Is ROCE a factor that affects the stock return?

A study of the profitability factor using the Fama-French methodology on the OMX Nordic Index Stockholm

Authors: Maria Markusjan & Binxin Su

Supervisor: Jonas Colliander

Abstract

This study investigates the profitability factor proposed by Novy-Marx through the application of the methodology developed by Fama-French (1993, 2015). It particularly focuses on investigating Return on Capital Employed (ROCE) as a measurement for profitability and how this influences the stock market behaviour adjusted for market risk and size. The investigation used return data between July 2001 and June 2017, looking at a sample of 708 companies for a 192 month period on the OMX Nordic Index Stockholm. This research project compares the CAPM model with a two- and three-factor model including ROCE and size, concluding that additional factors improve the explanatory value of the model. This study has found that a profitability factor exists in the Nordic market but seems to be much smaller than what has been observed in the US market. However, a clear pattern is observed with portfolios of robust ROCE factor showing a higher positive impact.

Keywords: Profitability Factor, ROCE, Fama-French, Factor model

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1. Introduction

Research done on the behaviour of stock returns from the mid-1900s has resulted in theories that are widely used today. One of the most important findings was the Capital Asset Pricing Model, which has been developed by Sharpe (1964), Lintner (1965) and Mossin (1966). CAPM is today still a highly accepted model for security pricing, yet empirical studies have repeatedly found evidence rejecting its applicability (see Basu, 1977; Banz, 1981; Rosenberg, Reid & Lanstein, 1985; DeBondt, Thaler, 1985; Bhandari, 1988; Jegadeesh, 1990). The contradicting research has driven scholars to adjust the CAPM to better explain the markets by adding new factors.

One of the most influential findings was by Fama-French (1992), who showed that size and book-to-market ratio explains the variation of average stock return in cross-sectional regressions better than CAPM. In 1993, Fama-French then published an article which suggested a model with three factors, including market risk, size and book-to-market factors. The publications of Fama-French (1992, 1993), and earlier results from various researchers, resulted in disputes leading scholars to investigate the reasons behind these anomalies.

Consequent research of stock returns split academics into two groups: one group supposed the hypothesis that psychological factors were the main explanation behind the abnormal return behaviour, and the second group supported the hypothesis that the observed abnormal returns arose because of unexplained risk. These arguments are still alive and relevant. More recent research has found additional factors that show a strong association with average returns. For instance, Aharoni, Grundy, and Zeng (2013) found a profitability factor; they showed that there is a statistically significant association between average return and an investment proxy. Moreover, Novy-Marx (2013) found a profitability factor; he showed that companies with higher profitability generate higher return, and thus that there is a statistically significant association between average return and a profitability proxy.

The study by Novy-Marx (2013) confirms what has been suggested by several value investors, amongst others: Graham and Dodd (2008), Greenblatt (2006) and Marshall (2017), stating that profitable companies tend to outperform the market. Novy-Marx (2013) suggests that the strategies presented by well-known value investors, such as Greenblatt, are indeed capable of producing abnormal returns, even when correcting for risk using a three-factor model as defined by Fama-French (1993).

Fama-French incorporated the Investment and Profitability factor in their 2015 study. They presented a five-factor model which better explained the average returns than the earlier three-factor model (1993).

1.1 Relevance of the Topic

In the same way that the five-forces model proposed by Michael Porter in 1979 made history in Management, in Finance and Investment Management the factor models proposed by Fama-French at the end of the ’80s have impacted the entire domain.

Explaining the market behaviour was firstly initiated in the famous Capital Asset Pricing Model (CAPM) which was developed in the ’60s. According to the model, the only factor that should affect the expected return is the risk, which is defined as the volatility of the stock price. However, many empirical studies show that the CAPM model explains around 70% of the market behaviour. Additional factors were therefore proposed by researchers and these were put together by Fama-French in their three- and later their five-factor model. The idea of the model is to understand the drivers of the stock market and hence has a large overall economic value.

The latest factor that has been included in the Fama-French model is the profitability factor. In this thesis we intend to investigate this factor specifically by using a measurement that is commonly preferred by value investors and often used by institutional investors: ROCE (Return on Capital Employed).

To test Return on Capital Employed, we used the same methodology as proposed by Fama-French in 1993 and 2015. The study has been performed on a sample of Nordic Stocks using the OMX Nordic Index Stockholm, which predominantly consists of Swedish stocks. Therefore, this study gives insight into the behaviour of small stocks whose return patterns have often been overlooked in studies of asset pricing models and CAPM anomalies.

If a profitability factor, defined as ROCE, would be found, it would have implications from a theoretical as well as practical and societal perspective. From a theoretical perspective it could contribute to a better understanding of the profitability factor (proposed by Novy-Marx) on the Nordic market. From a practical perspective it could be directly relevant for investment management professionals given that it provides additional understanding of the market behaviour. Since investment decisions have a big impact on retirement savings, it can have implications on a larger societal scale by providing fund managers with better decision-making tools.

1.2 Sequence of the Thesis

The thesis is divided into the following sections. The first part presents the theoretical framework and previous empirical studies of factors affecting stock price behaviour. The second part describes the data used in the analysis and explains the factor and portfolio creation process. The third section states the hypotheses and presents the results of the study. Finally, the findings are discussed, and conclusions are made, with suggestions for further research.

1.3 Limitation of the Study

The thesis looks at how ROCE affects average stock returns, adjusting for market risk and size. While there are more factors that have been proven to contribute to a portfolio’s return, such as book-to-market ratio and investment, these factors will not be part of this analysis. The main purpose of this study is to look at the profitability defined as ROCE and its effect on average stock returns. Previous studies have shown that Return on Equity (ROE) and gross profitability have an effect on return (Fama-French, 2015; Novy-Marx, 2013), however the factor ROCE (commonly used within the value investing community) has not been tested.

The data that is used in this study is extracted from the Capital IQ database. The data contains all available stocks listed on the stock exchange, OMX Nordic Index Stockholm. There are however some limitations:

- Only companies which were listed in February 2018 are included in the analysis, creating a survival bias.
- The time frame of the study is December 2000 - December 2015 (with monthly stock return data for July 2001 – June 2017). The number of companies listed prior to 2000 are very few and have therefore been excluded in the analysis. Furthermore, finding a suitable benchmark for the market risk and risk-free rate prior to 2000 was difficult.

Analysis is made on all listed equities on the OMX Nordic Index Stockholm. Factors and regression portfolios are created using this sample data.

2. Literature review

2.1 Historical Overview of Asset Pricing Models

During the (1950s) an important concept arose, which was the idea of the Efficient Market. Fama (1970) described the The Efficient Market theory as follows: “the security prices in the market always fully reflect all available information”. This hypothesis suggests that investors would not be able to gain excess risk-adjusted returns since current pricing would reflect the historical data.

The theories about stock price behaviour have been developed from the 1950s onwards, with Harry Markowitz (1952) as the founding father who put diversification into mathematical terms and created what has become the portfolio theory. His model illustrates the importance of diversification. Starting from a set of stocks, his findings illustrate how an investor can choose an efficient portfolio. Using his theory, and plotting the highest return per variance which would give the most efficient returns, would depict a hyperbola. This methodology is based on calculation of a variance/covariance matrix which was a complicated and time-consuming assignment during the 1950s. Therefore, in his paper from 1959, Markowiz suggested that an “index model” might be a more simplistic way to solve the problem. Several research papers investigating this idea resulted in the well-known CAPM model.

During the mid-’60s, Sharpe, Lintner and Mossin independently developed the Capital Asset Pricing model. They all presented a single index model, building on the work of Markowitz. The difference between their assumptions to that of Markowitz was that they assumed that i) there is a risk-free rate at which there is an unlimited borrowing and lending, ii) that investors have the same predictions, and iii) that supply and demand are balanced, resulting in a stable price.

However, these assumptions have been criticized for being too strict and there have been many researchers who have attempted to develop the model (Black, 1972; Melton, 1973; Rubinstein, 1976; Lucas, 1978 and more).

2.1.1 Abnormalities of CAPM Model

If the Efficient Market hypothesis is true, there should be no mispricing. Since the investors are assumed to be rational they would individually look for mispricing and thus the prices of assets would be driven towards their correct value. Fama-French (2008) wrote that, “a return pattern, which cannot be explained by the chosen asset pricing model, is referred to as an anomaly”.

To test the efficient market hypothesis, an asset pricing model is needed. Empirical studies conducted to test the efficient market hypothesis have shown different results. However, it should be noted that since the hypothesis is empirically tested using CAPM, rejection of the hypothesis can be due to either the hypothesis itself or the CAPM. Studies have also been conducted using multifactor models, giving similar results.

Around the 1970s, tests on asset pricing models and the abnormalities of CAPM became a popular area of research due to the development of databases that had become widely accessible at that point.

Since the 1970s, several studies have found anomalies. An empirical study by Black (1972) showed that stocks with low beta outperformed those with high beta on the American market. This might be due to the speculative overpricing, more often observed in stocks with higher betas (Hong and Sraer, 2016). Moreover, researchers have found additional explanatory factors. Basu (1977) found that stocks with low P/E ratio generated higher returns than stocks that had high P/E, meaning that market risk was not the sole explanatory factor of returns. Banz (1981) found that size was a significant factor; he showed that small stocks demonstrated a higher return than what would be expected by the market betas alone. Rosenberg, Reid, and Lanstein (1985) showed that firms with higher book-to-market ratios (B/M) had higher returns than those with lower B/M ratios. In their 1992 study, Fama-French brought together many of the previously found abnormalities. Their study showed that the stock risks are multidimensional and that CAPM is not sufficient in fully capturing the average stock returns.

According to another school of thought, Behavioral Finance, the anomalies in empirical tests were due to irrationality. They argue that the assumption that the markets are rational and friction-free is wrong and state that the abnormalities arise because investors process information irrationally and make sub-optimal decisions.

For example, Lakonishok, Shleifer, and Vishny (1994), who looked at the B/M ratio, argued that investors overestimate growth prospects of “popular” and hyped stocks (those with low B/M) compared to value stocks (high B/M stocks). Moreover, Odean (1998) and Barber and Odean (1999) stated that investors keep losing investments for too long, and sell winning stocks too early, indicating an overconfidence in their ability.

2.2 Development of Factor Models

Asset pricing provides a very useful tool in understanding the performance of a portfolio. The development started with the CAPM model which established the relationship between risk and return. The model essentially expected investors to drive down prices of stocks until the expected return of owning them compensated for the risk. Stocks with higher volatility relative to the market would expect lower prices, and achieve higher returns. The CAPM model uses a single factor (proportional market risk). However elegant this model appears, it does not fully explain the observed market returns. Empirical studies, as discussed previously, have shown several anomilies.

The Fama-French three-factor model started out by looking at what investors were concerned about. By empirically testing different factors they found that the factors that best explain the performance are the market, size and value factors. While the CAPM model explains around 70% of return, the three-factor model increases the model’s explanatory value.

During the following decades, the result of empirical trials of the three-factor model revealed some fundamental flaws. Novy-Marx showed, in his study, that there seems to be a profitability premium that is unexplained, and in 2004 Titman, Wie and Xie showed that companies that invested in growth seemed to demonstrate lower returns. In 2015, Fama-French revised the model by including five factors, adding the two new factors of profitability and investment.

2.2.1 CAPM

Originally the works of Shape (1964), Lintner (1965) and Black (1972) were the foundation of the asset pricing model. Sharp, Markowitz and Miller jointly received the Nobel Prize in Economics for this contribution. The model was then developed by Black (1972) who presented a model that did not assume riskless assets.

The CAPM model includes i) the expected return from the market (Rmt) which often uses a market index proxy, ii) the risk-free rate (from the government bond yield), and iii) the beta value:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it}$$

2.2.2 Fama-French Three-Factor Model

Fama-French (1992) developed a three-factor model, which in addition to the market-risk includes i) size factor and ii) book-to-market ratio. They observed that portfolios consisting of companies with small market capitalization outperform those with large market capitalization. Moreover, portfolios with higher book-to-market ratio outperform those with lower book-to-market ratio. Having CAPM as a starting point, Fama-French therefore added these two factors to better reflect the portfolio's exposure.

Small firms and distressed firms have lower stock prices to compensate investors for these risks. Small firms must pay more for capital when borrowing or issuing securities in the capital markets. Distressed firms, those that have poor prospects, bad financial performance, irregular earnings and/or poor management, must also pay more for capital. This might explain the anomality found by the size and book-to-market ratio.

All investors that trade stocks are exposed to market risks. If an investor’s portfolio consists solely of stocks that mirror the total market (in terms of size, industry. etc.), then the CAPM model would have a high explanatory value. However, if the portfolio differs in the composition of average size or the ratio between growth/value stocks, then the empirical results would differ from what the CAPM model would predict. A portfolio that is tilted away from the centre of the market will act differently from the market but it is not necessarily more risky. In other words, there seems to be factors other than market risk that explain the total risks. These factors are size and value. However, these factors do not necessarily add to the total risk of the portfolio but help explain it better.

The new factors that were included in the model are the size factor, called SMB (small minus big), and the value factor, HML (high minus lhow). The size factor captures the excess return of a small stocks portfolio by calculating the return of portfolios with small stocks minus the return of portfolios with big stocks. Similarly, the value factor captures the excess return of portfolios with high B/M-ratio by calculating the return from a portfolio of stocks with high B/M-ratio minus the return of a portfolio with low B/M. Below, the three-factor formula can be observed:

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

Nonetheless, the Fama-French (1993) model also faced critique. Investors discussed whether small stocks and value stocks generate higher return because they are actually riskier or because they allow investors to capture risk adjusted return or alpha. However, this model explained 20% more than the CAPM model.

2.2.3 Fama-French Five-Factor Model

The five-factor model introduces two additional factors, namely the investment factor and the profitability factor. Conceptually, companies with higher future earnings should give higher stock market returns. The problem has always been finding a proxy for predicting the earnings. However, Robert Novy-Marx introduced the groundbreaking profitability factor.

With regard to the “investment factor”, in 2004 Titman, Wie and Xie conducted a study controlling for relevant variables, which shows that firms that significantly increase capital investment tend to achieve sub-par subsequent returns. It should be noted that this investment factor has a high correlation with the value and profitability factors. However, it is still significant.

One way to understand the investment factor is to look at the dividend discount model. The model states that the value of a stock today will be the sum of all its future dividends. Stocks like Berkshire Hathaway, that have never paid dividends, are priced with the assumption that they will pay dividends someday in the future.

The new factors that were included in the five-factor model are the profitability factor, called RMW (robust minus weak), and the investment factor, CMA (conservative minus aggressive). The profitability factor captures the excess return of a portfolio with robust stocks (in terms of ROE) by calculating the return of portfolios with robust stocks minus the return of portfolios with weak stocks. Similarly, the investment factor captures the excess return of portfolios with conservative companies (those that do not have low investment ratio) by calculating the return from a portfolio of stocks with conservative firms minus the return of a portfolio with aggressive firms. Below, the five-factor model formula is presented:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it}$$

2.3 The Profitability Factor

The relationship between profitability and stock market returns has been further studied by Novy-Marx. In his 2013 paper he argues that gross profitability, as measured by gross profit-to-assets, has roughly the same predictive power as book-to-market values for forecasting the cross-section of average returns. He also notes that profitable firms often generate significantly higher equity returns than unprofitable firms, despite often having higher valuation ratios.

A question that arises when looking at profitability is understanding and defining what profitability is. High-quality firms are often described as profitable. Profitability is often measured by accounting ratios such as gross profit over assets (as defined by Novy-Marx), and operating profit over assets (as used in Fama-French, 2015). Other profitability measures include: Return on Assets (ROA), Return on Invested Capital (ROIC) and Return on Capital Employed (ROCE), and more. Novy-Marx argues that the gross profit is the cleanest accounting measure because its measure is relatively unaffected by accounting estimates.

In his paper, Novy-Marx constructed long-short portfolios similar to the method proposed by Fama-French (1993) where he looks at gross profitability. The procedure can be explained as utilizing a strategy that takes long positions in stocks with high gross profitability and short position companies with low profitability. He showed that adding gross profitability as a factor for stock returns improves the explanation of excess return of the tested model. The result of this study contradicts previous research that has dismissed probability as a metric. Novy-Marx looked at the momentum of gross profitability and showed that using a "gross profit strategy" can be an efficient tool for reducing volatility in portfolios when applying a value strategy. By combining a gross-profit strategy and a value strategy, the produced portfolios never generated a losing year for a five-year period. This opens up the question of whether there are other profitability measurements that produce a similarly significant result.

Novy-Marx shows that gross profitability is a better indicator than other metrics such as ROIC (suggested by Greenblatt); this is true among large-cap US stocks. Similarly, Fama-French (2015) present evidence that operating profitability minus interest expense is associated with higher stock returns. Chen, Novy-Marx and Zhang (2011) shows that ROE earned a statistically significant average return of 71bp per month over the period from 1972 to 2010.

2.3.1 Explanation of ROCE

The goal of any firm is to generate profit for its stakeholders. Return on capital employed (ROCE) is a key measurement for assessing the returns against the total capital employed. ROCE is calculated by measuring the aggregate profit of a company (earnings before interest and tax) against its total capital minus its current liabilities (capital employed). Capital employed measures a company's required financial base that is needed to maintain its current level for operations (Marshal, 2017). ROCE can be used internally within a firm as a means to benchmark against a target return and judge profitability of investments; it can also be used to analyze competitors on the market.

ROCE was introduced during the 1960s by Bishop (1969) and later by White, Sondhi & Fried (1998) who describe it as a powerful instrument for measuring performance. Changes in the firm's earnings, costs and use of resources can be seen and reflected through the use of the ROCE ratio and is a way to measure the efficiency of managers' ability to utilize a firm's given assets to generate profits.

ROCE is also a useful ratio from an investment perspective and is implemented in many value investing strategies. Joel Greenblatt (2006) wrote the bestseller "The Little Book that Beats the Market", which was also featured in John Reese's (2009) book "The Guru Investor". In the book, Greenblatt summarize the principles of value investing in what he calls "the magic formula". The book consists of an overview of his investment philosophy which, most importantly, uses a similar measurement to ROCE which is called Return on Invested Capital (ROIC).

In his book, Greenblatt explicitly comments that ROIC is a more preferable ratio than the more commonly used ROA because it gives a better indication of how the firm is allocating its resources. The only formal difference between ROIC and ROCE is that ROIC excludes non-operating cash and cash equivalents. Theoretically speaking, ROIC is a superior measurement to ROCE, but technically it is very difficult to determine which part of a firm's cash and cash-equivalents are part of the operating business and which are not by looking at its balance sheet. This is why we believe that ROCE is a more suitable variable to test as a profitability factor.

As we have discussed in previous sections, Fama-French (2015) expanded the famous three-factor model by introducing a new profitability factor. This factor was called Operating Profitability and was measured by ROE. The factor was included in the model after the discovery by Novy-Marx (2013). However, instead of using gross profitability as a proxy (as proposed by Novy-Marx), Fama-French used ROE.

As an indicator of profitability, ROCE avoids the bias of ROE in companies with high leverage (Vernimmen and Quiry, 2009). It is possible to increase the ratio ROE by simply increasing a company's debt level since the ratio ROE only looks at the return on equity. By increasing the debt level, the ratio will show a more attractive investment without accounting for the much-increased risk. Another weakness of the measurement is that ROE uses net-income in its calculations. According to Marshal (2017), using net–income to compare different companies reduces comparability since companies differ in terms of debt structures and tax regimes. Using operating income (which is used in calculations of ROCE) better captures the “true” profitability of a company, disregarding the capital structure or tax regime.

Several studies performed by practitioners in the industry have confirmed that a profitability factor seems to exist. In their book “Valuation. Measuring and Managing the Value of Companies” (McKinsey & Company, 2018), Koller, Goedhart and Wessels show that profitable companies tend to continue being profitable (see Appendix A). This indicates that there should be a premium for firms with high profitability (measured as ROIC).

Furthermore, a whitepaper published by CFO Connect (Pattabiraman, 2013) shows that ROCE is associated with stock return. Pattabiraman showed that firms with higher ROCE tend to demonstrate a higher stock return. The article also shows that there is a linkage between ROCE and the 5-year stock returns, with the portfolio with highest ROCE generating a higher stock return than the portfolio with the lowest ROCE (see Appendix A).

Even though ROCE is widely used as a profitability ratio and often preferred by value investors (such as Greenblatt and others), it is peculiar from an accounting perspective. This is because profit (gross profit, operation profit or net income) is measured against a portion of the capital (since capital employed is total assets – current liabilities). Although ROCE might be odd from an accounting perspective, it is a widely used and a well-established measure, and thus interesting to investigate from an empirical perspective.

2.4 Purpose of Study

Given the evidence from Novy-Marx and value investors, we focus on testing the relevance of ROCE as a factor for explaining the market behaviour. We will adjust our results with already know factors, size and market risk. However, this thesis will not include all factors proposed by Fama-French (namely investment and book-to-market ratio) but rather it will focus on the profitability factor defined as ROCE in our case.

The research question of this thesis is:

To what extent does ROCE explain average return of the OMX Nordic Stockholm Market?

The purpose of this paper is to assess whether the profitability factor, ROCE, has an affect on the return of a portfolio. To do this, the method presented by Fama-French (1993, 2015) will be implemented. The model will adjust for some already well-established factors: market risk and size, to evaluate whether ROCE is a variable that affects the return of a portfolio. While it is possible to obtain Nordic data of a big enough size, the Nordic market is relatively young compared to the North American, European or Asian markets. Therefore, the portfolios in this analysis will use a 3x3 sort instead of the more common 5x5 in order to keep the portfolios well diversified and of a sufficient size.

3. Methodology

3.1 The Sample

The sample which was used in this analysis consists of market data (monthly total return) and accounting data downloaded from Capital IQ database. The collected accounting data includes: Total Assets, Current Liabilities, Shares Outstanding, and Operating Income (Capital IQ, 2018). Data was collected for all available active stocks listed on OMX Nordic Exchange Stockholm from July 2001 to June 2017. The raw downloaded sample consisted of 708 stocks with all data figures being denoted in Euro.

3.2 Filtering the Sample

The downloaded sample included some stocks which had missing data as well as data errors which ought to be removed. The process started by downloading data from Capital IQ for all available stocks listed on OMX Nordic Exchange Stockholm. The sample return was then manually cleaned for the most extreme observations which were likely data errors, although this is hard to prove without comparison data from other sources. Possible sources of extreme observations are merger or acquisitions situations where stocks accounting data are joined. Capital IQ might fail to book these events simultaneously. Stocks with returns of above 600% for any given month were also taken out. The manual screening removed around 55 extreme/incorrect observations along with the data surrounding the observations.

3.3 Choice of Market Proxy

In order to find a suitable proxy to reflect the market premium (R_m-R_f) in our regressions, a very simple correlation was done by creating an value-weighted[1]

[1] Value-weighted in this paper means that the portfolio of companies are weighted on the basis of each companies' market cap. This means that the effect of a single company's total return on the whole portfolio's average total return is adjusted according to its market size. The reason for doing this is to represent the market as correctly as possible, since the larger companies often have a larger shareholder base and should thus have a larger weighting in the total return calculation.

index of the whole sample and testing it against different benchmark indices. The result concludes that the best index that reflects the movement in our portfolios (with coefficient values near one for R_m-R_f) was the OMXS30, which is why this will be used in this study.

3.4 Constructing the Factors

In the analysis the factors were constructed according to the process described in Fama-French (1993, 2015). However, the analysis relied solely on 2 x 3 sorts when creating the factors. We chose this approach since it is the most common method. Additionally, Fama-French (2015) found no differences in model performance when testing different sorting methods. We also choose to include the SMB in addition to the RMW factor, to control for the size effect since Nordic markets tend to include smaller companies.

3.4.1 Variable Definitions

This section provides definitions of the variables that are needed in the factor creation process.

Market capitalization (market cap) was used as a measure of size for each company. The market capitalization was calculated by multiplying the Average Stock Price between 1st Jan of year t to 31st December of the same year with Number of Shares Outstanding at 31st December for the same year.

Using the yearly data, ROCE was calculated by dividing Operating Income by Capital Employed (total assets – current liabilities). In our thesis ROCE was used as the profitability factor instead of the ROE (which was used by Fama-French).

Market cap and ROCE is calculated on yearly bases and is used in the sorting process to create the nine portfolios and our factors (RMW and SMB). These regression variables are then matched with their monthly returns to conduct the regressions.

Monthly returns for stocks, market premium and risk-free rate were all calculated as the Total Return indices from Capital IQ which accounts for split, cash dividend, rights offering and spin-offs and is calculated by R_{it} minus R_{it}-1 divided by R_{it}-1.

OMXS30 Index was used as a proxy for the market return and 1-month Stibor rate as a proxy for the risk-free rate.

In the next subsection, the sorting process for creating the factor portfolios is presented.

3.4.2 The Sorting Process and Factor Construction

This chapter explains the sorting process that are used in order to create the variables in our regression models. Below is a step-by-step explanation of the creation process for the RHS (right-hand-side) of our regressions. These portfolios were created in order to obtain the return series of the factors, Size and ROCE (similar to the factor presented as RMW in Fama-French, 2015). A description of the mathematic formulas for computing the return series for each of the factors can be observed in table 1.

The portfolios were sorted at the end of December each year and matched with monthly return data from the subsequent year from July to June the year after (for example accounting data for 2000 would be matched with monthly return data between July 2001- June 2002). Thus, the time-period for the actual analysis is July 2001 to June 2017, or 192 months of return data.

The first step in the sorting process was establishing the breaking points for size and ROCE variables. Similar to the approach used in Fama-French, 2015, the yearly sample market cap median was taken as the size breaking point (in their earlier studies 10% and 90% were used as breaking points for size, however in order to have a larger part of the data in the sorting portfolios, the approach presented in the 2015 report was used). For the ROCE factor a 30th and 70th percentile breaking point was used. Having sorted the data into portfolios, the stocks were paired into six size-ROCE portfolios. Following this step, the portfolios were value-weighted using their market cap as weights and returns were then calculated for each sorted portfolio.

The steps of the process are presented below along with a presentation of the construction of the factors (Table 1).

Step 1: Raw Data

The raw data contains a table of monthly stock returns. These returns will be sorted by annual data from the previous Annual report. For instance, the period July 2016 to June 2017 would be sorted on annual data from the annual report 2015.

Step 2: Creating the Portfolios

In order to obtain the portfolios, the breaking points are calculated. Each breaking point is calculated separately from the whole data set. For example, to create a 2 x 3 sorting, the median of market cap is used to create the breaking point for size, while the 30th and 70th percentile are used as breaking points for ROCE. Thus, 6 portfolios are obtained.

Step 3: Calculating the Monthly Portfolio Returns

After the companies are sorted into their respective portfolios, we simply calculate the value-weighted-returns for each portfolio (using the market cap as the weights).

Step 4: Calculating the SMB and ROCE Factors

Fama-French traditionally calculated their factors as the differences in average portfolio returns (see Table 1 for illustration). For SMB, this indicates the average return for all small portfolios minus the average returns of all big portfolios. For ROCE this means the average returns of all robust ROCE portfolios minus the average returns for all weak ROCE portfolios.

Steps 1-4 will be repeated for every single year (for the period of 2000-2015).

Table 1: Factor Calculation

Stocks were distributed into two Size portfolios and three ROCE portfolios. These independent sorts are used when creating the risk factors. We have labeled them with two letters, With the first letter attributing to the Size portfolios described as small (S) and big (B) and the second letter attributing to the ROCE portfolios described as robust (R), neutral (N) and weak (W). Stocks are value-weighted when calculating the monthly returns. Appendix B shows descriptive statistics of the factors calculated.

Breakingpoints	Factors calculation
Size: yearly sample median	SMB = (SR + SN + SW) / 3 - (BR + BN + BW) / 3
ROCE: Yearly sample 30^{th} and 70^{th} percentiles	RMW = (SR + BR) / 2 - (SW + BW) / 2

3.5 Construction of the Regression Portfolios

Regressions were conducted on 9 LHS (left-hand-side)[2] regression portfolios. The monthly returns of the portfolios were constructed in a similar way to the factor portfolios, using the same stepwise process presented in section 3.4.2 except for step 4.

Value-weight portfolios were constructed using a 3 x 3 sort with 33^{rd} and 66^{th} yearly sample percentiles as breakpoints for both sorting variables. This way the sample was split into 9 portfolios and matched with their monthly return data. Thus, regressions were run on 27 portfolios, 9 for each of the three models that are compared in the study. The three models test the factors R_m-R_f, RMW and SMB factor in different combinations. The choice of using 3 x 3 sorts instead of the more common 5 x 5 sorts was done in order to keep the regression portfolios diversified and large enough.

To have a regression made of these portfolios, a proxy of market return and the risk-free rate is needed. The OMXS30 Index was used as the market index, and for the risk-free-rate the 1-month Stibor was used as a proxy.

Table 2 Average Number of Stocks in Regression Portfolios and Yearly Sorts

Panel A shows average yearly number of stocks and Panel B shows average number of stocks for portfolios formed on size and ROCE for the distributed sample between year 2000 and 2015. At the end of June each year, stocks are allocated to three size groups using sample tertile breakpoints. Similarly, stocks are allocated independently into three ROCE groups using sample tertile breakpoints. The intersections of the two sorts produce 3 x 3 Size-ROCE portfolios.

[2] Following the methodology proposed by Fama-French (1993, 2015), the left-hand-side regressions refer to the portfolios that will be used as the dependent variable in the regression model. Similarly, the right-hand-side refers to the factors that will be used as independent variables in the regression.

Panel A:

Year	Number of avg. stocks
2000	139
2001	153
2002	159
2003	166
2004	179
2005	190
2006	217
2007	256
2008	269
2009	282
2010	297
2011	319
2012	333
2013	355
2014	404
2015	467

Panel B:

		ROCE		
		Weak	Neutral	Robust
	Small	46	21	20
Size	Medium	20	34	35
	Big	7	39	40

In Table 2, Panel A, we can observe the number of stocks included in the analyses on average for each year. This increases from 139 in 2000, to 190 in 2005, to 297 in 2010 and 467 in 2015. Due to the survival bias discussed in Chapter 1.3, only a portion of the companies listed today were listed in 2000, leading to a larger amount of stocks in the recent years. Fewer companies were listed on the exchange in 2000 than in 2015. Even so, using only the current listed companies (companies that were listed in Feb 2018 on the exchange and looking at these companies' data for the previous years) still leads to data loss.

In Table 2, Panel B, we can see the average number of stocks in each of the regression portfolios. The goal was to have at least 20-30 stocks in each portfolio to obtain a sufficient diversification of risk. One of the portfolios still has, on average, very low sample size (portfolio 'Weak-Big' with 7 stocks on average), making it a "problem portfolio". Since some companies might have data either for size or for ROCE but not both, some of the companies cannot be included in the portfolios since they are defined by both criteria. Because the data includes First North which has some very small companies, some of which might not have yet reached profitability (since they are in early stage), it might create a skew with smaller companies tending to have weak ROCE in our study.

As observed in Table 2, Panel B, midsized and large companies with neutral or robust ROCE tend to have on average a higher number of stocks per year. An explanation for this is that these companies tend to be well-established and have been listed for a long time, thus having more data available.

3.5.1 Descriptive Statistics

This section describes the regression portfolios along with the factors which will be used in the regression model.

We will investigate how well the regression models can explain the average excess return on portfolios with differences in size and profitability. Table 3 below examines the mean excess-return patterns (return above the risk-free rate) and standard deviations for the 3 x 3 LHS-portfolios.

Table 3: Excess returns of the Regression Portfolios

The table shows average monthly excess returns (in percent) and standard deviations for the value-weighted portfolios constructed on size and ROCE on sorting between 2000-2015 and return data for July 2001 – June 2017. At the end of June each year, assets are grouped into three size groups using sample tertile breakpoints. Similarly, stocks are allocated independently to three ROCE groups using sample tertile breakpoints. The intersections form the 3 x 3 value-weight portfolios. The table shows average monthly returns, in excess of the one-month Stibor rate.

		Mean excess return					Standard deviation		
			ROCE					ROCE	
		Weak	Neutral	Robust			Weak	Neutral	Robust
	Small	1.09	1.17	1.33		Small	7.35	5.43	6.47
Size	Medium	0.26	1.38	1.33	Size	Medium	9.28	6.43	5.90
	Big	1.16	0.77	0.41		Big	11.77	7.63	4.67

The return patterns of the portfolios show the two highest ROCE-columns (neutral and robust) indicating a somewhat linear size effect, with small and medium size stocks generally yielding higher average returns (similarly to what has been discovered in Fama-French, 1993 and 2015). For example, the ‘Small-Robust’ portfolio has a return of 1.33, while the ‘Big-Robust’ portfolio has a mean excess return that is three times lower (0.41). It should be noted that the portfolio, ‘Big-Weak’, has a high average monthly return of 1.16 percent and an abnormally high standard deviation of 11.77 which implies that it is not well diversified (as presented in Table 2, it has only 7 stocks on average) and thus can explain the deviation from the pattern in Table 3. Moreover, the highest return can be found in the ‘Neutral-Medium’ portfolio. It should be noted that this portfolio also has a relatively large standard deviation (6.43). Also, a strong profitability effect can be observed in the small size rows, whilst a reversed effect is evident in the big size row.

3.6 Risk-factors

Following Tables 2 and 3, which presented the descriptive statistics for the LHS regression portfolio, this part of the essay summarizes the statistics for the RHS factor returns. The mean return and standard deviation of the market premium are presented below in Table 4.

Table 4 Summary Statistics for Monthly Factor Returns

R_m – R_f is the monthly return of the OMX Nordic Stockholm Exchange Index minus the one-month Stibor rate. At the end of each June, stocks are assigned to two size groups using sample median as the breakpoint. Stocks are also independently distributed into three ROCE groups, using 30th and 70th sample percentile breakpoints. The RMW and SMB factors are formed from the intersections of these value-weighted portfolios of size and ROCE (see portfolio calculations described in Table 1). Panel A of the table shows average monthly returns (mean) and standard deviations of monthly returns. Panel B shows the correlations between each factor.

Panel A: Averages, standard deviations

	$R_M – R_f$	RMW	SMB
Mean	0.24	0.20	0.47
Std. Deviation	5.20	7.51	4.62

Panel B: Factor Correlations

Correlations

		RM_RF	RMW	SMB
RM_RF	Pearson Correlation	1	-.478**	-.381**
	Sig. (2-tailed)		0.000	0.000
RMW	Pearson Correlation	-.478**	1	.457**
	Sig. (2-tailed)	0.000		0.000
SMB	Pearson Correlation	-.381**	.457**	1
	Sig. (2-tailed)	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

Panel A of Table 4 shows average returns and standard deviations for the factor returns (see also Appendix D). The average market premium (R_M – R_f) is 0.24 percent per month with a standard deviation of 5.20. In the 2016 study, Fama-French obtained similar mean values with slightly lower standard deviations for Europe and North America, and a somewhat higher mean values with a comparable standard deviation in the Asian Pacific market.

The RMW factor (M=0.2, SD=7.51) is weaker and more volatile than the observations that Fama-French (2015, 2016) has showed in other markets. Similarly, the average return of the SMB premium is positive and significantly distinguishable from zero (M=0.47, SD=4.62). It is interesting to note that Fama-French (2015, 2016) showed that the size effect has been decreasing. However, the methodology used was somewhat different for the one we have used, having the 10^{th} and 90^{th} percentile as the breaking point (instead of the median).

In Table 4, Panel B, the correlation matrix shows a moderate relationship between all the factors (i.e. R_M – R_f, SMB and RMW). It can be observed that there is a moderate highly significant negative correlation between R_M – R_f and RMW (r=-

0.478, p= 0.000), and between $R_M - R_f$ and SMB (r=-0.381, p= 0.000). On the contrary, there is a moderate highly significant positive correlation between RMW and SMB (r=0.457 P=0.000).

As none of the correlation coefficients in Panel B have values above 0.7, it is unlikely that collinearity between the predictors would affect the regression results. In order to further investigate if multicollinearity exists, a factor spanning regression will be conducted.

3.6.1 Factor Spanning Regression

To establish that all the factors that are included in the analysis are relevant, we used an innovative method proposed by Fama-French: a spanning factor regression. This method is used as a tool to investigate whether a factor remains relevant and statistically significant even in combination with the other factors. Spanning regression tests are conducted by regressing the return of each factor (considered as dependent variable) against all other factors (considered as independent variables). If the coefficients are strong, this would show that one factor is a significant predictor of the other and thus might potentially replace them in the regression models performed in section 4.

Table 5: Spanning Regressions

Table 5 shows regressions for the factors $R_m - R_f$, Size and RMW, where two-factors explain returns of the third. The regression is performed on return data for 192 months between July 2001 – June 2017. $R_M - R_f$ is the value-weight return on the OMXS30 minus the one-month Stibor rate. SMB is the size factor (calaulated by using market cap) and RMW is the profitability factor (calculated using ROCE). The factors are formed using individual sorts of stocks into two size groups and three ROCE groups. Int. shows the regression intercepts with the bold t-statistics showing significance at a 0.05 level.

	Int	Rm-Rf	SMB	RMW	R^2
Rm-Rf					
Coefficient	0.41		-0.23	-0.27	0.25
t-statistics	1.24		**-2.93**	**-5.46**	
SMB					
Coefficient	0.47	-0.19		0.22	0.24
t-statistics	1.62	**-2.93**		**4.95**	
RMW					
Coefficient	0.08	-0.51	0.52		0.31
t-statistics	0.17	**-5.46**	**4.95**		

The above factor spanning regression model indicates that when using each variable sequentially as predictor and outcome, we obtained only significant factors. Practically, SMB and RMW are predicting R_m-R_f significantly, explaining 25% of its variability (adj. R^2 = 0.25). Similarly, R_m-R_f and RMW are predicting SMB, explaining 24% of its variability (adj. R^2 =0.23). And SMB and R_m-R_f are predicting RMW, explaining 31% of the variability (adj. R^2 = 0.31). Overall this indicates that each of the variables is a significant predictor of the other and the factor can be used as a predictor together with the other factors, meaning multicollinearity is low. This means that we can proceed using all of the factors in our analysis.

4. Results

The research question of the thesis is to assess if ROCE is a factor in explaining the stock markets using the Fama-French methodology applied on OMX Nordic Index Stockholm data (see section 2). This thesis investigated the problem by comparing the performance of a CAPM, a two-factor model (including market risk and ROCE) and a three-factor model (including market risk, ROCE and Size) on a Nordic sample data. Firstly, we test if the regressions of the sorted portfolios presented in Table 6 can explain the average excess returns. To understand if the factors are the sole driver, we looked at the alpha values of the 27 regression and analyzed whether these were significantly different from zero. The regression formulas used include the explanatory factors for each of the three models. If a model fully detentions expected returns, the intercept would be indistinguishable from zero. Thus, the statistical hypothesis for each regression is:

H_0 = The regression alpha is not significantly different from zero

H_1 = The regression alpha is significantly different from zero

4.1 Regression Details

The regression intercepts (alpha values), their corresponding t-values, and adjusted R^2 values are presented next in order to provide a better understanding of the model performance. Focusing on the number of significant alpha values (0.05 level), the CAPM has the least number of significant alphas. R^2 values in the regression models improve with additional factors (the R^2 is improved in the two- and three-factor model).

From a descriptive perspective, as can be observed in Appendix B, smaller stocks have higher average ROCE, with the portfolio ‘Robust-Small’ demonstrating the highest average ROCE of all the portfolios. Moreover, a relatively clear pattern can be observed, for example bigger stocks illustrating lower ROCE. Portfolio ‘Robust-Medium’ has an average of 0.23 in ROCE whereas ‘Robust-Big’ illustrates an average ROCE of 0.22.

4.1.1 Model Performance Summary

Table 6 Regressions for 9 Value-Weight Size-ROCE Portfolios

Regressions for 9 value-weight Size-ROCE portfolios: July 2001 – June 2017, 192 months. At the end of each June, stocks are assigned to three size groups using sample tertile breakpoints. Stocks are independently allocated to three ROCE groups, again using sample tertile breakpoints. The intersections of the two sorts produce 9 Size-ROCE portfolios. The LHS variables are the monthly excess returns on the 9 Size-ROCE portfolios. The RHS variables are $R_M – R_f$ for the CAPM, $R_M – R_f$, RMW for the two-factor model and $R_M – R_f$, RMW and SMB for the three-factor model. Factors are constructed with an independent 2 x 3 sort on size and ROCE. Table 6 shows α (intercept), t-statistics and R^2 values for the three regression models. Bolded t-statistics show significance at the 0.05 level.

$$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt}-R_{ft}) + \varepsilon_{it}$$

Size	α ROCE Weak	α ROCE Neutral	α ROCE Robust	t(α) ROCE Weak	t(α) ROCE Neutral	t(α) ROCE Robust	Adj. R^2 ROCE Weak	Adj. R^2 ROCE Neutral	Adj. R^2 ROCE Robust
Small	0.77	1.07	1.03	1.96	**3.24**	**3.18**	0.39	0.33	0.39
Mid	-0.24	0.91	1.04	-0.45	**2.68**	**3.61**	0.41	0.46	0.54
Big	0.76	0.23	0.11	1.15	0.72	0.48	0.48	0.65	0.50

$$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt}-R_{ft}) + h_i RMW_t + \varepsilon_{it}$$

Size	α ROCE Weak	α ROCE Neutral	α ROCE Robust	t(α) ROCE Weak	t(α) ROCE Neutral	t(α) ROCE Robust	Adj. R^2 ROCE Weak	Adj. R^2 ROCE Neutral	Adj. R^2 ROCE Robust
Small	0.91	1.04	0.98	**2.55**	**3.15**	**3.08**	0.51	0.34	0.40
Mid	-0.07	0.93	1.02	-0.14	**2.74**	**3.54**	0.51	0.46	0.54
Big	1.19	0.24	0.05	**3.21**	0.74	0.22	0.84	0.65	0.56

$$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt}-R_{ft}) + h_i RMW_t + S_i SMB_t + \varepsilon_{it}$$

Size	α ROCE Weak	α ROCE Neutral	α ROCE Robust	t(α) ROCE Weak	t(α) ROCE Neutral	t(α) ROCE Robust	Adj. R^2 ROCE Weak	Adj. R^2 ROCE Neutral	Adj. R^2 ROCE Robust
Small	0.50	0.75	0.66	**1.96**	**2.68**	**2.62**	0.75	0.52	0.63
Mid	-0.48	0.67	0.76	-1.12	**2.21**	**3.15**	0.64	0.58	0.68
Big	1.42	0.21	0.11	**4.10**	0.66	0.47	0.86	0.65	0.57

As we observe when looking at the adj. R^2 values, the value of the adj. R^2 increases with the addition of another factor (e.g. the 'Weak-Small portfolio increases from 0.39 in the CAPM model to 0.51 in the two-factor model, and to 0.75 for the three-factor model). The key difference between R^2 and adj. R^2 is that while R^2 is always increasing with the addition of new factors, the adj. R^2 can increase if the added factor significantly improves the model or can decrease if the new predictor does not improve the model. Looking at the adj. R^2 from Table 6 we can therefore say that the model is improved with additional factors, RMW and SMB. Since this tendency can be observed in most portfolios we can conclude that there is an improvement in the explanatory power of the models.

On the other hand, looking at the t-values and their significance in the three models that are tested, it can be observed that four are significant in the CAPM model, six are significant in the two-factor model and five are significant in the three-factor model. Since four of these portfolios are significant in all three models, we can conclude that the variability in the total return is not completely accounted for by the factors. The increase of significant alphas generated by the addition of a new factor is in-line with previous literature (Fama-French, 2015). Even so, the risk of having significant alpha is increasing as new factors are included. While the model has more predictors, the degrees of freedom of the t-value are increasing, making the critical value, with which our obtained t-value is compared, smaller. Consequently, the risk of having a significant alpha is increased for each model.

If in Table 6 the intercepts and R^2 values were discussed, in Table 7 the coefficients for the three regression models are presented. Panel A reveals the coefficients of R_m-R_f as predictors, Panel B presents R_m-R_f and RMW as predictors, and Panel C presents R_m-R_f, RMW and SMB as predictors for each of the 9 LHS regression portfolios.

Table 7 Characteristics of Regressions

CAPM, two-factor model and three-factor model regressions for 9 value-weight Size-ROCE portfolios: July 2001 – June 2017, 192 months. At the end of each June, stocks are assigned to three size groups using sample tertile breakpoints. Similarly, stocks are allocated to three ROCE groups using tertile breakpoints. The intersections of the two sorts produce 9 Size-ROCE portfolios. The LHS variables are the monthly excess returns on the 9 Size-ROCE portfolios. The RHS variables are $R_M - R_f$ for the CAPM model, $R_M - R_f$ and RMW for the two-factor model, and $R_M - R_f$ for the three-factor model. Factors are constructed with an independent 2 x 3 sort on size and ROCE. Panel A shows the CAPM model, Panel B the two-factor model and Panel C the three-factor model.

Panel A:

$$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt} - R_{ft}) + \varepsilon_{it}$$

		Coefficient					t		
			ROCE					ROCE	
		Weak	*Neutral*	*Robust*			*Weak*	*Neutral*	*Robust*
R_M-R_F	*Small*	0.85	0.62	0.68	Size	*Small*	**11.16**	**9.74**	**10.99**
	Mid	1.20	0.84	0.83		*Mid*	**11.49**	**12.90**	**15.05**
	Big	1.70	1.15	0.64		*Big*	**13.25**	**18.77**	**13.86**

Panel B:

$$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt} - R_{ft}) + h_i RMW_t + \varepsilon_{it}$$

			ROCE					ROCE	
		Weak	*Neutral*	*Robust*			*Weak*	*Neutral*	*Robust*
R_M-R_F	*Small*	0.60	0.69	0.76	Size	*Small*	**7.66**	**9.51**	**10.97**
	Mid	0.87	0.80	0.87		*Mid*	**8.07**	**10.82**	**13.84**
	Big	0.90	1.14	0.76		*Big*	**11.09**	**16.22**	**15.43**

			ROCE					ROCE	
		Weak	*Neutral*	*Robust*			*Weak*	*Neutral*	*Robust*
RMW	*Small*	-0.37	0.09	0.12	Size	*Small*	**-6.78**	1.88	**2.48**
	Mid	-0.47	-0.06	0.05		*Mid*	**-6.31**	-1.09	1.24
	Big	-1.16	-0.02	0.18		*Big*	**-20.66**	-0.50	**5.16**

Panel C:

$$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt} - R_{ft}) + h_i RMW_t + S_i SMB_t + \varepsilon_{it}$$

			ROCE					ROCE	
		Weak	*Neutral*	*Robust*			*Weak*	*Neutral*	*Robust*
R_M-R_F	*Small*	0.76	0.80	0.89	Size	*Small*	**13.21**	**12.74**	**15.95**
	Mid	1.03	0.91	0.97		*Mid*	**10.90**	**13.53**	**18.21**
	Big	0.81	1.15	0.74		*Big*	**10.53**	**15.97**	**14.79**

			ROCE					ROCE	
		Weak	*Neutral*	*Robust*			*Weak*	*Neutral*	*Robust*
RMW	*Small*	-0.55	-0.04	-0.03	Size	*Small*	**-13.40**	-0.84	-0.72
	Mid	-0.66	-0.18	-0.07		*Mid*	**-9.70**	**-3.67**	-1.73
	Big	-1.05	-0.04	0.20		*Big*	**-19.06**	-0.69	**5.63**

			ROCE					ROCE	
		Weak	*Neutral*	*Robust*			*Weak*	*Neutral*	*Robust*
SMB	*Small*	0.85	0.60	0.68	Size	*Small*	**13.34**	**8.61**	**10.91**
	Mid	0.87	0.55	0.55		*Mid*	**8.25**	**7.40**	**9.26**
	Big	-0.48	0.05	-0.12		*Big*	**-5.68**	0.65	**-2.14**

Comparing Panels A, B and C, we can observe that Rm-Rf is a significant predictor, by itself, of all 9 LHS portfolios, and remains significant even when controlling for profitability factor RMW and size factor SMB. As can be observed in Panel A, the coefficients for Rm-Rf are strong and close to 1. However, we can see that portfolio 'Weak-Big' has a coefficient of 1.7, meaning that this portfolio has almost 2 x the volatility of the index. This portfolio is however the "problem portfolio" that has been discussed in Table 2, Panel B, since it only has 7 companies on average and should be disregarded. Moreover, in general we can see that the small portfolios have lower coefficients; this is because OMXS30 mainly consists of larger companies and thus does not resemble the smaller size companies' market movements as accurately. In addition, comparing Panels A, B and C we can see that the magnitude of Rm-Rf is improved for most portfolios and kept close to 1. For example, looking at the portfolio 'Robust-Mid', in Panel A the coefficient is 0.83 and increases to 0.87 in Panel B and finally increases to 0.97 in Panel C.

Looking at the RMW coefficients from Panels B and C, we can observe that the coefficients are relatively weak. However, the majority of the portfolios are significant. Moreover, a clear pattern can be observed with higher and more positive values for RMW in the robust portfolios compared to the weak portfolios, similar to what has been observed by Fama-French (2015). Interestingly, the 'Robust-Big' portfolio has the highest coefficient; this is contradicting what would be expected since a 'Small-Robust' portfolio would be expected to demonstrate the highest coefficient (Fama-French, 2015). One explanation for this might be that the 'Big-Robust' companies are the ones that are most hyped by research analysts, and hence people will follow their profitability much more closely. 'Small-Robust' companies are often ignored by larger investors and most big funds cannot analyze and invest in such small companies and so their prices will not be driven as much by RMW. Moreover, when looking at Nordic companies one should remember that compared to Fama-French the majority of the portfolios for Nordic companies would be in the smallest portfolio of the Fama-French, 2015 research. When controlling for Size (Panel C) for the robust column only, the 'Big-Robust' portfolio remains significant.

In order to understand if these results are economically interesting for investors (meaning to have a practical relevance not simply statistical significance), in Appendix C the economic impact of the factors for each portfolio is presented. The table is obtained by simply multiplying the factor premium from Table 4, Panel A with the coefficients from Table 7. For example, for RMW the factor premium is 0.2 (see Table 4, Panel A), and similarly the coefficient value for portfolio 'Robust-Big' is 0.2 (see Table 7, Panel C). Therefore, in Appendix C, Panel C, the economic impact for RMW is 0.04. In economic terms this means that on average a 'Robust-Big' portfolio gives an excess return associated with the factor of 0.04% per month or ~2% per year.

5. Discussion

In the beginning of this study we expected to find results supporting the idea that ROCE has an explanatory value, similar to the finding of Novy-Marx (2013) and later Fama-French (2015). This was also confirmed in this study (see Tables 6 and 7), however the factor was smaller than observed in the Fama-French five-factor model. One likely explanation is inefficient pricing of small stocks. Since our universe (OMX Nordic Index Stockholm) contains, on average, smaller firms than that of the US stock exchange as a result of containing First North. As smaller stocks are often off-limits for many institutional investors, there is a possibility that many of our defined portfolios might include pricing inefficiencies. Another possible explanation is currency fluctuations as well as macro-economic risks that are not accounted for and thus dilute the factor premiums, which in turn affect portfolio returns.

In Table 7 the coefficient for the factors can be found. Having OMXS30 as the proxy for market risk and Stibor as a proxy for risk-free rates produced coefficients around one for mid-sized and big portfolios. However, the smaller companies illustrate much coefficients. This is due to the OMXS30 market proxy consisting mostly of big and mid-sized companies. Moreover, in Table 7 a clear pattern of increasing coefficients, from weak to robust, can be observed for the RMW coefficient. A similar pattern for the profitability factor has been observed in previous empirical studies on other regions (Fama & French, 2015), though with much stronger coefficients. When looking at the average for the two-factor model (consisting of factors RMW and Rm-Rf), RMW is positive for all robust portfolios, meaning it is positively associated with returns. But when you take into account the size effect, you find RMW is negative (but not significant) in most cases. In the three-factor model (Rit - Rft= αi + β(Rmt-Rft) + hiRMWt + SiSMBt + εit), most of the RMW coefficients are negative. However, many of the coefficients are not significant. Note that the negative impact decreases going from weak to robust portfolios. In previous studies, portfolios have been constructed using 5x5 sort while our study used 3x3 sort. This might be the reason for not obtaining more positive coefficients for the robust portfolios. Due to the restriction of the number of companies in this study we would not be able to construct diversified portfolios with higher number sorting (for example 4x4 or 5x5); this is because the number of stocks in each portfolio would be too few. Another explanation is that the new SMB has a positive collinearity with the profitability factor RMW that can be seen in Table 4. Another explanation is that there might be market discrepancies that are unaccounted for in our regression model that differ between the US stock market and the Nordic stock market.

Following the results in Appendix C which show the economic impact and illustrate the practical implications of the results in economic terms, we observed that the 'Robust-Big' portfolio has the highest positive economic impact for the factor RMW. As can be observed, the values for RMW are significant but small. For example, if we compare it to the market risk and size factor these demonstrate a much stronger economic impact. As discussed previously, one reason for obtaining such weak results compared to studies conducted on the US market (Fama French 2015) is due to our sample size having many small companies which are not as followed by institutional investors and thus the price would not be driven by the profitability factor RMW as strongly. Looking at Appendix C, Panels B and C this tendency seems to be correct, with companies in the small portfolios demonstrating much lower RMW values.

The model that is tested in this study was conducted following the methodology of Fama-French (1993, 2015), our sample with Nordic data provides a different base the factor creation. In the 2016 study of Fama-French they used size groups that were roughly resembling the NYSE breakpoints. However, the breakpoints that are used in this thesis are calculated by splitting the sample into size groups with a similar number of companies. One could argue that this difference reduces comparability with the Fama-French results. It should be noted however that studies have repeatedly found that constructed risk premiums are specific to the sample in regards to region and time-frame. Looking at a sample containing larger numbers of smaller stocks should fall into the same category.

6. Conclusion

This study investigated whether ROCE is a factor that explains the stock returns using the methodology proposed by Fama-French (1993, 2015). Moreover, this study compared the performance of three models. One model includes only CAPM, the second model additionally includes ROCE factor (RMW), and the third model additionally includes a size factor (SMB). The study aims to understand which of the three models best predicts the returns of the 9 LHS-portfolios. To quantify the performance of the models, the significance of the alphas and the adjusted. R^2 values are studied in the same manner as Fama-French did in their earlier studies from 1993.

This thesis used companies listed on the OMX Nordic Stockholm exchange as the sample, with OMXS30 as a proxy for market risk and Stibor as a proxy for the risk-free rate.

The analysis was conducted in a similar manner as presented in the Fama-French 1993 article. For the factors a 2x3 sort was used with median breaking point for size and 30th and 70th percentile as breaking point for ROCE. After obtaining 6 portfolios from the 2x3 sort, the factors RMW (robust portfolio – weak portfolio) and SMB (small portfolio – big portfolio) were obtained. These factors represent the excess return that a “robust” company (a company with high ROCE) generates compared to a “weak” ROCE company. Similarly, the SMB factor illustrates the excess return a “small” company generates compared to a “big” company. As presented in Table 4, RMW factor is on average 0.20 and SMB factor is 0.47. In addition, the market risk was calculated using OMXS30 minus Stibor to obtain the R_m-R_f factor.

Following the construction of the variables, the regression portfolios were calculated using a 3x3 sort of size and ROCE with 33rd and 66th percentile as the breaking points. These portfolios were constructed in the similar manner, following steps 1-3 as presented in section 3.3.2.

Having obtained these portfolios, regressions were run with the portfolio returns as the dependent variable and the factors as independent variables. A comparison of a one-factor model (CAPM), two-factor model (R_m-R_f and RMW) and a three-factor model (R_m-R_f, RMW and SMB) was conducted.

The results show that the two- and three-factor models outperform the CAPM for our sample (OMX Nordic Index Stockholm). However, the result of the regression also showed that additional factors lead to an increasing number of significant intercepts (similar to what was found in the study by Fama-French, 1993).

We have found that the profitability factor significantly explains the market behaviour when controlling for market risk and size. However, this factor is smaller and more volatile than what has been found in the study conducted on US markets by Fama-French (2015). As can be observed in Table 7, we found that the strongest coefficient for RMW was in portfolio ‘Robust-Big’ for the three-factor model (in contrast to what would be expected since Fama-French has found that the ‘Robust-Small’ portfolio has the strongest coefficient). One explanation for this is that the companies that are included in our study are much smaller and most of them are of the same size as the small companies from the sample investigated by Fama-French. Furthermore, the companies that are included in our small portfolios are often ignored by larger investors and not analysed by research analysts, thus the prices might not be driven as much by the profitability factor RMW.

6.1 Implication

By applying the Fama-French model on the OMX Nordic Stockholm exchange, this thesis becomes part of the research body that looks at market inefficiencies. Previous studies focused mainly on larger markets (for example US, Europe and Asia) with very few studies conducted on the Nordic market. Since our thesis has looked at a sample containing many small stocks, it elucidates the limited theoretical understanding of the behaviour of small stocks. In previous studies, the profitability factor was measured as ROE (Fama-French, 2015) or gross profitability (Novy-Marx, 2013). While these are clear measurements from an accounting perspective, ROCE tries to capture the true operating profitability by taking into account the assets and liabilities that are used to drive profit. Thus, this thesis contributes to a better understanding of the profitability factor.

Except for the theoretical contribution as underlined in the above paragraph, this thesis also has practical implications. Since we have found that the ROCE factor is a small but significant predictor of the Swedish stock market, it helps to improve investment decisions by giving a better understanding of the risk associated with the measurement. This in turn could lead to fewer market inefficiencies and better predictability of stock price and market movements. By focusing on ROCE, a measure which is commonly applied by value investors and stock market analysts, this thesis proposes findings which are directly applicable by this community of professionals.

Investment decisions impact the economy as a whole, and citizens on an individual level. Since pension funds often manage the retirement savings for large numbers of people, their decisions impact the everyday lives of citizens. Creating higher predictability in the market could lead to better economic stability and investment decisions. Moreover, it could help in making wiser decisions regarding the comparability of risk levels for different asset classes.

6.2 Further Research

Our research question was to analyze if ROCE is a factor that explains the stock returns for the OMX Nordic Stockholm exchange. In section 4, Tables 6 and 7 in this report, we conclude that the profitability factor RMW, in our analysis, has a significant but small explanatory value. Given little research has been done looking particularly at the profitability factor in the Nordic region, this thesis therefore aims to add to the scarce amount of insight. In future research it could be interesting to incorporate the entire Nordic region in the sample by adding Danish, Finnish, Norwegian and Icelandic companies. Furthermore, it would also be interesting to look at the countries in isolation and to look at the differences that can be found.

The findings in Appendix C try to demonstrate the economic relevance of the investigated factors for investors. However, given these calculations are done by simply calculating the coefficients obtained from the regressions and multiplying with the factor premiums calculated as a simple mean, it has a very low statistical significance. In order to obtain more reliable values, one might run a Fama-Macbeth regression. By doing so the factor premiums are obtained as regression coefficients in the second step, making the calculations much more reliable.

As a part of the Nordic stock market, our universe consists of First North in addition to OMX Stockholm. As a result of this, we also encounter discrepancies that differ from the US stock market (Fama-French, 2015). This is because of the size of the stocks in our universe, with our sample consisting of smaller firms than that of the US stock market. Even the large firms that exist are much smaller in size in terms of market capitalization and therefore would fall into the category of “small” stocks for the Fama-French Study. This study thus gives well-needed insight into the behaviour of small stocks which are often overlooked. In future research one can wish to include a larger sample of bigger stocks by including indices from other Nordic companies and comparing the results of the profitability factor for large cap stocks and small cap stocks.

Secondly, the database we chose to utilize was Capital IQ which limits the ability to collect data (it should be noted that a check on the Eikon database was done without successfully obtaining a larger sample size). Since we define our universe consisting of firms that are listed on the OMX Nordic Stockholm exchange at present, we also create a survival bias. This survival bias occurs because our universe does not include “dead time series” (companies that have been delisted on the exchange). As an improvement for future research, it would be preferred to obtain data that consists of all available stocks for each time period in the timeseries. This would eliminate the survivalist bias and thus create a better comparability to previous research.

In this paper we have focused on studying the factor RMW calculated using the ROCE as the measurement for profitability. However, this study only adjusts for size and market risk. In future research it would be interesting to also include the B/M- and Investment factor and thus test the whole Fama-French five-factor-model using the ROCE as profitability factor. Here it would be particularly interesting to investigate if any of the factors would be driven out. Fama-French, 2015 showed that by introducing two additional factors to the original three-factor model (Profitability and Investment), the new factors cause problems with collinearity that result in the previous value-factor being obsolete in the five-factor model. This occurred because the new factors, profitability and investment, already explained a large portion of the value factor. Following the same reasoning, it would be interesting to examine if the ROCE factor is explained by other factors or if it is unique and has a significant explanation value on its own in the five-factor model.

ROCE is one of many profitability measurements that are commonly used in value investing to gauge a firm’s operating profitability. For future research, it would be interesting to look at how ROCE compares to other profitability measures. These measurements could include a comparison of the original RMW factor (ROE) and comparing it to ROCE, ROIC and ROA. This could give insight into which profitability factor gives the highest explanatory value.

Another form of methodology of calculating ROCE is by using an average of beginning and ending balances. This is commonly used by accounting practitioners and could also be interesting to investigate. In this case, we would suggest comparing ending balances as used in this study with an average of beginning and ending balances of ROCE, to see if this methodology might result in stronger and more significant coefficients for the profitability factor (RMW). Moreover, a similar comparison for both ROCE and ROCE minus cash (ROIC) with ending balance, and average beginning and ending balance, might be of interest.

7. Bibliography

Aharoni, G., Grundy, B. & Zeng, Q. 2013, "Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama-French analysis", *Journal of Financial Economics,* vol. 110, no. 2, pp. 347-357.

Banz, R.W. 1981, "The relationship between return and market value of common stocks", *Journal of Financial Economics,* vol. 9, no. 1, pp. 3-18.

Barber, B.M. & Odean, T. 1999, "The Courage of Misguided Convictions: The Trading Behavior of Individual Investors", *Financial Analysts Journal,* vol. 55, no. 6, pp. 41-55.

Basu, S. 1977, "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis", *The Journal of Finance,* vol. 32, no. 3, pp. 663-682.

Bishop, E.B. 1969. ROCE as a tool for planning and control. *Long Range Planning*, 2(4): 80-87.

Bhandari, L.C. 1988, "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence", *The Journal of Finance,* vol. 43, no. 2, pp. 507-528.

Black, F. 1972, "Capital Market Equilibrium with Restricted Borrowing", *The Journal of Business,* vol. 45, no. 3, pp. 444-455.

Chan, L.K.C., Hamao, Y. & Lakonishok, J. 1991, "Fundamentals and Stock Returns in Japan", *The Journal of Finance,* vol. 46, no. 5, pp. 1739-1764.

Chen, L., Novy-Marx, R. and Zhang, L., 2011, “An Alternative Three-Factor Model” (April 2011). Available at SSRN: https://ssrn.com/abstract=1418117

DeBondt, W.F.M. & Thaler, R. 1985, "Does the Stock Market Overreact?", *The Journal of Finance,* vol. 40, no. 3, pp. 793-805.

Fama, E.F. 1970, "Efficient Capital Markets: A Review of Theory and Empirical Work", *The Journal of Finance,* vol. 25, no. 2, pp. 383-417.

Fama, E.F. & French, K.R. 1992, "The Cross-Section of Expected Stock Returns", *The Journal of Finance,* vol. 47, no. 2, pp. 427-465.

Fama, E.F. & French, K.R. 1993, "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics,* vol. 33, no. 1, pp. 3-56.

Fama, E.F. & French, K.R. 2008, "Dissecting Anomalies", *Journal of Finance,* vol. 63, no. 4, pp. 1653-1678.

Fama, E.F. & French, K.R. 2015, "A five-factor asset pricing model", *Journal of Financial Economics,* vol. 116, no. 1, pp. 1-22.

Fama, E.F. & French, K.R. 2016, "International tests of a five-factor asset pricing model", *Journal of Financial Economics*, vol. 123, no. 3, pp. 441-463.

Graham, B., Dodd, D. 2008. *Security Analysis*. 6th ed. New York: McGraw-Hill.

Greenblatt, J. (2006), “The Little Book that Beats the Market”, N.J. John Wiley & Sons.

Hong, H. & Sraer, D. 2016, "Speculative Betas", *The Journal of Finance,* vol. 71, no. 5, pp. 2095-2144.

Huberman, G. & Kandel, S. 1987, "Mean-Variance Spanning", *Journal of Finance,* vol. 42, no. 4, pp. 873-888.

Jegadeesh, N. 1990, "Evidence of Predictable Behavior of Security Returns", *Journal of Finance,* vol. 45, no. 3, pp. 881-898.

Marshall, K.J. 2017, “Good Stocks Cheap: Value Investing with Confidence for a Lifetime of Stock Market Outperformance”, McGraw-Hill Education

Koller, T., Goedhart, M. and Wessels, D., 2018, Valuation: Measuring and Managing the Value of Companies, 6th edition (McKinsey & Company), John Wiley & Sons.

Lakonishok, J., Shleifer, A. & Vishny, R.W. 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance,* vol. 49, no. 5, pp. 1541-1578.

Lintner, J. 1965, "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets", *The review of economics and statistics, vol. 47, no. 1, pp. 13-37.*

Lucas, R. 1978, "Asset Prices in an Exchange Economy", *Econometrica,* vol. 46, no. 6, pp. 1429-1445.

Markowitz, H. 1952, "Portfolio Selection", *The Journal of Finance,* vol. 7, no. 1, pp. 77-91.

Merton, R.C. 1973, “An Intertemporal Capital Asset Pricing Model”, *Econometrica*, vol. 41, no. 5, pp. 867-887.

Mossin, J. 1966, "Equilibrium in a Capital Asset Market", *Econometrica,* vol. 34, no. 4, pp. 768-783.

Novy-Marx, R. 2013, "The Other Side of Value: The Gross Profitability Premium", *Journal of Financial Economics,* vol. 108, no. 1, pp. 1-28.

Odean, T. 1998, "Are Investors Reluctant to Realize Their Losses?", *Journal of Finance,* vol. 53, no. 5, pp. 1775-1798

Pattabiraman, S, 2013. Growth vs Profitability: The Importance of ROCE. *CFO Connect*, March 2013. 30-31.

Roll, R. 1977, "A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory", *Journal of Financial Economics,* vol. 4, no. 2, pp. 129-176.

Rosenberg, B., Reid, K. & Lanstein, R. 1985, "Persuasive evidence of market inefficiency", *Journal of Portfolio Management,* vol. 11, no. 3, pp. 9-17.

Rubinstein, M. 1976, "The Valuation of Uncertain Income Streams and the Pricing of Options", *The Bell Journal of Economics,* vol. 7, no. 2, pp. 407-425.

Sharpe, W.F. 1964, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk", *The Journal of Finance,* vol. 19, no. 3, pp. 425-442.

Stattman, Dennis, 1980, Book values and stock returns, *The Chicago MBA: A Journal of Selected Papers* 4, pp. 25-45.

Titman, S., Wei, K. C., Xie, F. “Market development and the asset growth effect: International evidence”, *Journal of Financial & Quantitative Analysis*. Dec 2004, Vol. 39 Issue 4, p677-700. 24p. 8 Charts.

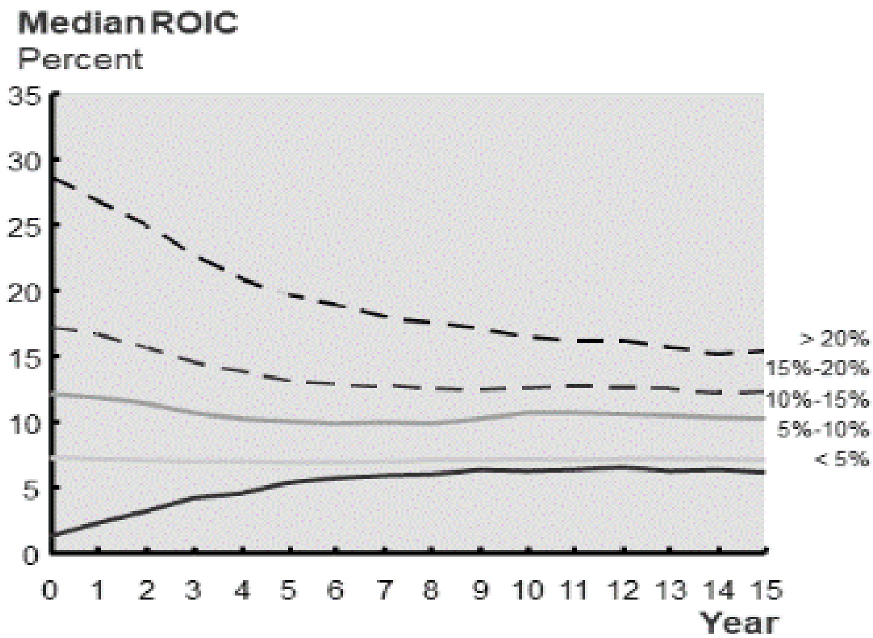
Vernimmen, P. & Quiry, P. 2009. Corporate Finance: Theory and Practice. Chichester: John Wiley.

White, G.I., Sondhi, A.C. & Fried, D. 1998. *The analysis and use of financial statements*. 2nd ed. New York: Wiley.

8. Appendix

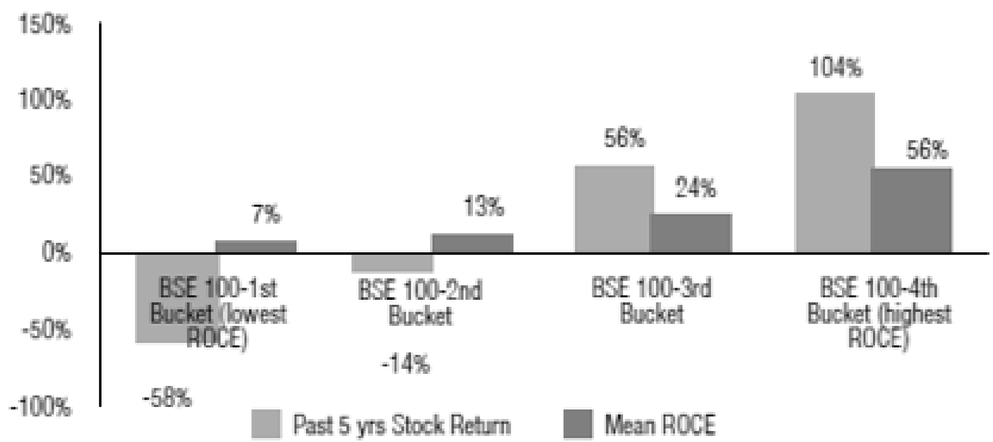
Appendix A – Illustrations of ROCE

Companies can typically sustain superior ROIC



Source: Koller, Goedhart and Wessels (McKinsey & Company, 2018)

ROCE Impact on Stock Returns



Source: CFO CONNECT (Pattabiraman, 2013)

Appendix B - Characteristics of Stocks in Sorted Portfolios

At the end of each June, stocks are assigned to three size groups using sample tertile breakpoints. Similarly, stocks are allocated to three ROCE groups using tertile breakpoints. The intersections of the two sorts produce 9 Size-ROCE portfolios. The table shows the average of Size-ROCE portfolios for the Market Capitalization (Size) and ROCE for all the data points of each portfolio between 2000 – 2015.

Size-ROCE sorted Portfolios

Size		*Weak*	*Neutral*	*Robust*
	Small	17	25	24
	Medium	131	185	185
	Big	4555	6498	10614

ROCE		*Weak*	*Neutral*	*Robust*
	Small	-0.66	0.06	0.47
	Medium	-0.27	0.07	0.23
	Big	-0.08	0.07	0.22

Appendix C – Economic Impact

Three-factor regressions for 9 value-weight size-ROCE portfolios with return data for July 2001 – June 2017, 192 months. At the end of each June, stocks are assigned to three size groups using sample tertile breakpoints. Similarly, stocks are allocated to three ROCE groups using tertile breakpoints. The intersections of the two sorts produce 9 Size-ROCE portfolios. The table shows the economic impact calculated by multiplying coefficient value from table 7 with the factor premiums from table 4 Panel A.

Economic Impact

Panel A

$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt}-R_{ft}) + \varepsilon_{it}$

		ROCE		
		Weak	*Neutral*	*Robust*
R_M-R_F	*Small*	**0.21**	**0.15**	**0.17**
	Mid	**0.29**	**0.20**	**0.20**
	Big	**0.41**	**0.28**	**0.16**

Panel B $R_{it} - R_{ft} = \alpha_i + \beta(R_{mt}-R_{ft}) + h_iRMW_t + \varepsilon_{it}$

		ROCE		
		Weak	*Neutral*	*Robust*
R_M-R_F	*Small*	**0.15**	**0.17**	**0.18**
	Mid	**0.21**	**0.19**	**0.21**
	Big	**0.22**	**0.28**	**0.18**

		ROCE		
		Weak	*Neutral*	*Robust*
RMW	*Small*	**-0.07**	0.02	**0.02**
	Mid	**-0.09**	-0.01	0.01
	Big	**-0.23**	0.00	**0.04**

Panel C

$R_{it} - R_{ft} = \alpha_i + \beta(R_{mt}-R_{ft}) + h_iRMW_t + S_iSMB_t + \varepsilon$

		ROCE		
		Weak	*Neutral*	*Robust*
R_M-R_F	*Small*	**0.18**	**0.19**	**0.22**
	Mid	**0.25**	**0.22**	**0.24**
	Big	**0.20**	**0.28**	**0.18**

		ROCE		
		Weak	*Neutral*	*Robust*
RMW	*Small*	**-0.11**	-0.01	-0.01
	Mid	**-0.13**	**-0.04**	-0.01
	Big	**-0.21**	-0.01	**0.04**

		ROCE		
		Weak	*Neutral*	*Robust*
SMB	*Small*	**0.40**	**0.28**	**0.32**
	Mid	**0.41**	**0.26**	**0.26**
	Big	**-0.23**	0.02	**-0.06**

Appendix D - Factor Calculation

Three-factors calculated for the Nordic market with return data for July 2001 – June 2017. 192 months. Market risk factor (R_M – R_F) was calculating using the OMX Nordic Index Stockholm and 1 month Stibor rate as a proxy for the risk free rate. At the end of each June stocks are sorted into 2 size groups with median as breaking point. Companies are assigned to 3 ROCE groups using 30th and 70th percentiles as breakpoints. Intersections of each Size/ ROCE form value-weighted portfolios. The Size factor. SMB. is the average of small stock portfolio returns minus the average of big stock portfolio returns. The profitability factor. RMW. is the average of the robust ROCE portfolio returns minus the weak ROCE portfolio returns (see Table 1).

No. Months	Year	$R_M - R_F$	RMW (ROCE Factor)	SMB
1	Jul-01	-1.39	4.47	-4.58
2	Aug-01	-8.72	9.24	-4.34
3	Sep-01	-11.54	7.36	-2.42
4	Oct-01	6.87	-15.79	-5.19
5	Nov-01	12.13	-10.14	4.20
6	Dec-01	1.23	2.92	0.30
7	Jan-02	-7.76	2.67	8.91
8	Feb-02	-0.25	8.04	3.15
9	Mar-02	0.44	1.28	1.69
10	Apr-02	-10.70	15.70	8.29
11	May-02	-7.77	7.58	1.53
12	Jun-02	-8.03	2.10	4.58
13	Jul-02	-11.31	15.27	10.04
14	Aug-02	-0.92	8.89	-0.59
15	Sep-02	-15.40	31.34	5.94
16	Oct-02	12.65	-66.13	-22.39
17	Nov-02	14.31	-14.02	-5.46
18	Dec-02	-14.40	20.79	4.42
19	Jan-03	-3.26	-8.25	-6.31
20	Feb-03	-1.78	15.87	7.73
21	Mar-03	-2.73	3.33	-2.30
22	Apr-03	12.91	-8.63	-7.94
23	May-03	-1.57	-5.07	4.41
24	Jun-03	3.18	-4.57	0.67
25	Jul-03	9.20	-19.41	-12.97
26	Aug-03	3.03	-11.37	3.09
27	Sep-03	-5.37	1.95	11.52
28	Oct-03	7.74	-8.33	-5.33
29	Nov-03	-0.61	4.73	8.27
30	Dec-03	2.30	-0.52	3.06
31	Jan-04	5.79	-22.57	-3.30
32	Feb-04	3.49	-12.79	-7.04
33	Mar-04	-2.13	3.50	0.00
34	Apr-04	-2.86	8.14	3.30
35	May-04	-1.80	0.70	0.04
36	Jun-04	4.71	-3.90	-1.61
37	Jul-04	-2.20	3.65	-1.55
38	Aug-04	0.15	0.72	-1.74
39	Sep-04	1.68	-4.27	5.50
40	Oct-04	-2.13	0.79	3.76
41	Nov-04	4.38	-4.34	6.86
42	Dec-04	-1.20	-3.11	4.20
43	Jan-05	-0.15	-0.38	1.64

No. Months	Year	$R_M - R_F$	RMW (ROCE Factor)	SMB
44	Feb-05	2.56	5.03	5.14
45	Mar-05	-0.32	1.99	2.55
46	Apr-05	-3.84	6.55	-1.61
47	May-05	5.62	0.82	-4.76
48	Jun-05	3.28	-3.68	2.85
49	Jul-05	3.97	2.10	1.76
50	Aug-05	-1.64	2.51	7.42
51	Sep-05	5.13	1.25	2.45
52	Oct-05	-1.61	-1.10	0.53
53	Nov-05	2.78	1.39	3.01
54	Dec-05	3.46	-1.56	4.66
55	Jan-06	0.12	-0.51	0.55
56	Feb-06	2.60	-0.17	-0.13
57	Mar-06	5.26	0.70	2.42
58	Apr-06	-2.28	1.54	4.33
59	May-06	-8.67	1.60	-0.74
60	Jun-06	-0.71	4.61	1.10
61	Jul-06	-1.18	-3.62	-2.86
62	Aug-06	6.56	-0.47	-5.36
63	Sep-06	4.07	0.72	1.91
64	Oct-06	4.33	-0.51	-0.59
65	Nov-06	-2.57	2.50	5.74
66	Dec-06	8.13	-0.63	5.74
67	Jan-07	3.25	-2.23	-0.53
68	Feb-07	-2.97	2.51	-2.34
69	Mar-07	5.36	-0.29	-0.51
70	Apr-07	4.76	2.28	2.18
71	May-07	0.06	-1.00	-1.11
72	Jun-07	-3.01	1.80	1.83
73	Jul-07	-1.01	3.00	1.22
74	Aug-07	-1.77	0.73	-5.90
75	Sep-07	1.20	1.91	1.30
76	Oct-07	-3.90	-8.42	-4.49
77	Nov-07	-5.43	-2.24	-2.80
78	Dec-07	-2.44	1.28	-2.65
79	Jan-08	-12.39	3.67	5.78
80	Feb-08	-1.29	0.00	7.18
81	Mar-08	-1.52	2.31	6.34
82	Apr-08	0.34	-1.72	-1.18
83	May-08	1.75	0.70	1.96
84	Jun-08	-14.81	-1.35	6.41
85	Jul-08	2.98	5.70	-3.33
86	Aug-08	1.74	2.47	-1.84
87	Sep-08	-12.17	-3.35	-0.57
88	Oct-08	-17.12	5.04	-3.91
89	Nov-08	0.29	2.38	0.92
90	Dec-08	8.99	-2.84	-17.26
91	Jan-09	-6.89	-3.84	20.79
92	Feb-09	3.63	-4.67	1.07
93	Mar-09	1.91	1.65	-1.43
94	Apr-09	12.36	-9.38	-3.64
95	May-09	1.60	4.58	5.14
96	Jun-09	-0.77	2.71	1.84
97	Jul-09	8.37	-2.55	-4.37
98	Aug-09	2.56	-0.08	0.18
99	Sep-09	0.90	2.37	4.95
100	Oct-09	7.53	1.68	-3.68
101	Nov-09	-0.92	2.44	-0.31

No. Months	Year	$R_M – R_F$	RMW (ROCE Factor)	SMB
102	Dec-09	-0.25	-1.02	-1.15
103	Jan-10	0.18	2.61	4.65
104	Feb-10	-2.13	2.94	1.83
105	Mar-10	5.63	-2.34	2.12
106	Apr-10	1.61	-4.00	-1.90
107	May-10	-6.98	3.49	-0.48
108	Jun-10	2.49	-0.47	-0.46
109	Jul-10	6.65	-0.68	-2.91
110	Aug-10	-3.44	2.00	-0.73
111	Sep-10	3.61	-2.87	1.78
112	Oct-10	0.58	3.31	1.67
113	Nov-10	1.33	-6.87	-1.97
114	Dec-10	1.80	-5.87	-0.21
115	Jan-11	-0.81	-0.72	7.98
116	Feb-11	-1.67	2.94	-0.52
117	Mar-11	1.31	0.03	1.01
118	Apr-11	1.41	0.39	-2.65
119	May-11	-1.09	5.27	-1.18
120	Jun-11	-3.92	2.39	-2.16
121	Jul-11	-4.76	1.05	0.43
122	Aug-11	-8.23	3.11	-2.91
123	Sep-11	-5.45	1.72	-0.65
124	Oct-11	8.71	0.23	-2.42
125	Nov-11	3.44	5.64	-5.17
126	Dec-11	2.02	-5.60	-3.37
127	Jan-12	4.80	-1.89	3.26
128	Feb-12	3.32	2.50	-0.41
129	Mar-12	-2.82	-1.92	-1.15
130	Apr-12	-1.48	1.50	2.00
131	May-12	-7.99	-6.26	1.19
132	Jun-12	6.43	2.39	-1.71
133	Jul-12	4.72	-2.75	-4.69
134	Aug-12	-2.15	-3.37	3.54
135	Sep-12	2.65	-1.24	-2.00
136	Oct-12	-3.12	-0.17	-4.33
137	Nov-12	2.12	-0.28	-4.95
138	Dec-12	1.66	-1.28	-1.67
139	Jan-13	5.77	-8.69	8.29
140	Feb-13	1.92	3.18	-0.66
141	Mar-13	0.10	3.79	-0.17
142	Apr-13	-0.25	1.04	-5.99
143	May-13	1.25	4.48	-1.89
144	Jun-13	-5.32	-1.11	1.95
145	Jul-13	5.81	1.15	-0.97
146	Aug-13	-2.79	-2.39	2.29
147	Sep-13	3.66	-4.36	0.23
148	Oct-13	1.13	-2.55	0.01
149	Nov-13	2.23	-0.62	-3.05
150	Dec-13	1.87	0.97	1.59
151	Jan-14	-2.19	-0.67	6.30
152	Feb-14	4.91	-1.33	-3.34
153	Mar-14	-0.36	4.06	-1.53
154	Apr-14	-0.82	8.50	-0.15
155	May-14	2.71	1.04	1.82
156	Jun-14	-1.86	-0.19	0.29
157	Jul-14	-0.35	-0.12	0.36
158	Aug-14	1.99	2.44	-2.80
159	Sep-14	1.13	7.04	2.61

No. Months	Year	$R_M - R_F$	RMW (ROCE Factor)	SMB
160	Oct-14	2.23	6.63	-1.00
161	Nov-14	3.42	5.87	-0.73
162	Dec-14	0.99	5.19	0.84
163	Jan-15	7.43	8.12	0.39
164	Feb-15	7.46	-2.29	-2.88
165	Mar-15	-1.38	4.44	6.92
166	Apr-15	-2.47	-8.39	-3.43
167	May-15	1.07	-0.95	2.93
168	Jun-15	-6.51	-1.71	5.63
169	Jul-15	2.58	4.67	3.14
170	Aug-15	-7.06	2.34	7.11
171	Sep-15	-3.57	3.34	3.23
172	Oct-15	6.78	-0.38	0.37
173	Nov-15	2.50	-0.07	0.71
174	Dec-15	-5.40	4.95	11.08
175	Jan-16	-6.21	-1.35	0.42
176	Feb-16	2.29	-1.17	-5.38
177	Mar-16	-1.79	-4.16	-1.17
178	Apr-16	0.24	-2.46	-4.02
179	May-16	0.71	2.96	2.69
180	Jun-16	-2.37	1.77	-1.37
181	Jul-16	3.55	3.06	4.48
182	Aug-16	2.89	-4.03	1.47
183	Sep-16	1.60	-0.02	0.00
184	Oct-16	0.58	2.00	-0.10
185	Nov-16	3.51	0.32	-0.64
186	Dec-16	2.76	-2.01	-2.39
187	Jan-17	1.37	2.16	5.70
188	Feb-17	1.54	5.06	0.10
189	Mar-17	-0.17	3.38	-0.49
190	Apr-17	2.54	4.24	3.14
191	May-17	0.81	3.72	-0.69
192	Jun-17	-2.29	-2.27	4.37
Mean		**0.24**	**0.20**	**0.47**
STD		**5.20**	**7.51**	**4.62**

Appendix E - Output

Regression analysis stata code

```
regress B11 RMRF
regress B12 RMRF
regress B13 RMRF
regress B21 RMRF
regress B22 RMRF
regress B23 RMRF
regress B31 RMRF
regress B32 RMRF
regress B33 RMRF

regress B11 RMRF RMW
regress B12 RMRF RMW
regress B13 RMRF RMW
regress B21 RMRF RMW
regress B22 RMRF RMW
regress B23 RMRF RMW
regress B31 RMRF RMW
regress B32 RMRF RMW
regress B33 RMRF RMW

regress B11 RMRF RMW SMB
regress B12 RMRF RMW SMB
regress B13 RMRF RMW SMB
regress B21 RMRF RMW SMB
regress B22 RMRF RMW SMB
regress B23 RMRF RMW SMB
regress B31 RMRF RMW SMB
regress B32 RMRF RMW SMB
regress B33 RMRF RMW SMB
```

Spanning regression Stata code

```
regress RMRF RWM SMB
regress RWM RMRF SMB
regress SMB RWM RMRF
```

Regression output

```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis

     User: Test
  Project: Test

1 . regress P11 RMRF

      Source |       SS       df       MS              Number of obs =     192
-------------+------------------------------           F(1, 190)     =  124.57
       Model |  3731.08313     1  3731.08313           Prob > F      =  0.0000
    Residual |  5690.98445   190  29.9525497           R-squared     =  0.3960
-------------+------------------------------           Adj R-squared =  0.3928
       Total |  9422.06759   191  49.3301968           Root MSE      =  5.4729

------------------------------------------------------------------------------
         P11 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8496344   .0761257    11.16   0.000     .6994742    .9997946
       _cons |   .7731833   .3954064     1.96   0.052    -.0067669    1.553134
------------------------------------------------------------------------------

2 .
3 . regress P12 RMRF

      Source |       SS       df       MS              Number of obs =     192
-------------+------------------------------           F(1, 190)     =  132.10
       Model |   7394.6562     1   7394.6562           Prob > F      =  0.0000
    Residual |  10635.6815   190  55.9772709           R-squared     =  0.4101
-------------+------------------------------           Adj R-squared =  0.4070
       Total |  18030.3377   191  94.3996736           Root MSE      =  7.4818

------------------------------------------------------------------------------
         P12 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   1.196117   .1040688    11.49   0.000     .9908383    1.401395
       _cons |  -.2406757   .5405459    -0.45   0.657    -1.306918    .8255664
------------------------------------------------------------------------------

4 .
5 . regress P13 RMRF

      Source |       SS       df       MS              Number of obs =     192
-------------+------------------------------           F(1, 190)     =  175.66
       Model |  14865.7747     1  14865.7747           Prob > F      =  0.0000
    Residual |  16079.3262   190  84.6280327           R-squared     =  0.4804
-------------+------------------------------           Adj R-squared =  0.4777
       Total |  30945.1009   191  162.016235           Root MSE      =  9.1993

------------------------------------------------------------------------------
         P13 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   1.695932   .1279593    13.25   0.000     1.443529    1.948335
       _cons |   .7610565    .664636     1.15   0.254    -.5499567     2.07207
------------------------------------------------------------------------------

6 .
7 . regress P21 RMRF

      Source |       SS       df       MS              Number of obs =     192
-------------+------------------------------           F(1, 190)     =   94.79
       Model |  1993.93235     1  1993.93235           Prob > F      =  0.0000
    Residual |  3996.56049   190  21.0345289           R-squared     =  0.3328
-------------+------------------------------           Adj R-squared =  0.3293
       Total |  5990.49284   191  31.3638368           Root MSE      =  4.5863
```

P21	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	.6211119	.0637942	9.74	0.000	.4952761	.7469477
_cons	1.073132	.3313547	3.24	0.001	.4195256	1.726739

8 .
9 . regress P22 RMRF

Source	SS	df	MS			
				Number of obs	=	192
				F(1, 190)	=	166.49
Model	3654.92217	1	3654.92217	Prob > F	=	0.0000
Residual	4171.11306	190	21.9532266	R-squared	=	0.4670
				Adj R-squared	=	0.4642
Total	7826.03523	191	40.9740064	Root MSE	=	4.6854

P22	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	.8409181	.0651724	12.90	0.000	.7123636	.9694725
_cons	.9066656	.3385135	2.68	0.008	.2389383	1.574393

10 .
11 . regress P23 RMRF

Source	SS	df	MS			
				Number of obs	=	192
				F(1, 190)	=	352.30
Model	6875.93639	1	6875.93639	Prob > F	=	0.0000
Residual	3708.23157	190	19.5170083	R-squared	=	0.6496
				Adj R-squared	=	0.6478
Total	10584.168	191	55.4144919	Root MSE	=	4.4178

P23	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	1.153402	.0614499	18.77	0.000	1.03219	1.274613
_cons	.2288009	.3191783	0.72	0.474	-.4007873	.8583892

12 .
13 . regress P31 RMRF

Source	SS	df	MS			
				Number of obs	=	192
				F(1, 190)	=	120.88
Model	2403.14943	1	2403.14943	Prob > F	=	0.0000
Residual	3777.39778	190	19.881041	R-squared	=	0.3888
				Adj R-squared	=	0.3856
Total	6180.54722	191	32.3588859	Root MSE	=	4.4588

P31	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	.6818754	.0620203	10.99	0.000	.5595385	.8042123
_cons	1.02544	.3221412	3.18	0.002	.3900074	1.660873

```
14 .
15 . regress P32 RMRF

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(1, 190)       =    226.51
       Model |  3595.92739         1  3595.92739   Prob > F        =    0.0000
    Residual |  3016.31253       190  15.8753291   R-squared       =    0.5438
-------------+----------------------------------   Adj R-squared   =    0.5414
       Total |  6612.23992       191  34.6190572   Root MSE        =    3.9844

------------------------------------------------------------------------------
         P32 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8341038   .0554212    15.05   0.000     .7247839    .9434236
       _cons |    1.04023   .2878645     3.61   0.000      .472409    1.608051
------------------------------------------------------------------------------

16 .
17 . regress P33 RMRF

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(1, 190)       =    191.96
       Model |  2124.91427         1  2124.91427   Prob > F        =    0.0000
    Residual |  2103.18402       190  11.0693896   R-squared       =    0.5026
-------------+----------------------------------   Adj R-squared   =    0.5000
       Total |   4228.0983       191  22.1366403   Root MSE        =    3.3271

------------------------------------------------------------------------------
         P33 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .6411679   .0462782    13.86   0.000     .5499029     .732473
       _cons |   .1143158   .2403746     0.48   0.635    -.3598299    .5884615
------------------------------------------------------------------------------

18 .
19 .
20 .
21 . regress P11 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =    100.02
       Model |  4844.74446         2  2422.37223   Prob > F        =    0.0000
    Residual |  4577.32313       189  24.2186409   R-squared       =    0.5142
-------------+----------------------------------   Adj R-squared   =    0.5091
       Total |  9422.06759       191  49.3301968   Root MSE        =    4.9212

------------------------------------------------------------------------------
         P11 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .5971663   .0779224     7.66   0.000     .4434571    .7508756
         RMW |  -.3660118   .0539751    -6.78   0.000    -.4724828   -.2595408
       _cons |     .90762   .3561031     2.55   0.012     .2051729    1.610067
------------------------------------------------------------------------------

22 .
```

```
23 . regress P12 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     99.47
       Model |  9246.02903         2  4623.01452   Prob > F        =    0.0000
    Residual |  8784.30863       189  46.4778234   R-squared       =    0.5128
-------------+----------------------------------   Adj R-squared   =    0.5076
       Total |  18030.3377       191  94.3996736   Root MSE        =    6.8175

------------------------------------------------------------------------------
         P12 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8705975   .1079469     8.07   0.000      .657662    1.083533
         RMW |  -.4719168   .0747724    -6.31   0.000    -.6194125   -.3244211
       _cons |   -.06734    .4933143    -0.14   0.892    -1.040449    .9057694
------------------------------------------------------------------------------

24 .
25 . regress P13 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =    498.03
       Model |  26009.8231         2  13004.9115   Prob > F        =    0.0000
    Residual |  4935.27785       189  26.1125812   R-squared       =    0.8405
-------------+----------------------------------   Adj R-squared   =    0.8388
       Total |  30945.1009       191  162.016235   Root MSE        =      5.11

------------------------------------------------------------------------------
         P13 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8972913   .0809119    11.09   0.000      .737685    1.056898
         RMW |  -1.157817   .0560458   -20.66   0.000    -1.268373   -1.047261
       _cons |   1.186325   .3697649     3.21   0.002     .4569281    1.915721
------------------------------------------------------------------------------

26 .
27 . regress P21 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     49.79
       Model |  2067.08719         2   1033.5436   Prob > F        =    0.0000
    Residual |  3923.40565       189    20.75876   R-squared       =    0.3451
-------------+----------------------------------   Adj R-squared   =    0.3381
       Total |  5990.49284       191  31.3638368   Root MSE        =    4.5562

------------------------------------------------------------------------------
         P21 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .6858189    .072142     9.51   0.000      .543512    .8281258
         RMW |    .093808   .0499711     1.88   0.062    -.0047648    .1923808
       _cons |   1.038676   .3296868     3.15   0.002     .3883377    1.689015
------------------------------------------------------------------------------

28 .
29 . regress P22 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     83.93
       Model |  3681.13161         2   1840.5658   Prob > F        =    0.0000
    Residual |  4144.90362       189   21.930707   R-squared       =    0.4704
-------------+----------------------------------   Adj R-squared   =    0.4648
       Total |  7826.03523       191  40.9740064   Root MSE        =     4.683
```

```
         P22 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8021871   .0741504    10.82   0.000     .6559183    .9484558
         RMW |  -.0561497   .0513623    -1.09   0.276    -.1574668    .0451674
       _cons |   .9272895   .3388653     2.74   0.007     .2588454    1.595734
------------------------------------------------------------------------------

30 .
31 . regress P23 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =    175.58
       Model |  6880.80516         2  3440.40258   Prob > F        =    0.0000
    Residual |   3703.3628       189  19.5945122   R-squared       =    0.6501
-------------+----------------------------------   Adj R-squared   =    0.6464
       Total |   10584.168       191  55.4144919   Root MSE        =    4.4266

------------------------------------------------------------------------------
         P23 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   1.136708   .0700898    16.22   0.000     .9984497    1.274967
         RMW |  -.0242007   .0485496    -0.50   0.619    -.1199694     .071568
       _cons |   .2376899   .3203082     0.74   0.459    -.3941485    .8695283
------------------------------------------------------------------------------

32 .
33 . regress P31 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     65.14
       Model |  2521.85671         2  1260.92835   Prob > F        =    0.0000
    Residual |  3658.69051       189  19.3581508   R-squared       =    0.4080
-------------+----------------------------------   Adj R-squared   =    0.4018
       Total |  6180.54722       191  32.3588859   Root MSE        =    4.3998

------------------------------------------------------------------------------
         P31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .7643022   .0696657    10.97   0.000     .6268799    .9017245
         RMW |    .119497   .0482559     2.48   0.014     .0243077    .2146864
       _cons |   .9815486   .3183705     3.08   0.002     .3535326    1.609565
------------------------------------------------------------------------------

34 .
35 . regress P32 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =    114.36
       Model |  3620.46005         2  1810.23003   Prob > F        =    0.0000
    Residual |  2991.77987       189  15.8295231   R-squared       =    0.5475
-------------+----------------------------------   Adj R-squared   =    0.5428
       Total |  6612.23992       191  34.6190572   Root MSE        =    3.9786

------------------------------------------------------------------------------
         P32 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8715753   .0629972    13.84   0.000     .7473074    .9958433
         RMW |   .0543239   .0436368     1.24   0.215    -.0317538    .1404015
       _cons |   1.020277   .2878954     3.54   0.000     .4523755    1.588178
------------------------------------------------------------------------------
```

```
36 .
37 . regress P33 RMRF RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =    122.28
       Model |  2384.95669         2  1192.47834   Prob > F        =    0.0000
    Residual |  1843.14161       189  9.75207202   R-squared       =    0.5641
-------------+----------------------------------   Adj R-squared   =    0.5595
       Total |   4228.0983       191  22.1366403   Root MSE        =    3.1228

------------------------------------------------------------------------------
         P33 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .7631857   .0494465    15.43   0.000     .6656477    .8607237
         RMW |   .1768645   .0342505     5.16   0.000     .1093021    .2444268
       _cons |   .0493532   .2259692     0.22   0.827    -.3963925     .495099
------------------------------------------------------------------------------

38 .
39 .
40 .
41 . regress P11 RMRF RMW SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(3, 188)       =    188.45
       Model |  7070.75989         3  2356.91996   Prob > F        =    0.0000
    Residual |   2351.3077       188  12.5069558   R-squared       =    0.7504
-------------+----------------------------------   Adj R-squared   =    0.7465
       Total |  9422.06759       191  49.3301968   Root MSE        =    3.5365

------------------------------------------------------------------------------
         P11 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .7561909   .0572514    13.21   0.000     .6432532    .8691287
         RMW |  -.5522163   .0412225   -13.40   0.000    -.6335344   -.4708982
         SMB |   .8494975   .0636757    13.34   0.000     .7238868    .9751082
       _cons |   .5046566   .2576802     1.96   0.052    -.0036594    1.012973
------------------------------------------------------------------------------

42 .
43 . regress P12 RMRF RMW SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(3, 188)       =    112.48
       Model |  11579.0788         3  3859.69293   Prob > F        =    0.0000
    Residual |  6451.25886       188  34.3152067   R-squared       =    0.6422
-------------+----------------------------------   Adj R-squared   =    0.6365
       Total |  18030.3377       191  94.3996736   Root MSE        =    5.8579

------------------------------------------------------------------------------
         P12 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |     1.0334   .0948318    10.90   0.000     .8463294    1.220472
         RMW |  -.6625454   .0682813    -9.70   0.000    -.7972414   -.5278494
         SMB |   .8696811    .105473     8.25   0.000     .6616184    1.077744
       _cons |  -.4798776   .4268236    -1.12   0.262    -1.321857    .3621015
------------------------------------------------------------------------------
```

44 .
45 . regress P13 RMRF RMW SMB

Source	SS	df	MS			
				Number of obs	=	192
				F(3, 188)	=	397.58
Model	26731.6434	3	8910.54778	Prob > F	=	0.0000
Residual	4213.45758	188	22.4120084	R-squared	=	0.8638
				Adj R-squared	=	0.8617
Total	30945.1009	191	162.016235	Root MSE	=	4.7341

P13	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	.8067359	.0766392	10.53	0.000	.6555526	.9579191
RMW	-1.051784	.0551822	-19.06	0.000	-1.16064	-.9429285
SMB	-.4837406	.085239	-5.68	0.000	-.6518885	-.3155928
_cons	1.415789	.3449416	4.10	0.000	.735336	2.096243

46 .
47 . regress P21 RMRF RMW SMB

Source	SS	df	MS			
				Number of obs	=	192
				F(3, 188)	=	70.76
Model	3176.91604	3	1058.97201	Prob > F	=	0.0000
Residual	2813.5768	188	14.965834	R-squared	=	0.5303
				Adj R-squared	=	0.5228
Total	5990.49284	191	31.3638368	Root MSE	=	3.8686

P21	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	.7981055	.0626269	12.74	0.000	.6745638	.9216473
RMW	-.0376703	.045093	-0.84	0.405	-.1266235	.051283
SMB	.599827	.0696544	8.61	0.000	.4624224	.7372317
_cons	.7541453	.2818744	2.68	0.008	.1981022	1.310188

48 .
49 . regress P22 RMRF RMW SMB

Source	SS	df	MS			
				Number of obs	=	192
				F(3, 188)	=	90.15
Model	4616.76442	3	1538.92147	Prob > F	=	0.0000
Residual	3209.27081	188	17.0705894	R-squared	=	0.5899
				Adj R-squared	=	0.5834
Total	7826.03523	191	40.9740064	Root MSE	=	4.1317

P22	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RMRF	.9052857	.0668859	13.53	0.000	.7733423	1.037229
RMW	-.1768696	.0481596	-3.67	0.000	-.2718722	-.081867
SMB	.5507452	.0743913	7.40	0.000	.4039963	.6974942
_cons	.6660407	.3010436	2.21	0.028	.0721832	1.259898

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50 .
51 . regress P23 RMRF RMW SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(3, 188)       =    116.83
       Model |  6889.04959         3  2296.34986   Prob > F        =    0.0000
    Residual |  3695.11837       188   19.654885   R-squared       =    0.6509
-------------+----------------------------------   Adj R-squared   =    0.6453
       Total |   10584.168       191  55.4144919   Root MSE        =    4.4334

------------------------------------------------------------------------------
         P23 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   1.146386   .0717705    15.97   0.000     1.004807    1.287965
         RMW |  -.0355327   .0516766    -0.69   0.493    -.1374732    .0664078
         SMB |   .0516986    .079824     0.65   0.518    -.1057672    .2091643
       _cons |   .2131664   .3230282     0.66   0.510    -.4240592    .8503921
------------------------------------------------------------------------------

52 .
53 . regress P31 RMRF RMW SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(3, 188)       =    110.21
       Model |  3940.08183         3  1313.36061   Prob > F        =    0.0000
    Residual |  2240.46539       188  11.9173691   R-squared       =    0.6375
-------------+----------------------------------   Adj R-squared   =    0.6317
       Total |  6180.54722       191  32.3588859   Root MSE        =    3.4522

------------------------------------------------------------------------------
         P31 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .8912347   .0558857    15.95   0.000      .780991    1.001478
         RMW |  -.0291303   .0402391    -0.72   0.470    -.1085085     .050248
         SMB |   .6780639   .0621567    10.91   0.000     .5554496    .8006782
       _cons |   .6599056   .2515332     2.62   0.009     .1637154    1.156096
------------------------------------------------------------------------------

54 .
55 . regress P32 RMRF RMW SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(3, 188)       =    139.02
       Model |  4557.68716         3  1519.22905   Prob > F        =    0.0000
    Residual |  2054.55277       188  10.9284722   R-squared       =    0.6893
-------------+----------------------------------   Adj R-squared   =    0.6843
       Total |  6612.23992       191  34.6190572   Root MSE        =    3.3058

------------------------------------------------------------------------------
         P32 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .9747618   .0535168    18.21   0.000     .8691912    1.080332
         RMW |  -.0664988   .0385335    -1.73   0.086    -.1425124    .0095148
         SMB |   .5512143    .059522     9.26   0.000     .4337974    .6686312
       _cons |   .7588053   .2408712     3.15   0.002     .2836477    1.233963
------------------------------------------------------------------------------
```

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56 .
57 . regress P33 RMRF RMW SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(3, 188)       =     84.58
       Model |  2428.68991         3  809.563302   Prob > F        =    0.0000
    Residual |  1799.40839       188  9.57132124   R-squared       =    0.5744
-------------+----------------------------------   Adj R-squared   =    0.5676
       Total |   4228.0983       191  22.1366403   Root MSE        =    3.0938

------------------------------------------------------------------------------
         P33 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |   .7408959   .0500837    14.79   0.000     .6420976    .8396942
         RMW |   .2029639   .0360616     5.63   0.000     .1318267    .2741012
         SMB |  -.1190704   .0557037    -2.14   0.034     -.228955   -.0091858
       _cons |   .1058349   .2254193     0.47   0.639    -.3388414    .5505111
------------------------------------------------------------------------------
```

Spanning Regression output

```
2 . regress RMRF SMB RMW

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     33.50
       Model |  1352.83281         2  676.416407   Prob > F        =    0.0000
    Residual |  3815.74149       189  20.1891084   R-squared       =    0.2617
-------------+----------------------------------   Adj R-squared   =    0.2539
       Total |   5168.5743       191  27.0605984   Root MSE        =    4.4932

------------------------------------------------------------------------------
        RMRF |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         SMB |  -.2315673   .0791286    -2.93   0.004    -.3876559   -.0754786
         RMW |  -.2658538   .0486733    -5.46   0.000    -.3618666   -.1698411
       _cons |   .4058294   .3260552     1.24   0.215    -.2373454    1.049004
------------------------------------------------------------------------------

4 . regress SMB RMW RMRF

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     30.37
       Model |  991.266463         2  495.633231   Prob > F        =    0.0000
    Residual |  3084.63606       189  16.3208257   R-squared       =    0.2432
-------------+----------------------------------   Adj R-squared   =    0.2352
       Total |  4075.90252       191  21.3398038   Root MSE        =    4.0399

------------------------------------------------------------------------------
         SMB |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         RMW |   .2191937   .0443088     4.95   0.000     .1317905    .3065969
        RMRF |  -.1871984   .0639673    -2.93   0.004    -.3133801   -.0610167
       _cons |    .474355    .292329     1.62   0.106    -.1022917    1.051002
------------------------------------------------------------------------------

5 . regress RMW RMRF SMB

      Source |       SS           df       MS      Number of obs   =       192
-------------+----------------------------------   F(2, 189)       =     43.81
       Model |  3412.20933         2  1706.10467   Prob > F        =    0.0000
    Residual |  7360.08842       189  38.9422668   R-squared       =    0.3168
-------------+----------------------------------   Adj R-squared   =    0.3095
       Total |  10772.2978       191  56.3994647   Root MSE        =    6.2404

------------------------------------------------------------------------------
         RMW |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        RMRF |  -.5127988   .0938848    -5.46   0.000    -.6979955   -.3276022
         SMB |   .5230066   .1057228     4.95   0.000     .3144583    .7315549
       _cons |   .0771034   .4546558     0.17   0.866    -.8197484    .9739552
------------------------------------------------------------------------------
```