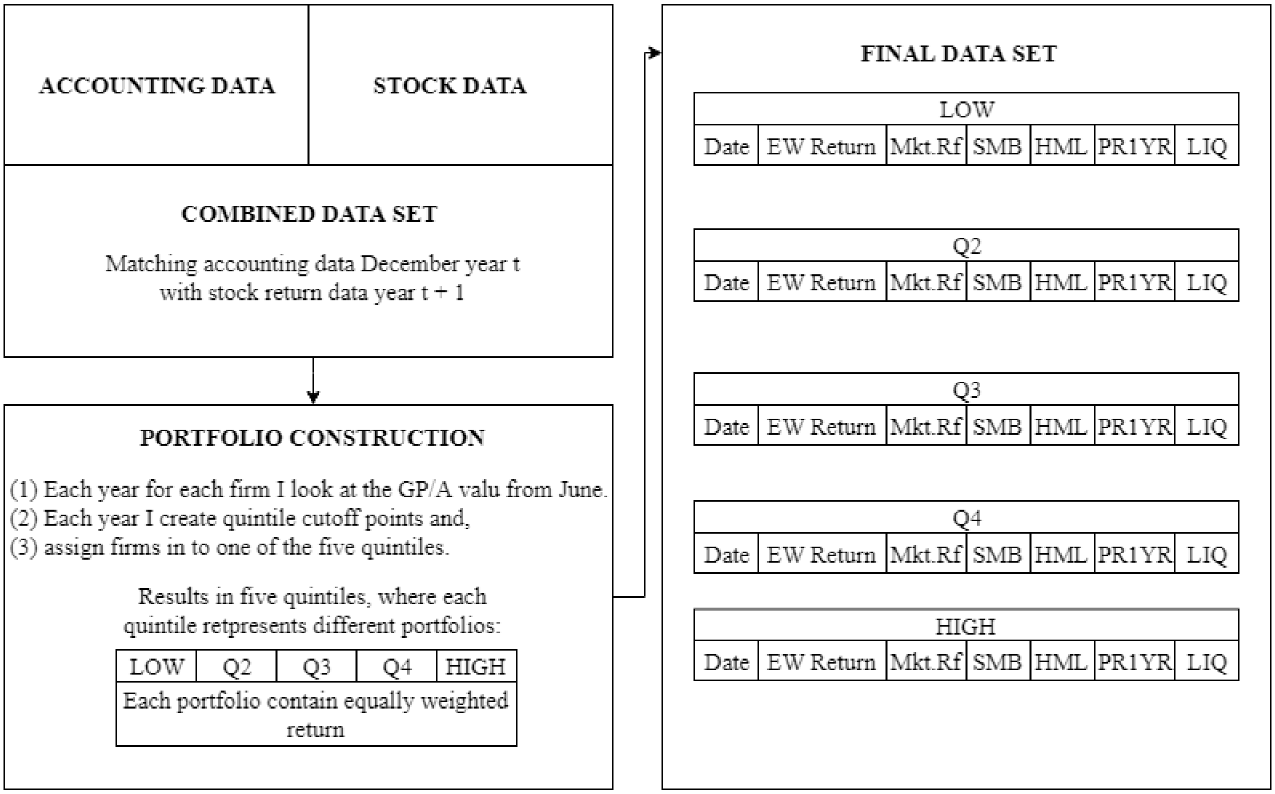

Figure A1: Data combining and portfolio construction

```python
def get_columns(m):
    # 3 Factor
    if m =='3F':
        cols =  ["Return", "RmRf", "SMB", "HML"]
        x_cols = ["RmRf", "SMB", "HML"]
        y_col = ["Return"]

    # C4 Factor
    if m == 'C4':
        cols =  ["Return","RmRf", "SMB", "HML", 'MOM']
        x_cols =  ["RmRf", "SMB", "HML", 'MOM']
        y_col = ["Return"]

    # P4 Factor
    if m == 'P4':
        cols = ["Return","RmRf", "SMB", "HML", 'LIQ']
        x_cols = ["RmRf", "SMB", "HML", 'LIQ']
        y_col = ["Return"]
    return cols, x_cols, y_col
```

```python
def run_regresion(cols, x_cols, y_col):
    reg_results = []

    for i in range(0,6):

        if i!=0:
            Cols = [item + '.'+ str(i) for item in cols ]
            X_cols = [item + '.'+ str(i) for item in x_cols  ]
            Y_col = [item + '.'+ str(i) for item in y_col ]
        if i==0:
            Cols = cols
            X_cols = x_cols
            Y_col = y_col

        # Perform regression
        DF = df[Cols].dropna()

        x = DF[X_cols]
        x['const'] =1
        y = DF[Y_col]

        mod = sm.OLS(y,x)
        res = mod.fit()
        reg_results.append(res)
    return reg_results
```

Figure A2: Regression code used in Python (1)

```python
def format_output(reg_results):
    # Format output

    n = x_cols.copy()
    n.append('α')
    n.append('R2')

    Output = []
    T = []


    for i in range(0,6):
        T.append(pd.DataFrame(reg_results[i].tvalues.tolist()))

        dummy = reg_results[i].params.tolist()
        dummy.append(reg_results[i].rsquared_adj)
        D = pd.DataFrame(dummy).T
        D.columns = n
        Output.append(D)
    D = pd.concat(Output).reset_index(drop=True).T
    D.columns = ['Low', 'Q2', 'Q3', 'Q4', 'High', 'H-L']

    n.pop(-1)
    dT = pd.concat(T, axis=1)
    dT.columns = ['Low', 'Q2', 'Q3', 'Q4', 'High', 'H-L']
    dT = dT.T
    dT.columns = n
    return D.T, dT
```

```python
m = '3F' #'C4' 'P5'
cols, x_cols, y_col = get_columns(m)
reg_results = run_regresion(cols, x_cols, y_col)
D, dT = format_output(reg_results)
print(D.round(4))
print()
print(dT.round(2))
```

Figure A3: Regression code used in Python (2)

Figure A4: Monthly risk-free rate from the time period 1990 to 2018

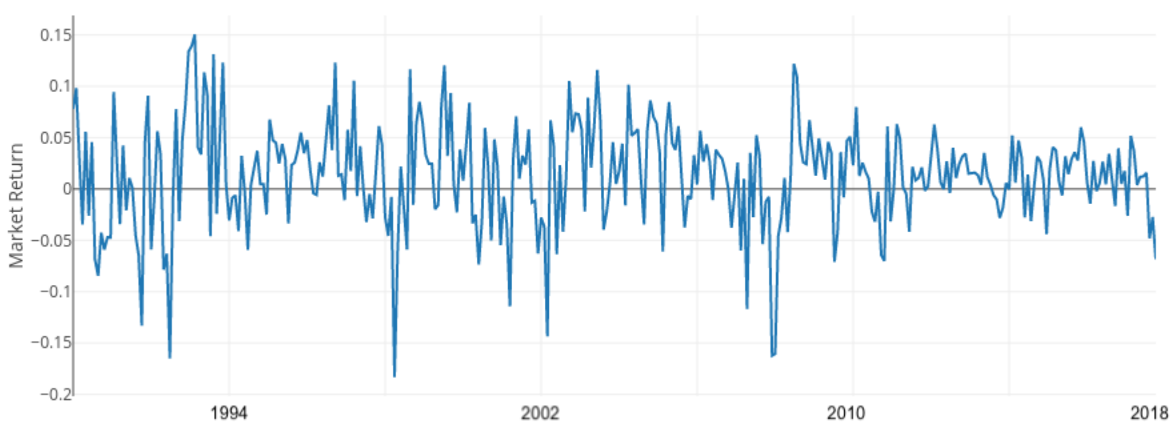

Figure A5: Market return from the time period 1990 to 2018

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf	1.4539	0.125	11.662	0.000	1.208	1.699
SMB	-0.4359	0.147	-2.958	0.003	-0.726	-0.146
HML	-0.1677	0.132	-1.270	0.205	-0.428	0.092
const	-0.0084	0.006	-1.437	0.152	-0.020	0.003

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.1	1.6367	0.112	14.669	0.000	1.417	1.856
SMB.1	-0.0936	0.132	-0.710	0.478	-0.353	0.166
HML.1	0.1280	0.118	1.083	0.280	-0.105	0.361
const	-0.0171	0.005	-3.272	0.001	-0.027	-0.007

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.2	1.7083	0.179	9.530	0.000	1.355	2.061
SMB.2	-0.2991	0.212	-1.412	0.159	-0.716	0.118
HML.2	0.0969	0.190	0.510	0.610	-0.277	0.471
const	-0.0010	0.008	-0.115	0.908	-0.018	0.016

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.3	1.2535	0.134	9.370	0.000	0.990	1.517
SMB.3	-0.0111	0.158	-0.070	0.944	-0.322	0.300
HML.3	-0.6843	0.142	-4.828	0.000	-0.963	-0.405
const	-0.0063	0.006	-1.003	0.317	-0.019	0.006

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.4	1.2787	0.109	11.716	0.000	1.064	1.494
SMB.4	-0.0297	0.129	-0.231	0.818	-0.284	0.224
HML.4	-0.1867	0.116	-1.615	0.107	-0.414	0.041
const	-0.0015	0.005	-0.291	0.771	-0.012	0.009

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.5	-0.1752	0.174	-1.009	0.314	-0.517	0.167
SMB.5	0.4062	0.205	1.979	0.049	0.002	0.810
HML.5	-0.0191	0.184	-0.104	0.918	-0.381	0.343
const	0.0069	0.008	0.849	0.397	-0.009	0.023

Figure A6: Regression details for portfolios sorted on GP/A regressed against FF3

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf	-0.5800	0.325	-1.785	0.076	-1.222	0.062
SMB	-0.1651	0.332	-0.498	0.619	-0.821	0.491
HML	-0.4683	0.341	-1.373	0.172	-1.142	0.206
const	-0.0136	0.012	-1.114	0.267	-0.038	0.011

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.1	-0.5129	0.272	-1.883	0.062	-1.051	0.026
SMB.1	-0.0998	0.278	-0.359	0.720	-0.650	0.450
HML.1	0.6186	0.286	2.164	0.032	0.054	1.184
const	0.0047	0.010	0.465	0.643	-0.015	0.025

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.2	-0.9540	0.272	-3.512	0.001	-1.491	-0.417
SMB.2	0.5119	0.277	1.845	0.067	-0.037	1.060
HML.2	0.1315	0.285	0.461	0.645	-0.432	0.695
const	0.0221	0.010	2.170	0.032	0.002	0.042

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.3	-0.5445	0.276	-1.971	0.051	-1.091	0.002
SMB.3	-0.5935	0.282	-2.103	0.037	-1.151	-0.036
HML.3	0.2918	0.290	1.007	0.316	-0.281	0.865
const	0.0265	0.010	2.558	0.012	0.006	0.047

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.4	-0.2460	0.278	-0.885	0.378	-0.796	0.304
SMB.4	0.2126	0.284	0.749	0.455	-0.349	0.774
HML.4	-0.1508	0.292	-0.517	0.606	-0.727	0.426
const	0.0224	0.010	2.155	0.033	0.002	0.043

Figure A7: Regression details for portfolios double sorted (GP/A Strategies)

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.5	-0.3442	0.365	-0.943	0.347	-1.066	0.378
SMB.5	-0.0927	0.373	-0.249	0.804	-0.830	0.645
HML.5	-0.2140	0.383	-0.559	0.577	-0.972	0.543
const	-0.0675	0.014	-4.934	0.000	-0.095	-0.040

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.6	-0.1263	0.315	-0.401	0.689	-0.749	0.496
SMB.6	0.0454	0.322	0.141	0.888	-0.590	0.681
HML.6	0.4778	0.330	1.446	0.150	-0.176	1.131
const	-0.0400	0.012	-3.393	0.001	-0.063	-0.017

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.7	0.5309	0.226	2.348	0.020	0.084	0.978
SMB.7	0.4703	0.231	2.036	0.044	0.014	0.927
HML.7	0.3990	0.237	1.682	0.095	-0.070	0.868
const	-0.0442	0.008	-5.219	0.000	-0.061	-0.027

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.8	0.1829	0.238	0.767	0.444	-0.289	0.654
SMB.8	0.4216	0.244	1.731	0.086	-0.060	0.903
HML.8	-0.5516	0.250	-2.204	0.029	-1.046	-0.057
const	-0.0183	0.009	-2.051	0.042	-0.036	-0.001

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.9	-0.0102	0.210	-0.049	0.961	-0.425	0.405
SMB.9	0.2851	0.214	1.330	0.186	-0.139	0.709
HML.9	0.1034	0.220	0.470	0.639	-0.332	0.539
const	-0.0315	0.008	-4.006	0.000	-0.047	-0.016

Figure A8: Regression details for portfolios double sorted (B/M Strategies)

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf	1.5403	0.159	9.673	0.000	1.227	1.854
SMB	-0.4162	0.188	-2.212	0.028	-0.787	-0.046
HML	-0.4005	0.169	-2.374	0.018	-0.733	-0.068
const	-0.0060	0.007	-0.803	0.423	-0.021	0.009

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.1	1.4642	0.113	12.914	0.000	1.241	1.688
SMB.1	-0.0752	0.134	-0.561	0.575	-0.339	0.189
HML.1	0.1000	0.120	0.832	0.406	-0.137	0.337
const	-0.0161	0.005	-3.032	0.003	-0.027	-0.006

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.2	1.4532	0.121	12.057	0.000	1.216	1.691
SMB.2	-0.2768	0.142	-1.944	0.053	-0.557	0.004
HML.2	0.0933	0.128	0.731	0.465	-0.158	0.345
const	-0.0069	0.006	-1.216	0.225	-0.018	0.004

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.3	1.5887	0.165	9.633	0.000	1.264	1.913
SMB.3	-0.2400	0.195	-1.231	0.219	-0.624	0.144
HML.3	0.0605	0.175	0.346	0.729	-0.284	0.405
const	-0.0119	0.008	-1.539	0.125	-0.027	0.003

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.4	1.1839	0.092	12.812	0.000	1.002	1.366
SMB.4	0.0158	0.109	0.144	0.885	-0.199	0.231
HML.4	-0.3905	0.098	-3.989	0.000	-0.583	-0.198
const	0.0068	0.004	1.576	0.116	-0.002	0.015

	coef	std err	t	P>|t|	[0.025	0.975]
RmRf.5	-0.3564	0.194	-1.838	0.067	-0.738	0.025
SMB.5	0.4320	0.229	1.885	0.061	-0.019	0.883
HML.5	0.0100	0.205	0.049	0.961	-0.395	0.415
const	0.0128	0.009	1.410	0.160	-0.005	0.031

Figure A9: Regression details for portfolios sorted on OP/A regressed against FF3