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# Quality momentum

Evidence from Nordic stock markets

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**ABSTRACT:**
Multi-factor investing has gained wide attention in recent years from both investors and researchers. Prior research on multi-factor investing has found that combined strategies outperform single-factor strategies. Given the increased attention towards this field the primary objective of this study is to examine multi-factor investing in the context of momentum and quality, measured by profitability, in the Nordic stock markets from 1996 to 2020. Gross profitability has been suggested as the cleanest measure of profitability in prior research that outperforms other profitability measures in the power of predicting future returns. Furthermore, operating profitability and later an extension to operating profitability that amends it as a cash-based measure have challenged the position of gross profitability as a profitability measure with the most predicting power of future returns. Previous studies have concluded that combining gross profitability and momentum factors into a joint strategy provides excess returns in the U.S. stock markets.

The scope for this study consists of Nordic stock markets including Finland, Sweden, Norway and Denmark. The purpose is to investigate the possibility of combining momentum and quality into a joint strategy and if exploiting a joint strategy enhances the performance compared to the Nordic Market index and single-factor strategies formed solely based on momentum and quality. The portfolios in this study are formed as long-only and as long-short portfolios, and quality in this study is measured by three profitability factors: gross profitability, operating profitability and cash-based operating profitability. This study contributes to the existing literature of multi-factor investing by providing evidence of a multi-factor strategy returns in the Nordic stock markets. In addition, it adds to the field of quality investing by comparing the performance of the different profitability measures in the Nordic stock markets.

The results suggest that a joint strategy increases the performance of a portfolio compared to a single-factor portfolio during the sample period in the Nordic stock markets. The performance of the joint strategies is the highest when momentum is joint with gross profitability or cash-based operating profitability as a long-short portfolio. Combining the two factors, by utilizing either gross profitability or cash-based operating profitability as the quality measure, into a joint strategy offers investors excess returns and in addition a decreased risk compared to a portfolio based on solely momentum. The results propose that investors could increase their portfolio performance by accounting for quality of the underlying companies in addition to the past performance of the stock.

**KEY WORDS:** multi-factor investing, asset pricing, momentum, quality investing, profitability

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# 1 Introduction

Trading of securities has been available for individual investors and institutions for centuries. During this time one of the key interests of investors and researches has been to find abnormal returns and to exploit strategies that manage to outperform the markets. The development of technology and globalization have allowed the field of finance to develop rapidly in the past decades. This has led to researchers establishing different financial models and investment strategies to support investors in their investment decisions.

One of the key theories in the literature of finance is the efficient market hypothesis founded by Fama (1970). The academic field of finance and the developed models consider financial markets to be efficient and to follow the random walk. As the stock prices are assumed to move randomly and the movements cannot be predicted, the only possibility to generate higher returns is to take higher risk. This relationship between risk and return is described with the capital asset pricing model (CAPM).

Even though financial models and the academic field considers markets efficient researchers have found many anomalies that contradict the efficient market hypothesis. Graham and Dodd (1934) have been credited for discovering the value anomaly, a strategy chasing for profitable but undervalued stocks that sell at a bargain compared to the company's book value. Furthermore, in 1981 Banz discovered that firm size is a factor in explaining stock returns. He observed that smaller firms generate on average higher returns than larger firms. Following these anomalies Fama and French (1993) extended the capital asset pricing model by adding size and value as factors in addition to the market risk factor in CAPM and created a Three-Factor Model.

The three-factor model was developed to explain returns on assets more precisely. Fama and French (1992) argue that CAPM is a weaker proxy for explaining returns since beta coefficient has only a little information about average returns but by adding size and value as coefficients the three-factor model has been taken as a key part of the existing financial models. However, even the three-factor model was not able to explain some anomalies. Due to the Three-Factor model being inadequate at explaining expected returns, Fama and French (2015) added profitability and investment as factors in their model to better explain the average stock returns which resulted in the introduction of the Five-Factor Asset pricing model. In the model profitability is measured by operating profitability.

There are multiple ways to measure profitability although Novy-Marx (2013) argues that gross profits is the cleanest measure for companies' true economic profitability. He introduced gross profitability as a measure for quality and argue that the measure has roughly the same power in predicting the cross-section of average returns as book-to-market ratio. Novy-Marx's findings have challenged the position of book-to-market ratio as the élite measure of the stocks future profitability and opened a discussion to the alternative measures. This has even led to several investment managers such as AQR and Dimensional Fund Advisors to include similar measures to gross profitability into their investment strategies (CFA Institute Magazine 2014). Moreover, gross profitability measure opened up the dialogue and gave attention to the alternative profitability measures and the power of profitability to predict future returns. The re-evaluation of gross profitability by Ball, Gerakos and Nikolaev (2015) further led to the introduction of operating profitability which resulted to be a stronger predictor of expected returns than gross profitability. Soon operating profitability was revised by Ball et al (2016) to exclude accounting accruals and conformed into cash-based operating profitability. They concluded that cash-based operating profitability outperforms other profitability measures. Further focus has also been given to choosing the right deflator in the measurements (Cakici et al 2021).

By popular demand Fama and French (2018) ultimately added momentum as a factor in their factor model creating a six-factor model. Momentum refers to the occurrence where past winners continue to outperform in the future whereas the past losers continue to underperform. Momentum as an investment strategy has been extensively studied among the researchers since Jegadeesh and Titman (1993) uncovered this anomaly and it has been widely accepted. Momentum has also been documented in US and foreign markets, during different market conditions and in different asset classes such as foreign currency markets, commodity futures and government bonds (Asness, Moskowitz & Pedersen 2013). George and Hwang (2014) document that an alternative strategy of momentum that takes the current price to 52-week high price outperforms the momentum strategy introduced by Jegadeesh and Titman (1993). Multiple different hypotheses have also been proposed to explain the momentum anomaly. Jegadeesh at Titman (1996) among others have proposed that momentum arises from investor's underreaction to new information.

Momentum and quality are both investing styles that can be used as part of factor investing. Factor investing has been gaining a great amount of interest in the recent years. Especially multi-factor investing which seeks to combine multiple different factors into an investment strategy such as momentum, value, and quality has received tremendous attention and has led to the establishment of multiple exchange traded funds providing exposure to different combinations of such factors. One recent addition to the range of these exchange traded funds is Quality Momentum introduced by Virtus in late 2020 (Virtus 2020). In addition, researchers have examined the performance of multiple factors such as value and momentum and gross profitability and momentum (Asness et al. 2013; Bhootra 2018).

## 1.1 Purpose of the study

Traditional momentum strategies have been extensively studied across various asset classes and different markets, but still fundamental momentum is a relatively new field of study and the studies examining the relation between fundamental strength, referred as quality, and the stock returns have been increasing recently. In the past literature the attention has largely been on the correlation of momentum and earnings surprises (Chrodia and Shivakumar 2006; Novy-Marx 2015). Bhootra (2018) suggests that a possible reason for the lack of research on the relationship between momentum and earnings measures could lie in the past mixed evidence on the predictability of returns that firm’s earnings have had. However, Novy-Marx (2013) documents that a profitability measure scaling gross profits to assets represents the cleanest measure of economic profitability and it predicts the cross-section of average returns. Furthermore Ball et al. (2016) introduce cash-based operating profitability and they argue the measure outperforms other profitability measures and has a stronger ability to predict the future returns. Moreover Cakici et al. (2021) find that gross profits to market value performs better than other profitability measures suggesting that the choice of nominator can have a significant impact on the results. Considering this recent evidence on the ability of profitability measures to predict returns, the object of this thesis is to study the relationship between profitability and momentum.

The purpose of this study is to research momentum and quality in the Nordic stock markets. Profitability will be used in this thesis as a measure since it’s one dimension for quality of a company. Therefore, this study will exploit the eventual possibility of utilizing the two factors together in an investment strategy in order to improve the performance of momentum and quality strategies. The main goal of this thesis is to examine whether implementing a joint strategy earns abnormal returns and outperforms the usage of solely one of these factors as an investment strategy in the Nordic stock markets. The returns of the created portfolios are also benchmarked against a combined Nordic index consisting of OMXH, OMXC, OMXSPI and OSEBX. An additional object is also to examine the performance of gross profitability, operating profitability and cash-based operating profitability measures joined with momentum to study whether the choice of measurement for profitability has a significant role in the creation of returns.

The rising interest in multi-factor investing arises from the correlation between different factors. When the correlation is low or even negative it can provide investors an opportunity to decrease risk without compromising returns which leads to an improved Sharpe ratio as is in the case of value and momentum (Assness et al. 2013). Novy-Marx

(2013) also points out that profitability and momentum are orthogonal, which creates an interesting aspect for the joined momentum and profitability strategy in terms of diversification potential. This thesis and the joint study of momentum and quality, measured by profitability, in the Nordic stock markets contributes to the existing literature of multi-factor investing. In addition, this study contributes to the large body of literature documented on the efficient-market hypothesis of Fama (1970). Lastly this study adds to the growing string of literature studying the investment strategies in the Nordic stock markets.

## 1.2 Research question and hypotheses

This section discusses the research question and hypotheses of this study. The empirical tests cover a period from June 1996 until December 2020. This period can be considered to substantially cover the time horizon the Nordic stock markets have been active and developed enough for foreign institutional investors. The goal is to examine if a joined portfolio of momentum and quality measures can earn higher risk-adjusted returns in the Nordic stock market. There exists a broad variety of profitability measures and momentum strategies. The profitability measures this study focuses on consists of three measures including gross profitability, operating profitability and cash-operating profitability in order to test the joined strategy with multiple profitability measures. Following Bhootra (2018) the study will measure momentum with the 52-week high momentum strategy. The joined portfolios based on these measures are constructed as long-only and long-short portfolios. Since the purpose is to measure if controlling on profitability can enhance the performance of momentum strategies the first hypothesis studies the risk-adjusted returns of the joint portfolio.

$H_0 =$ Combining quality, measured by profitability, and momentum into a joined strategy does not generate superior risk-adjusted returns

$H_1 =$ Combining quality, measured by profitability, and momentum into a joined strategy does generate excess risk-adjusted returns

If the first hypothesis proves right, the second hypothesis H2 studies whether the choice of the measure has an impact on the returns. Gross profitability is chosen as a measure for profitability due to the findings of Novy-Marx (2013) indicating that gross profitability has the most predicting power of future returns. Later findings of Ball et al (2015;2016) contradict this finding suggesting that operating profitability or extending it as a cash-based operating profitability have better predicting power than gross profitability. This provides an interesting opportunity to study the three different measures and their ability to create abnormal returns when joint together with momentum.

$H_2 =$ The choice of profitability measure affects the magnitude of risk-adjusted returns of the joined portfolio

The presence of abnormal returns of the joined portfolios in the Nordic stock market are tested with Capital Asset Pricing Model as well as the three-factor model. Similar testing of excess returns is concluded for a single-factor profitability portfolios and single-factor momentum portfolio. The performance of the joined strategies is then benchmarked against the single-factor portfolio performances and against the combined Nordic index constructed in this study.

## 1.3 Structure of the study

This thesis proceeds in the following structure. Introduction has provided the research question and hypothesis. The first section sets out the introduction which has in prior section provided the research question and hypothesis. The second section discusses the efficient market theory (EMH) and its different forms as well as discusses the challenges EMH has faced over the years. Understanding the efficient market hypothesis is crucial for understanding the rest of this paper, since most of the models are based on the assumption that markets are efficient. The third section covers the different asset-pricing models. These models include dividend discount model, capital-asset pricing model (CAPM), arbitrage pricing model (APT) and the different factor models of Fama and French out of which the six-factor model is the latest addition.

Fourth section introduces the portfolio performance measures. These are further used in the research methodology in this thesis to measure the performance of the joint portfolio performance hence it is important that the reader is equipped with the understanding of these measures. The fifth section presents the most well-known previous studies regarding momentum strategy and quality with a greater focus on profitability as a measure for quality. Furthermore, the previous literature on the combined performance of these are presented. Section six discusses the data used to perform the study and moreover the methodology alongside with the regression methods used are provided. Lastly concluding remarks are presented in section eight.

# 2 Efficient Market Theory

In this chapter, the paper will focus on the relation between information and stock prices through the Efficient Market Hypothesis. Efficient Market Hypothesis (EMH) is one of the well-known basic theories in the academic literature on finance. Dimson and Mussavian (1998) state in their paper that every finance professional exploits the concept of market efficiency. EMH represents a theory that measures how the level of information affects stock prices.

Efficient Market hypothesis has been influenced by Maurice Kendall. In a paper regarding the past movements of stock prices, published in 1953, he concluded that the movements of share prices in the financial market were random, and the stock prices were determined efficiently (Kendall 1953: 11). However, the primary definition of EMH is taken from Eugene Fama's paper (1970) where it is stated that the basic idea of EMH is that a market in which prices always "fully reflect" available information is determined "efficient". The efficient market theory divides the market's in to three hypotheses based on the efficiency: the weak-form hypothesis, the semi-strong form hypothesis, and the strong-form hypothesis (Fama 1970).

Shleifer (2000) introduces three assumptions that the basic theoretical framework of EMH is built upon. The first assumption is that investors are rational hence the securities are valued rationally. Furthermore, the second assumption is that if there exist investors who are not rational, they are still trading randomly making them cancel each other out effectively not affecting the prices. Lastly if there are investors that are behaving in similar manner rational arbitrageurs trade against them offsetting them out and due to this the prices are not affected. (Shleifer 2000).

## 2.1 Different forms of efficiency

The weak-form hypothesis states that all information that is available by considering market data such as past prices, trading volume or short-term interest is already reflected in the prices of stocks. In this form of efficiency technical analysis loses its usability since there is no link between past stock prices and current price as they are seen being independent of each other. For the weak-form efficiency to hold the past stock price data should be free of charge and obtainable publicly. Under the weak-form hypothesis all investors should understand and utilize the historical market data. (Bodie, Kane & Marcus 2011: 348.)

Fama (1970) argues that most of the results in weak-form hypothesis are derived from random walk literature. Under the framework of weak-form hypothesis prices will follow random walk and under these circumstances making continuous excess returns by studying past market data is not possible (Brealey, Myer & Allen 2017: 332). The mathematical formula and the term of "random walk" was discussed in Pearson's (1905) paper where he established a mathematical formula for a drunken man walking across a field. According to Pearson (1905) a drunken man staggering totally unpredictably and randomly can be expected to end up closer to the starting point than any other point. (Pearson 1905: 342.)

Kendall (1953) studies the randomness of stock price movements and concludes that it is not possible to predict the future movements of a stock for one week in the future even if the stock behaves differently comparing to averagely similar stocks. In addition, Fama (1965) suggests that there is no memory attached to the stock price changes and hence the past price series will not predict the future movements. This statement is seen as the Random Walk Hypothesis in the Finance literature.

The semi-strong hypothesis assumes that the past prices and other publicly available information are reflected in the stock prices. Quality of management, earnings forecast, balance sheet structure and held patents can be viewed as examples of publicly available information. (Bodie et al. 2011: 348.) The semi-strong form of efficiency requires that when information becomes publicly available it is reflected into the stock prices and this way investors are not able to profit from this information by predicting returns. (Shleifer 2000: 6.)

The semi-strong form is seen as including the weak-form efficiency. Lastly the strong form efficiency is the strongest form of efficient market hypothesis. This form of efficiency differs from the semi-strong form of efficiency by considering all information relevant to the company's stock prices to be reflected in the prices including also the information that is only available for the insiders of the company. (Bodie et al. 2011: 348.) In this form of efficiency, it is not possible to profit from insider information since it is assumed to spread quickly and to be therefore incorporated into prices. (Shleifer 2000: 6). The formation of the different forms of efficiency is shown in Figure 1.

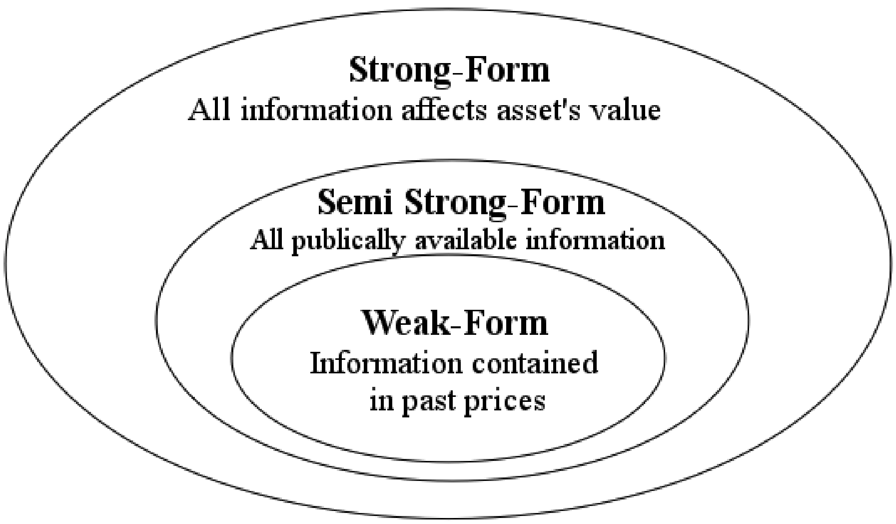


**Figure 1. Different forms of efficiency in Efficient Market Hypothesis.**

## 2.2 Challenges of EMH

The Efficient Market Hypothesis has been challenged on theoretical and empirical grounds. Economists in the twenty-first century have found that there exists predictability in the stock prices. The emphasis has been shifted towards the behavioral and psychological elements in the determination of the stock prices. (Malkiel 2003: 60.) Black (1986) finds that investors rather trade on noise than information. Investors tend to trade actively stocks, hold on to losers and sell winners, neglect diversification and trade based on the advice received from financial experts. This underlines that investors are not following the passive strategies expected from uninformed market contributors by the efficient market theory. (Black 1986: 531–533.) Efficient market theory expects investors to behave rationally, and it seems not to be the case in the real world.

Grossman and Stiglitz (1980) find that since there is encouragement for professionals to expose information that becomes quickly reflected in the stock prices the markets cannot be perfectly efficient. Anomalies would not be able to exist in a market that is fully efficient. However, researchers have found inefficiencies from the markets. French (1980) records a day-of-the-week anomaly that shows stock returns to be higher on Mondays. Haugen and Lakonishok (1988) among others document that the returns of the stock markets are unusually high during Januarys. Jegadeesh and Titman (1993) find that past prices do indicate the future prices documenting the momentum anomaly by implementing a strategy that holds the past winners and short sells the stocks that have performed poorly in the past on a 3–12-month timeframe. Their findings suggest that the strategy earns abnormal returns during the examination period. (Jegadeesh et al. 1993: 89).

Even though empirical issues exist with the efficient market hypothesis it still serves as a useful framework for understanding the relationship between information and prices. In modern finance the theory it should rather be considered how useful the model is rather than how well it manages to describe the reality.

# 3 Asset-pricing models

Understanding the relation between risk and return is key when observing asset-pricing. The models presented in this section browse risk and return through their own variables. Generally, it is assumed that risk and return are positively correlated meaning that investors demand more returns for more risk they take resulting in riskier assets requiring a higher rate of return. Furthermore, risk can be divided into two parts known as systematic and unsystematic risk. Systematic risk is also known as market risk since it arises from the financial markets, and it cannot be diversified away. Unsystematic risk is the part of the risk that is company based and unlike the market risk it can be diversified away.

The following chapter will present the different asset-pricing models. These models will define the basic characteristics of asset pricing. The models are presented in chronological order to represent the development of the asset pricing models withing the academic literature of finance. The chapter will cover Dividend discount model, Capital asset-pricing model, arbitrage pricing theory and the different factor models of Fama & French.

## 3.1 Dividend Discount Models

John Williams (1938) first introduced the dividend discount model (DDM). Different variations of the dividend discount model do exist however the focus on this paper is limited the focus on three of them. The logic behind the model is based on the theory that the stock price should represent the present value of all expected future dividends into perpetuity (Bodie et al 2011: 591). The model considers a basic approach in explaining the relationship between risk and return. The assumption that investors demand a return on their investment that consists of the change in price and the cash dividends is expected on all the dividend discount models (Bodie et al: 2000: 235). The dividend discount model assumes that the required discount rate of all investors is non-stochastic and constant over all the time periods and in addition the future divided flows are known with certainty. (Copeland et al. 2014: 18). The basic formula of DDM can be formed as follows:

(1) $P_0 = \frac{D_1}{(1+r)} + \frac{D_2}{(1+r)^2} + \cdots = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t}$,

where
$P_0$ is the current price of the stock,
$D_t$ is the expected dividend per share in year t,
$r$ represents the rate of return that investor requires.
Ains are disregarded

In the dividend discount model capital gains are disregarded and the focus is solely on dividends. The model requires dividend forecast for each year for the indefinite future making it somewhat unpractical. (Bodie et al. 2011: 591) Gordon and Shapiro (1956) offer an alternative model which adds into the basic model the growth rate. This model has become known as the Gordon's model or the constant growth dividend model discount model and is formed as follows:

(2) $P_0 = \frac{D_1}{r-g}$,

where
$D_1$ equals to dividends at time 1,
$g$ is the annual growth rate of dividends, which is expected to hold constant to infinity.

The model presumes that a constant rate can be used to model the growth of the dividends. The assumption of infinite dividends in the model does not mean that the stock will be held forever by the investor. There is no assumption of the investment horizon in the model since it has no bearing on the computed value of the stock. (Gitman, Joehnik & Smart 2011: 300.) A limitation of the model comes from the fact it can only be used when the required rate of return of the investor is higher than the growth rate. In a scenario where the dividends are expected to grow faster than the required rate of return the value of the stock would be infinite. (Bodie et al 2011: 593.) Another limitation is that the model does not take into account a situation where the company does not pay any dividends.

Due to the different dividend policies of companies' the usage of the dividend discount model can be challenging. An alternative valuation model is to consider the free cash flows of the company. The model of the free cash flow can be beneficial when a company does not pay any dividends. The free cash flow of a company can be determined as:

(3) $$FCF = EBIT \times (1 - t_c) + Capital\ expenditures - Increase\ in\ NWC,$$

where
$EBIT$ presents earnings before interest and taxes,
$t_c$ is the percent rate of taxes,
NWC is the net working capital.

The free cash flows are discounted year-by-year and added to discounted terminal value $V_T$. In order to avoid adding the present values of an infinite sum of cash glows the model takes into account the terminal value. (Bodie et al 2011: 612–613.) As a difference to formulas (1) and (2), the cash flow model is used to identify the present value of company, where the first two defines the value of a single stock. In order to calculate the stock price $P_0$, the value of the company is divided by the number of shares. The value of a company can be calculated now:

(4) $$Firm\ value = \sum_{t=1}^{T} \frac{FCFF_t}{(1+r_t)^t} + \frac{V_T}{(1+r_t)^T}, \text{ where } V_T = \frac{FCFF_{T+1}}{r_t - g},$$

## 3.2 Capital Asset Pricing Model

William Sharpe (1964), Jack Treynor (1962), John Litner (1965) and John Mossin (1966) have all been part of developing Capital Asset Pricing Model (CAPM). The CAPM is built on model of portfolio choice presented by Harry Markowitz (1959). The model of portfolio choice describes portfolio selection behavior of an investor. The CAPM presumes that investors choose mean-variance efficient portoflios meaning that investors are risk averse, and the mean and the variance of their investment is what they focus on. (Markowitz 1952: 79.)

Capital Asset Pricing Model in its basic form rests on four assumptions. The first assumption is that investors are rational price-takers, and they use Markowitz's portfolio selection model. In addition, all investors are assumed to have the same holding period. Secondly the investing opportunities are the same for all investors and there is a possibility to borrow or lend at the risk-free rate. Additionally, there are no taxes, transaction costs or short-selling restrictions. Lastly it is assumed that assets are evaluated and analyzed by all investors in a similar manner. This is executed by the usage of same rates of return, standard deviation and correlation between assets and returns. (Perold 2004: 15-16.)

The CAPM can be considered important for two reasons. Firstly, the model provides a methodology that can be used to estimate the expected rates of return for a variety of different financial applications. In addition, it validates the exercise of indexing, a passive investing style. The model offers a linkage between the risk of an asset and its expected returns. Furthermore, in the model it is assumed that the expected risk premium varies in direct proportion of the beta when markets are competitive. (Bodie et al. 2011: 279; Bodie & Merton 2000: 343-349.) The formula of the Capital Asset Pricing Model can be presented as

(5) $$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right],$$

where

$E(r_i)$ is the required return on an investment $i$,

$r_f$ equals the risk-free rate,

$\beta_i$ is the systematic risk of the asset

$E(r_m)$ describes the expected return of the market portfolio.

From the model, can be seen that the investments expected return consists of two sections, from the return of a risk-free investment and from the risk premium, which depends on the difference between the market return and the risk-free return. The CAPM states that since unsystematic risk can be diversified away, only market risk should affect the prices of assets. This risk that cannot be diversified away is measured in the model by the beta coefficient. The beta coefficient defines the relation between an individual stock and the expected returns of the financial markets. If the asset is considered to be risk-free the beta coefficient is zero since there is no covariance between the risk-free rate and the market portfolio. On the contrary the market portfolio has a beta of one. (Copeland, Weston & Shastri 2014: 149-151.) The beta coefficient is calculated by using the following formula:

$$(6) \qquad \beta_i = \frac{\sigma_{im}}{\sigma_m^2},$$

where

$\sigma_{im}$ is the covariance between the stock returns and the market returns,

$\sigma_m^2$ is the variance of the market portfolio.

The expected relationship between returns and beta can be presented as a security market line (SML) like presented in Figure 2 (Bodie et al 2011). The security market line can be utilised as a benchmark for the performance of an investment. The required rate of return can be implied from the security market line when the beta of an asset is known. In order to have an applicable risk-return relationship all the assets must lie on the security market line, and it can be utilised for individual assets as well as for portfolios. In the real world not all investments do lie on the security market line all the time. If an asset is underpriced, it will plot above the security market line where as over-priced assets plot below the line. This indicates that in the principle of CAPM, all investments are not priced correctly. (Bodie et al. 2011: 288-289.)

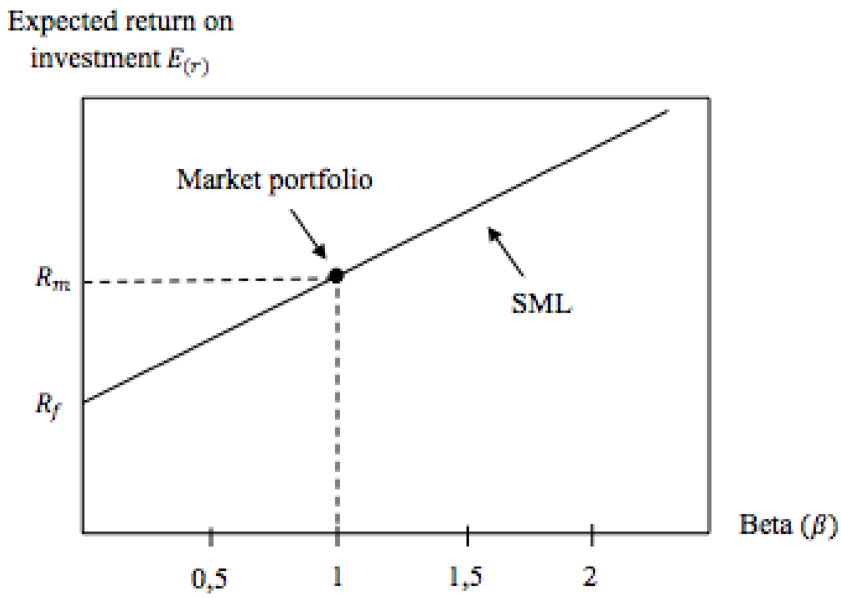


**Figure 2. The Security Market Line. (Brealey et al 2017: 199).**

Even though the CAPM is a widely used model, it has not managed well in empirical tests. Friend and Blume (1970) conclude that low-risk portfolios seem to perform better meanwhile high-risk portfolios represented poor performance. Fama and French (1992) argue that the CAPM is useless for what it was developed to do. They find that the beta coefficient fails to explain average returns. Later Fama and French (2004) propose that the reasons for the poor empirical test results may lie in the model's unrealistic assumptions and the difficulties in using the market portfolio in the tests of the CAPM. However, the temptation to use CAPM comes from the fact that they provide discipline to empirical tests by specifying the relation between risk and return and provide a usable measure of risk (Fama & French 2018).

## 3.3 Arbitrage Pricing theory

An alternative to the capital-asset pricing model was provided by Stephen Ross (1976) when he introduced the Arbitrage Pricing Theory. The capital-asset pricing model forms on the basis of the rate of return being linearly related to a common factor that is the market portfolio. The arbitrage pricing theory rests on similar logic but can be viewed as being more general than the capital-asset pricing model. (Copeland et al. 2014: 174). The arbitrage pricing theory relies on certain assumptions to be true, first one being that factor model can be used the describe the security model. Furthermore, that the variety of securities is wide enough to be able to diversify away the idiosyncratic risk. Lastly it is expected that no arbitrage opportunities exist in a financial market that is functioning well. (Bodie et al. 2011: 324.)

An arbitrage opportunity can be viewed as a situation where an investor is able to earn riskless profits without needing to make a net investment. In order for this to happen there has to be a possibility for a simultaneous purchase and sale of equivalent securities in order to be able to benefit from the difference in the prices of the securities. If such an opportunity presents itself investors will start to exploit this by buying the security from the place where it is provided with a lower price and sell where it trades with a more expensive price. This behavior will increase the price from the place where it is low and increase the price downwards where it is traded at a higher price. (Bodie et al 2011: 319–325.)

The arbitrage pricing theory implies that the returns on a stock are partially dependent on macroeconomic influences that are called factors and the other part comes from noise. Noise is an attribute that is unique to the company, however the there is no specification in the theory what these attributes are and how many there exists. (Brealey et al. 2017: 207.) The arbitrage pricing theory makes an assumption that the returns of a stock follow the relationship presented below:

(7) $$Return = a + b_1(r_{factor\ 1}) + b_2(r_{factor\ 2}) + \cdots + noise,$$

where

$a$ is a constant,

$b$ is the weight of the factor

As mentioned, the theory assumes that there are two types of risk. Similarly, to capital asset pricing model the arbitrage pricing model considers that the company-based risk is diversifiable away and leaves the investors to focus only on the factors as well as the macroeconomic risk. In the theory the expected risk premium of a security is driven by the expected risk premium associated with each of the factors and secondly the security's sensitivity to these factors. (Brealey et al. 2017: 207.) The above can be formed as the following formula:

$$(8) \qquad Expected\ risk\ premium = b_1\left(r_{factor\ 1} - r_f\right) + b_2\left(r_{factor\ 2} - r_f\right) + \cdots,$$

where

$r_f$ is the risk-free rate

## 3.4 Fama & French Factor Models

There have been multiple studies that have tried to explain the returns of securities via different variables that can be considered significant for asset-pricing and to explaining returns. When looking individually into size, book-to-market, earnings-per-share and leverage Fama and French (1992) find that these factors do explain returns but when book-to-market is combined with size they subsume the existence of leverage and earnings-per-share in explaining average returns. In addition, they suggest that the beta coefficient does not contain a lot of information about average returns making the capital asset pricing model weakening the explaining power that the model has over explaining returns. Instead Fama and French (1993) develop a three-factor model to be able to explain the returns of a security more accurately. They find that the three-factor model can be used in the selection of portfolios, evaluation of portfolio performance, predicting the cost of capital and even in measuring abnormal returns in event studies (Fama & French 1993: 53–54). This model has begun to dominate the field of empirical research and industry applications (Bodie et al. 2011: 336).

The relation that exists between risk and returns can be described with the three-factor model more precisely than in the capital asset pricing model since the three-factor model is observing returns from the perspective of risk-based factors. These factors are market return, size and book-to-market ratio. (Fama & French 1993.) The formula of the three-factor model can be formed as follows:

$$r_{it} = \alpha_i + \beta_{iM} R_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + e_{it}, \tag{9}$$

where

$\alpha_i$ is equal to the excess return,

$R_{Mt}$ presents the return on market index minus risk-free interest rate (which is in Fama's & French's study one-month bill rate),

$SMB_t$ (Small Minus Big) equals the difference between the returns on small- and big-stock portfolios,

$HML_t$ (High Minus Low) equals the difference between the average of the returns of high book-to-market portfolio and low book-to-market portfolio,

$\beta_{iM}$, $\beta_{iSMB}$ and $\beta_{iHML}$ describe the sensitivity of factors.

The size and book-to-market factors can explain the differences in average returns across stocks, but the market factor is needed to explain why stock returns are on average above the one-month bill rate (Fama & French 1993: 38). If these three factors are relevant, risk premiums should fully explain the excess returns making alpha zero (Bodie et al 2011: 420.)

The Three-Factor model was a significant improvement to asset pricing models since it captured the relation that average returns have with size and price ratios like book-to-market ratio which were left unexplained by CAPM. However, the Three-factor model has encountered some challenges since the model has not been able to explain some anomalies and specifically has missed the variation in average returns that link to profitability and investment. (Fama & French 2015). These issues in the three-factor model led Fama and French (2015) to adjust the model and introduce two new factors to the model making it a five-factor asset pricing model.

Motivated by the data providing a relation between profitability and average returns introduced by Novy-Marx (2014), profitability is added as a factor to the three-factor model. In addition, the findings of Titman, Wei and Xie (2004) of a relation between investment and average returns supported the addition of investment factor to the model. After the addition of the two factors the factor model can be computed as follows:

(10) $r_{it} = \alpha_i + \beta_{iM} R_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t + \beta_{iC} CMA_t + e_{it},$

where:
$RMW_t$ (Robust Minus Weak) equals the difference with strong and weak profitability,
$CMA_t$ (Conservative Minus Aggressive) represents the difference between high and low investment firms
$\beta_{iRMW}$ and $\beta_{iCMA}$ describe the sensitivity of factors

Profitability in the five-factor model is measured by operating profitability. This can be calculated by taking revenues and subtracting the cost of goods sold and selling, general and administrative costs and also deducting interest expenses. This figure is then divided by book equity. Investment factor is calculated by taking the change in total assets between years t-2 and t-1 and divided by the total assets at the end of year t-2. (Fama & French 2015). Both profitability and investment factors can be considered as measures for quality.

The five-factor model performs better than the three-factor model in explaining the returns. The five-factor model however struggles with explaining the low average returns for small stocks that have similar returns to companies that have low profitability but are high investment companies. (Fama & French 2015). In addition, the five-factor model still ignores momentum factor even though it has existed for over 20 years and is widely accepted by researchers.

Ultimately by popular demand Fama and French (2018) present a six-factor model including momentum as a factor. Differentiating from the other factors in the model, momentum factor is updated on a monthly basis. Their study also concludes that using cash-based operating profitability ratio introduced by Ball, Gerakos, Linnainmaa and Nikolaev (2016) beats the models that use operating profitability leading operating profitability to be replaced with cash-based profitability in the six-factor model. The model can be formed as follows:

(11) $$r_{it} = \alpha_i + \beta_{iM} R_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t + \beta_{iC} CMA_t + \beta_{iUMD} UMD_t + e_{it},$$

where
$UMD_t$ (Up Minus Down) represents the difference between the winner and loser stocks
$\beta_{iUMD}$ describe the sensitivity of factors

Predictably Fama and French conclude that the six-factor model outperforms the previous factor models in explaining the excess returns. Furthermore, Grobys and Kolari (2019) test the six-factor model in the international stock markets including North America, Europe and Asia. Their findings also suggest that apart from Japan momentum is a significant factor in the pricing of securities.

# 4 Performance measures for portfolios

This chapter discusses the most commonly used portfolio measures. Portfolio performance measures can be used by individuals to measure their own investment portfolios but also to measure the performance of asset managers since most of the financial assets are under the management of professional investors. (Bodie et al. 2018: 811). These presented measures combine risk and return measuring into one value, each with their own approach. Treasury bills (t-bills) are often used as a measure for risk free rate in these performance measures.

## 4.1 Sharpe ratio

In 1966 Sharpe introduced reward-to-variability ratio to measure the performance of mutual funds. While the measure became popular, the name did not attract the same popularity which led to Sharpe (1994) revising the name to Sharpe ratio. The purpose of the ratio is to measure for a zero-investment strategy the expected return per unit of risk and it can be used to measure the past performance (ex-post) or the expected performance (ex-ante) (Sharpe 1994). The measure implies the additional amount of return received for increasing the risk by one unit. It is measured by the trade-off of the reward to volatility and is calculated as follows:

(12) $$Sharpe\ ratio = \frac{E(R_a)-R_f}{\sigma_a},$$

where

$E(R_a) - R_f$ equals the portfolio's excess returns (over the risk-free rate),

$\sigma_a$ represents the standard deviation of returns over the measured period. (Bodie et al. 2018: 814).

Sharpe ratio has become widely used and it is commonly used to measure the performance of portfolio managers and mutual fund managers. A lower standard deviation implies lower risk and therefore increases the Sharpe ratio. The Sharpe ratio of the market index can be used as a benchmark for performance of a portfolio (Bodie et al. 2018: 815). Although the Sharpe ratio has become widely used by investors the ratio has received some critique for punishing the high return assets since higher returns also increase the standard deviation.

## 4.2 Sortino ratio

In 1994 Sortino introduced a modification of the Sharpe ratio that only accounts for the downside deviation of a portfolios return. The ratio uses lower partial standard deviation of excess returns which ignores the good returns in the calculation of the standard deviation and instead it only uses the bad returns (Bodie et al 2018: 139). Ignoring the upside volatility may be beneficial since most investors are not worried about the upside volatility. Sortino ratio can be computed as follows:

(13) $Sortino\ ratio = \frac{E(r_a)-r_f}{\sigma_d},$

where

$E(r_a) - r_f$ equals the portfolio’s excess returns (over the risk-free rate),

$\sigma_d$ represents the standard deviation of the downsize

## 4.3 Treynor measure

Treynor (1965) introduced reward to volatility ratio, also known as Treynor measure, to fulfill the gap in measuring mutual, trust and pension fund performance. Treynor measure's purpose is to compute the excess return generated for each unit of risk taken in a portfolio. The measure differs from Sharpe ratio by measuring risk with beta of the portfolio. Beta coefficient represents the systematic risk of the portfolio and is also known as the undiversifiable risk. (Bodie et al 2018: 816).

(14) $Treynor\ measure = \frac{E(r_{a)-}r_f}{\beta_p}$,

where

$E(r_a) - R_f$ equals the portfolio's excess returns (over the risk-free rate),

$r_f$ represents the return on risk-free rate

$\beta_p$ presents the beta of the portfolio

## 4.4 Jensen's alpha

In 1968 Jensen highlighted the persisting issue of assessing the risky portfolio's performance. He argues in his paper that portfolio performance measures need to take into account the different degrees of risk and that the measure needs to be an absolute measure of performance. Furthermore, he developed a measure that given the portfolio's beta and market return represents the average return on a portfolio above or below that forecasted by the CAPM (Bodie et al. 2018: 816) Furthermore this measure is also known as Jensen's alpha or just alpha and can be formed as follows:

(15) $Jensen's\ alpha = r_p - [r_f + \beta_p(r_M - r_f)]$,

where

$r_p$ presents the return of the portfolio

$r_f$ represents the return on risk-free rate

$\beta_p$ presents the beta of the portfolio

$r_m$ measures the return of the market portfolio

# 5 Previous literature

An extensive body of literature has been focusing on documenting the strong performance of past winners and the weak performance of past losers' across different countries and across different asset classes. The robust and persistent performance of momentum strategy has possessed challenges to asset pricing theories since it has been discovered and it has brought more attention to the discussion of market efficiency. Momentum has become widely used in factor investing that targets attributes related with higher returns. Moreover, quality can also be used in factor investing. Quality has gained more attention in the recent years from researchers since new profitability ratios with strong results have been discovered.

The following section will cover the previous studies related to momentum and quality. Since a considerable amount of research has been focusing on momentum strategy, this thesis will attempt to cover the most well-known research papers. The previous literature on quality will focus mostly on profitability as a measure for quality since the purpose of this thesis is also to measure quality through profitability.

## 5.1 Momentum

Momentum is a well-known investing style exploited commonly by investors. Momentum anomaly refers to the occurrence where securities that have performed well in the past continue to outperform and in contrast the securities that have not performed well in the past remain underperforming also in the future. The well performed securities are described as the winners and the underperformed securities are termed as losers. Investors using this method typically screen the asset class by looking at the past 12-months returns and buy the outperformers of the asset class while short-selling the underperformers.

In 1990 Jegadeesh studied the predictability of stock returns with US data from 1929 to 1982 and presents significant evidence that there is a positive serial correlation in the monthly stock returns especially when looking at 12-month serial correlations. Furthermore, these findings challenge the theory that stocks follow the random walk. Later Jegadeesh and Titman (1993) and Assness (1994) study the strategy of holding past winners and selling past losers and document that the strategy creates significant positive returns over 3 to 12 month holding horizon. Since then, a growing body of literature has been focusing on the momentum phenomenon and it has become well documented and widely accepted by researchers and investors.

In addition, Jegadeesh and Titman (2001) expand their research on momentum and examine the possible reasons for the momentum strategies profitability and examine whether the profitability of momentum strategies have continued for the following eight-year period after their previous study in the US stock markets. They conclude that momentum strategy is persistent and has continued to be profitable for the test period of 1990 to 1998. Furthermore, they document that momentum has continued to roughly earn a similar profit of one percent per month as documented in their previous study (see Jegadeesh et al. 1993).

Majority of the first studies researching momentum anomaly focus on the US equity market. However, Rouwenhorst (1998) fills the gap in the missing international evidence by studying the medium-term returns in 12 different European countries from 1978 to 1995. He documents that momentum strategy that takes a long position in the past winners and in contrast takes a short position in the past losers generates returns of roughly one percent per month in all the 12 different countries. These results are consistent with the findings of Jegadeesh and Titman (1993) from the US markets. The study also concludes that there is a correlation between momentum strategies across countries. Rouwenhorst (1999) also studies momentum in 20 emerging markets and concludes that momentum is present also in emerging markets.

Multiple hypothesis and theories have been proposed by various researchers to explain the momentum anomaly. One theory that researchers have proposed is that momentum arises from prices adjusting too slowly to news. Jegadeesh and Titman (1996) study the correlation between momentum and market's underreaction to earnings news to discover if underreaction to information could be an explanation to the existence of momentum anomaly. Their study proposes that market's do not reflect all available information directly but instead markets slowly adjust to new information.

The underreaction to news hypothesis is also tested by Hong, Lim and Stein (2000) in their study where they examine if there are signs that momentum is an echo of the slow dispersion of firm-specific information. They investigate the effect of firm-specific information to the momentum anomaly in the US stock market and conclude that momentum strategies are more profitable in smaller stocks and the profitability decreases with firm size. In addition, they find that momentum strategies are more successful in stocks that have low analyst coverage ratio and past loser stocks have higher analyst coverage than winner stocks. Similar results to firm-size were documented by Rouwenhorst (1998) with a dataset from 12 different European countries. Moreover, Fama and French (2012) document similar results regarding size finding that momentum is present in all size-groups, but it is more persistent with small stocks.

George and Hwang (2004) study an alternative momentum strategy where they examine the 52-week high price. They state that traders have a delayed reaction to good news. Furthermore, they argue that a stock trading near it's 52-week high has recently been exposed to good news. A comparison of the 52-week high price and the traditional momentum strategy of Jegadeesh and Titman (1993) shows that the closeness of 52-week high price better predicts the future returns than past returns.

Israel and Moskowits (2013) expand the existing literature on momentum strategies by investigating data for over 86 years in the US and in the international markets. They document the robustness of momentum anomaly prior and after to previously documented periods by Jegadeesh and Titman (1993; 1996) and Rouwenhorst (1998;1999). Their findings suggest that taking a short position on the past losers only plays a role in the strategy if investors are interested in the returns relative to a benchmark and shorting in a momentum strategy becomes more insignificant as firm size goes down. In contrast to Hong et al (2000) they also find that momentum is persistent throughout different size groups and over the time period documented there is no evidence that small cap stocks would experience a stronger momentum. Assness, Frazzini, Israel and Moskowitz (2014) further conclude that almost half of the premium comes from the upside of momentum and therefore momentum strategy can also be implemented as a long-only strategy.

Geczy and Samonov (2016) further expand the time horizon for testing of momentum strategy by taking a time period from 1801 to 2012 from the US security market. They document significant momentum returns since the beginning of 19$^{th}$ century. In addition, they also document seven over 10-year periods during which momentum has produced negative returns and point out that the market state affects the most the returns of momentum strategy. In order to take into account, the different market states in a momentum strategy the authors suggest a dynamically hedged portfolio which outperforms an unhedged strategy.

A key expectation in the overreaction theory has been that the mispricings will be corrected in the long run in the markets which leads to the reversals in the momentum gains. Lee and Swaminathan (2000) study the price and trading volume on the US markets. They contribute to the existing literature by documenting that the price momentum ultimately experiences a reversal, and the timing can be predicted based on historical trading volume. Similar results for momentum strategy yielding negative returns and experiencing reversals eventually were documented by Jegadeesh and Titman (2001).

Kent and Moskowitz (2016) study the market conditions in which momentum can produce persistent series of negative returns. Their findings suggest that momentum crashes occur in times of market stress, when markets are declining, and high volatility is present. During bear market conditions past losers experience high premiums which can cause momentum strategies to crash as the strategy holds short positions in these past losers. The study also suggests that these events can be partially predicted with bear market indicators and ex ante volatility estimates. These results are consistent with Cooper, Gutierrez and Hameed (2004) who document that the state of market determine the profitability of the momentum strategies.

In addition to stock markets momentum has been well documented also across different asset classes. Okunev and White (2003) study the foreign currency markets for eight currencies from 1980 to 2000. They find that by using moving averages rules a momentum strategy could be profitably applied to foreign currency markets. Erb and Harvey (2006) study the commodity futures and find that momentum exist in commodities as well. Moreover Moskowitz, Ooi and Pedersen (2012) find consistent return premia in equity index, currency, commodity and bond futures. Conclusively Asness, Moskowitz and Pedersen (2013) document persistent momentum profits in eight different markets and asset classes.

## 5.2 Quality

Benjamin Graham (1934) was not only interested in finding securities with good valuation metrics, but he was also interested in the quality of a company's assets. He considered what are the characteristics of a quality security and divided securities into high quality and low-quality securities. Even Berkshire Hathaway's, Warren Buffet's company's, performance is predominantly explained with buying high quality stocks (Frazzini, Kabiller, Pedersen 2012). While quality investing has existed for a long time the interpretation of quality in metrics and as a definition have not been unanimously defined by researchers. However, the principal behind quality investing is simple: high quality stocks should perform better than the low-quality stocks in terms of returns. During the last decade quality investing has received an increased amount of attention leading in discoveries of simpler quality measures.

Researchers have defined quality in various ways. Graham (1973) had seven criteria for quality including moderate P/B and P/E ratios, stability in earnings, uninterrupted dividend payments for 20 years, growth of earning-per-share ratio, stable earnings and sufficient firm size. The purpose of the first two measures is to ensure that the price is reasonable and the rest of the seven criteria measure the quality of the firms (Graham 1973). Moreover GMO, Graham's firm, discusses in a paper "The Case for Quality – The Danger of Junk" published in 2004 the criteria for quality firms. They suggest that firms with high profitability, low leverage and low earning volatility can be categorized as quality firms and tend to outperform in the long run. These findings have even influenced MSCI Quality Indices, Russel Defensive indices as well as Dow Jones Quality Index.

Sloan (1996) studies the accrual and cash flow components of firms as part of forecasting the future earnings. He creates an earning quality measure computed by taking the difference of cash and accounting earnings and further scaling it by firm assets. Additionally, he argues that investors fail to characterize the different components of earnings leading to firms with high levels of accruals to observe negative future abnormal stock returns focusing on future earnings announcements. This negative correlation between accruals and expected returns is known as accrue anomaly. The measure created by Sloan (1996) has become the dominating earnings quality measure (Novy-Marx 2014). Later Kozlov and Petäjistö (2013) document that earnings quality premium exists in the global developed markets. High earnings quality premium has established to be one of the most significant long-term patterns discovered in the academic literature (Sloan 1996; Fama & French 2008; Kozlov & Petäjistö 2013).

Another way to measure quality is introduced by Piotroski (2000) in his study. He constructs a measure by looking into nine components that each get assigned with a value of either 1 or 0 based on weakness (value of zero) or strength (value of one). The total F-score of a firm is therefore something between values from 0 to 9. Furthermore Piotroski (2000) argues that a firm with a score from 8-9 can be categorized as having the strongest fundamental signals and therefore to create the highest performance and in the contrary firms with a low score of 0 to 1 to have the lowest fundamental signals, hence creating the lowest returns. Out of these nine components four consist of profitability measures and other components measure liquidity and operating efficiency. F-score has been implemented at Societe General to construct the Global Quality Income Index. (Novy-Marx 2014).

Asness, Frazzini and Pedersen (2019) further divide quality into three categories. These categories are:

1. *Profitability.* Investors should be willing to pay a higher price for profitable companies. Profitability can be measured with for example earnings, accruals, gross profits, operating profitability or cash flows.
2. *Growth.* Companies with growing profits should earn a higher price.
3. *Safety.* A higher price should be also paid for companies that can be considered as safer stocks. Safety can be measure with for example low credit risk, low volatility or low leverage.

### 5.2.1 Profitability

Return on equity (ROE) has been the most commonly used ratio of profitability in earlier academic studies (Novy-Marx 2014). ROE has been one of the criteria used in Russel Defensive Indexes and MSCI Quality Indices. It measures the percentage of profit a company is able to produce with the invested equity capital of shareholders. ROE can be defined as follows:

(16) $$Retrun\ on\ equity = \frac{Net\ income}{Book\ value\ of\ equity},$$

where net income represents company's total earnings.

Novy-Marx (2014) implies that the financial economists have had a long-lasting belief that profitability should estimate returns. These economists have been struggling with the weak performance that have been achieved with return on equity (ROE) when studying the power to predict the cross-sectional differences in average security performance. To offer an alternative for the existing profitability measures Novy-Marx (2013) presents gross profitability as an alternative measure and argues that it outperforms other profitability measure in predicting the future returns.

Furthermore Novy-Marx (2013) suggests gross profitability to be an accounting measure that can be considered to be the cleanest out of true economic profitability measures. In his view the further down the income statement are gone, the more polluted the profitability measure becomes hence it starts to represent less true economic profitability. As an example, earnings are presented last on the income statement and thus they are more prone to be polluted. The pollution of the income statement profitability measures can occur from big investments in advertising in order to achieve higher sales. In a similar way investing in research and development increases the expenses for them and might lead to the firm's income outlook worse than in the benchmark companies even if the company would really be more profitable. (Novy-Marx 2013).

Gross profitability attempts to utilize data from the top lines of the income statement and further continues into dividing it by the assets of the company. Due to gross profitability being independent of leverage and hence not reduced by interest payments assets are chosen as the divider for the measure. (Novy-Marx 2013: 2–3.) The study further shows that there is a similar power of predicting the cross-section of average returns on gross profitability as there is with book-to-market ratio. When compared to earnings-to-book equity and free cash-flow-to-book equity the results imply a dominance of the gross profitability measure. In addition, Novy-Marx (2013) concludes that the gross profitability seems to outperform other profitability measures when predicting the cross-section of expected returns.

Ball, Gerakos, Linnainmaa and Nikolaev (2015) further study the profitability ratios and re-evaluate the power of gross profitability in predicting future returns. They find that net income and gross profitability have roughly the same power in predicting average returns when they are deflated consistently while Novy-Marx (2013) in his study divides gross profitability by the book value of total assets and net income is deflated by the book value of equity. Consequently, Ball et al (2015) argue that the superior explanatory power of gross profitability arises from this mismatch between deflators. Moreover, they conclude that the similar power of gross profitability and net income is perplexing since the claims for investors are what is left after reporting for all accounting items and therefore investors have no claims over gross profitability. In addition, there has been prior studies concluding that items such as research and development expenditures have power over predicting future returns (Chan, Lakonishok & Sougiannis 2001).

Ball et al (2015) further contribute to the academic literature by creating a measure of operating profitability. Operating profitability takes gross profitability and subtracts the selling, general and administrative costs and excludes research and development expenditures. Furthermore, the operating profitability is deflated by the total assets. Ball et al (2015) examine the performance of operating profitability as a proxy for future returns in the US stock markets and conclude that it outperforms gross profitability in predicting expected returns and does it as far as ten years ahead.

Accruals are an accounting component included in both gross profitability and operating profitability. Accruals are incomes or expenses relating to the current financial period that are taken into the result even though the cash transfer has not yet been processed. Accruals expose companies to counterparty credit risk since the cash transaction has not been completed. The negative relationship between accruals and future earnings has been documented by Sloan (1996) however it cannot be explained by the Fama and French five-factor model or the gross profitability of Novy-Marx (2013). More recently Hao and Lee (2019) document that firms continuously reporting high accruals observe low subsequent returns. The negative relationship further encourages Ball, Gerakos, Linnainmaa and Nikolaev (2016) to revisit their operating profitability measure. They create a profitability measure that excludes accruals from the operating profitability leading to the establishment of cash-based operating profitability. They test the measure in the US markets and confirm that cash-based operating profitability outperforms previous profitability measures including net income, gross profitability and operating profitability. Furthermore, their results suggest that the accrual anomaly is subdued due to the strong explanation power of cash-based operating profitability in the cross-section of expected returns. These results propose that an investing strategy's Sharpe ratio can be enhanced further by taking cash-based operating profitability factor into account rather than adding one factor for accruals and one for profitability.

Cakici, Chatterjee, Tang and Tong (2021) examine the different profitability measures in the international stock markets. They include 10 different profitability measures for a large sample of stocks and conclude that a new profitability measure that takes gross profitability deflated by market value (measured by market value of equity or enterprise value) performs better than the other profitability measures. Their findings agree with Novy-Marx (2013) who argues that gross profits are the cleanest measure for cash-flow. Correspondingly Cakici et al (2021) suggest that the choice of the scaling variable may have a significant result on the relation of profitability and stock returns.

## 5.3 Momentum and profitability

In the recent years the interest on multifactor investing has been increasing rapidly and the style has received attention from investors and exchange-traded funds. Multi-factor investing combines multiple factors into a strategy and factors such as momentum, quality, size, volatility and value have been increasingly popular to be combined together. An increasing amount of academic literature has been focusing on combining momentum with value or size (Asness et al 2013; Cakici et al. 2013; Fisher et al. 2016). Yet the relationship between profitability and momentum has not been extensively studied potentially due to the mixed evidence on the return predictability of companies' earnings (Bhootra 2018). However, after Novy-Marx (2013) introduced gross profitability and noted that gross profitability is orthogonal to momentum strategy several studies have been focusing on the relationship between profitability and momentum strategies.

Yu and Webb (2016) examine the possibility of enhancing price-based momentum strategies by adding a screening based on fundamental measures. They measure momentum based on similar methodology to George and Hwang (2004) 52-week high price. Fundamental measures are represented by gross profitability and a financial strength measure combined of eight factors. Their results conclude that adding either of the measures as a second screen improves the performance of a strategy of long-short price-based momentum. Correspondingly the findings suggest that the usage of gross profitability as an additional screening to momentum strategy is somewhat more effective than using the financial strength measure.

Bhootra (2018) study the combined strategy of momentum and profitability measured by gross profitability in the US equity markets. Their preference for gross profitability as profitability measure stems from the long-short strategy's ability to create greater abnormal returns on the long side whereas commonly the superior abnormal returns in a long-short strategy come from the short side. In addition, Novy-Marx (2013) proposes that the higher returns in gross profitability are a result from investor's underreaction to information on firm's gross profitability. Similarly, investor underreaction has been suggested to be the source for George and Hwang (2004) 52-week high momentum strategy's performance and therefore is chosen to be the measure for momentum in the study. The empirical test show that the joint profitability and momentum strategy which takes a long position in the high profitability and high ratio portfolio while taking a short position in the low profitability and low ratio portfolio earns a significant 1.24 percent monthly value-weighted return. In contrast profitability and momentum as, standalone strategies earn 0.38 and 0.48 percent monthly returns, respectively. In addition, they further document that a joint strategy of gross profitability and past-return based momentum of Jegadeesh and Titman (1993) earns a 0.83 percent value weighted monthly return while the past-return based momentum strategy earns 0.40 percent.

Arnott, Clements, Kalesnik & Linnainmaa (2019) study factor momentum in the US by utilizing an extensive amount of 51 factors that have been recognized in the academic literature as having ability to predict future returns. These factors can be categorized into accounting-based factors and return based factors. These categories include for instance measures of risk, illiquidity, firm age and several different profitability ratios such as operating profitability, gross profitability and cash-based profitability. Their results demonstrate that factor momentum is the cause of industry momentum and factor momentum includes industry momentum. Additionally, they conclude that almost all the factors included in the sample contribute towards factor momentum profits, some more significantly than others but there are no factors that would significantly lower the momentum profits.

# 6 Data and methodology

The purpose of this section is to present the data used in the research part of this thesis and the methodology used to construct portfolios and the measuring of their performance. Some data clustering is needed in order to create a stock universe that corresponds to a real-like investment scenario. The policies used to create the Nordic stock universe are documented and presented in this section. Furthermore, the risk-free rates and benchmark rates are presented.

## 6.1 Data

The sample used in this study is obtained from Thomson Reuters Datastream for annual financial data and historical returns. In addition, the Fama and French factor loading are acquired from the Kenneth French data library for European factors. The dataset contains the period from fiscal year 1995 to fiscal year 2019 and it includes OMX Stockholm, OMX Copenhagen, OMX Helsinki (previously Helsinki Stock Exchange HEX) and OMX Oslo main listed companies, with the following exceptions. Icelandic stock exchange, even though it's part of the Nordic markets, is excluded from the sample due to the small size limitations in terms of market capitalization. In addition, following Grobys and Huhta-Halkola (2018) stocks that are listed on First North or similar marketplace are omitted from the dataset. Following Novy-Marx (2013) all financial companies are eliminated due to the different business model that financial companies contain in comparison to non-financial companies. This is due to the high leverage that is normal for financial companies but for non-financial companies could be an indication of distress (Fama and French 1992). The sample also eliminates investments that are categorized as non-equity such as ETFs.

Due to potential liquidity issues the smallest 10% of the stocks are excluded from the sample following Tikkanen and Äijö (2018). The smallest stocks are often excluded in momentum literature to avoid an outcome where the results would be driven by illiquid and infrequently traded stocks (Bhootra 2011). In addition, the following conditions are applied to the stock universe. In case of a bankruptcy the return of the stock would be accounted as negative 100%. If a company is delisted the delisting return of the stock is expected to be zero in accordance with Tikkanen et al (2018). If the stock's primarily listing is not in the considered Nordic exchange it is omitted from the sample. Lastly including all the stocks that have been listed during the time horizon under examination should offer a real-like investment scenario subsuming survivorship bias. This should minimize the overestimation of historical performance.

The Nordic countries all have different monetary policy and have their own currency they use. Denmark uses Danish Krone (DKK), Finland uses Euro (EUR), Norway uses Norwegian Krone (NOK) and Sweden use the Swedish Krona (SEK). From these Nordic countries Finland is the only one that has taken the single European currency as their main currency. Denmark applies a fixed-exchange-rate policy implying that their aim is to keep the krone stable against the euro. Both Finland and Denmark have resiled their independent monetary policy in order to achieve stable exchange-rate relations. From 1995 the exchange rate for the Swedish krona has been determined by the markets and has not been managed by the central bank. Lastly, Norges Bank introduced an inflation target in 2001 but before that there was a long history of exchange rate targeting.

In order to be able to create a universe where all the measures are comparable the for the stocks traded in Norway, Sweden and Denmark the market values are converted into euros using the month-end closing spot prices for the respective rate areas. By doing so it is possible to distinguish between the market values. The foreign exchange rate fluctuation however withholds a possibility that there could be and FX effect embedded in the converted EUR values. The data for these spot prices is gathered from Thomson Reuters for the given time period from 1996 to 2019. The development of the Nordic currencies is visible in the figure below. As can be seen from the figure 2, the Danish Krone has been very stable over the years. There has been a more volatility over the EURNOK and EURSEK exchange rates over the years. However, the figure shows that the fluctuation in the EURSEK and EURNOK rates over the years has been modest apart from the time of the financial crisis.

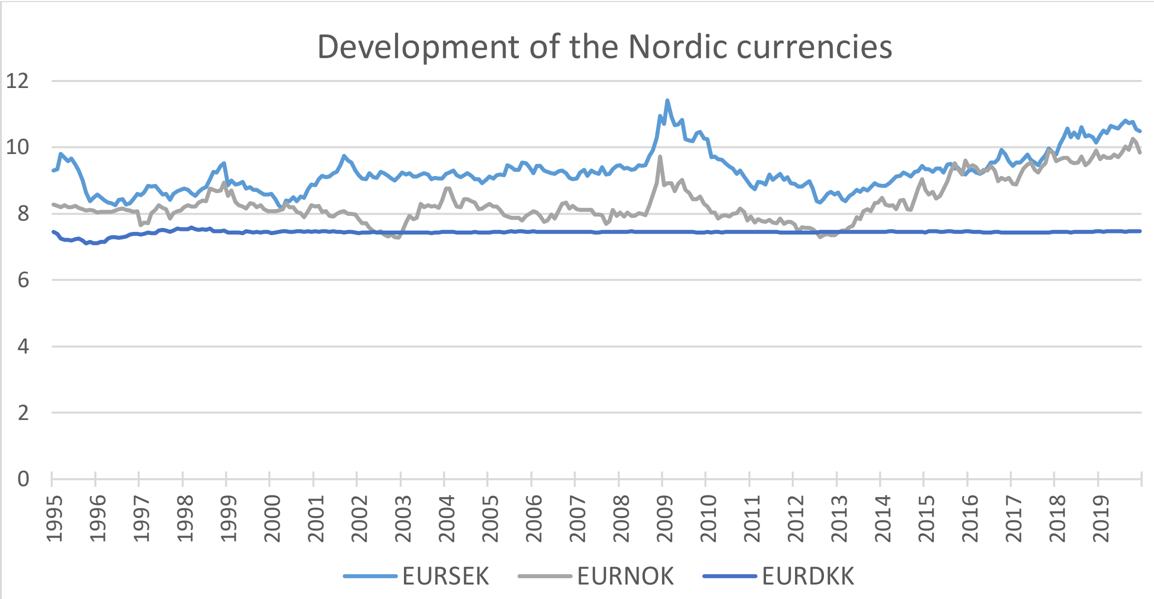


**Figure 3. The development of the Nordic currencies between 1995-2019**

### 6.1.1 Nordic Markets

The Nordics stock markets include Denmark, Finland, Iceland, Norway and Sweden. Often Iceland is excluded from the Nordic countries in the academic research due to the small size of the stock exchange. The number of stocks listed in these markets have been increasing over time as well as the foreign ownership. These economies have been experiencing continuous growth and most of the countries have nearly tripled their GDP from the beginning of 1990. Even though these markets are relatively new yet fairly developed these countries can be exposed to some extent to the "periphery syndrome". This becomes visible during turbulent times when international institutional investors pull out their equity positions from the furthest stock markets. This is also known as the herding behavior. The consequence of the behavior could potentially result in steeper decreases in the stock prices than would be seen on a more developed market in a similar occasion. (Pätäri and Leivo 2009). The herding behavior of these international institutional investors also affect the price momentum (Yu 2008).

The academic research has been traditionally highly focused on the U.S. markets due to the size and liquidity of these markets. Although the Nordic stock market do not compare to the U.S. markets in terms of for example market capitalization it does provide an interest alternative to study if different phenomenon also works outside of the United States. The Nordic countries are in the top 20 globally as measured by GDP per capita despite of being small countries on the North of Europe. In addition, these countries have a stable political environment, low levels of corruption and a low risk-profile.

The sample period used in this thesis contains data for over 20 years which should be adequate to study investment strategies, and it contains multiple market cycles like the dot-com bubble and the global financial crisis of 2008. Additionally, this time period is chosen since it describes the predominant part of the time horizon during which the Nordic stock markets have been developed enough for large overseas institutional investors to participate in.

### 6.1.2 Risk-free rate

Previous academic studies have been commonly using the US T-bill rate in Nordic studies as an estimate for the risk-free rate. The risk-free rate for this study is computed according to Grobys et al. (2018) and Silvasti, Grobys and Äijö (2021). The compiled Nordic rate is gathered by taking the interbank offered rates for the Nordic countries. These XIBOR-rates represent the benchmark interest rate at which the panel banks are willing to lend money on an unsecured basis to another bank with the given maturity. The XIBOR-rates used in this study consist of CIBOR, STIBOR, EURIBOR and NIBOR. EURIBOR has been established at the end of 1998 and for the period prior to EURIBOR this study will use HELIBOR. It is also noteworthy that Finland is the only Nordic country in this study that is a member of the Economic and Monetary Union (EMU) and thus the monetary policy is controlled and executed by the European Central Bank (ECB) including the setting of the short-term interest rates.

The 6-months XIBOR rates are chosen as the tenor following Grobys et al. (2018) due to the low interest rate environment that the global markets have experienced over the recent years. The usage of the longer tenor instead of the 3-months tenor is expected to create a slightly higher average return for the benchmark and therefore can be considered as a more conservative approach since the combined portfolios have a higher benchmark rate to surpass. (Grobys et al. 2018).

Furthermore, the XIBOR rates are used to combine a Nordic risk-free rate. Assembling a Nordic risk-free rate is anticipated to reflect better the true risk-free rate achievable for investors investing in the Nordic stock markets. The risk-free rate is computed by taking the average of the Nordic XIBOR rates. The development of the IBOR-rates and the combined Nordic risk-free rate is presented in Figure 3. As the figure 3 demonstrates the time period covers different lifecycles of the economy. The effects of the 1990's recession is visible in the interest rates in the mid-1990's in the Nordic countries and the time period also covers the financial crisis in 2007-2008 which can be observed as the hike in the rates around the time period and finally the beginning of the most recent COVID-19 pandemic during the most recent year of the observations.

In the most recent 5-year period the central banks have been exercising a non-traditional expansionary monetary policy resulting in negative interest rates. The negative rate environment has been most visible in the EURIBOR rates. However, as can be seen from figure 3 the Nordic risk-free rate combined in this study stays above zero for most of the observation period and only experiences a negative rate from mid-August 2020 onwards. The positive rate is mostly driven by the monetary policy of Norway which keeps the 6-months NIBOR at higher to the other interbank offered rates mainly due to Norway being a highly commodities driven economy compared to other Nordic countries. Taking a simple average of the 6-months XIBOR-rates increases the Nordic RF rate and again gives a higher benchmark for the combined portfolios to exceed.

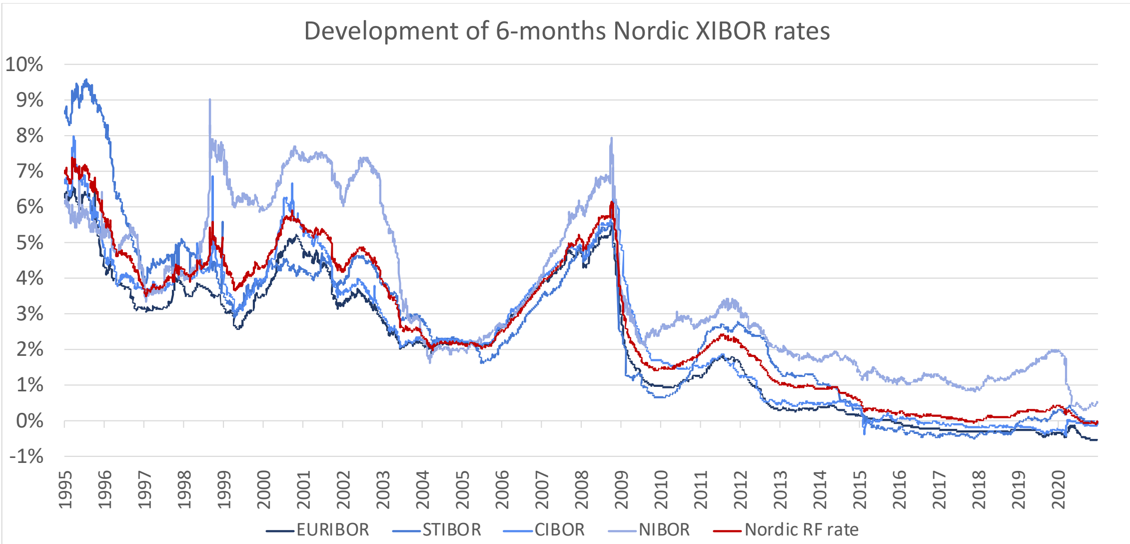


**Figure 4. The development of the 6-months XIBOR rates between 1995-2019.**

### 6.1.3 Market index

In order to benchmark the returns of the combined portfolio a Nordic stock market index is constructed. This study uses the indices from OMX Stockholm, Denmark, Helsinki and Norway to create the combined market index. The indices used are all-share total return indices. The total return indices are preferred over the price indices due to price return index only considering price movements. In addition to price movements total return indices account for all cash distributions such as dividend payments and assumes such distributions are reinvested. In case the total return indices are not available price indices are used instead in this study. This is the case for OMX Stockholm and Copenhagen prior to 2002 and 2001, respectively.

The Nordic market index in this study is constructed by taking an equal weighting of Nordic OMX indices.  These indices are not capped and therefore the maximum weight of a single stock is not limited. These indices contain returns also from smaller stocks hence creating a higher barrier for the quality momentum portfolios to surpass. Figure 4 demonstrates below the progression of the returns of the Nordic indices for a period of 25 years. As can be seen from the figure 4 the trend of all the Nordic indices has been relatively similar. The upward and downturn trends have occurred around the same time in all the indices mostly deviating in their magnitude.

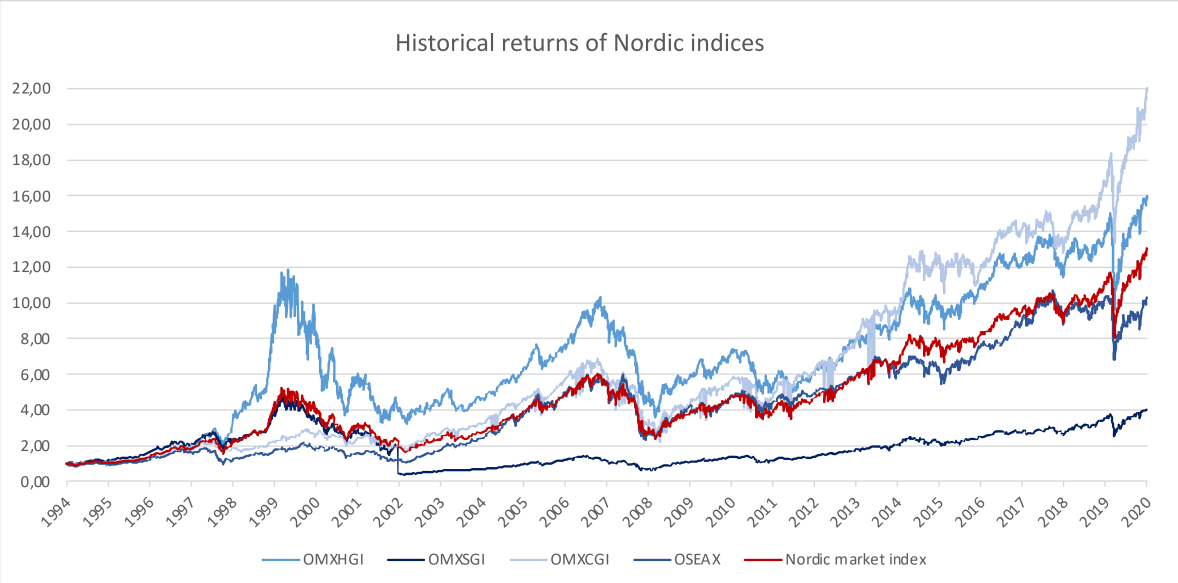


**Figure 5. Linear returns of the Nordic Indices between 1995-2020.**

## 6.2 Methodology

The purpose of this thesis is to study the possibility of utilizing momentum and profitability factors together in an investment strategy in order to improve the performance of momentum and quality strategies. The main goal of this thesis is to examine whether implementing a combined strategy earns abnormal returns and outperforms the combined Nordic market index and in addition the usage of solely one of these factors as an investment strategy in the Nordic stock markets.

Profitability, reflecting quality, is measured in this study by using three different ratios. These ratios are calculated by using data obtained from companies' balance sheets and profit and loss statements. The annual accounting data is gathered from Thomson-Reuters datastream for all the Nordic companies considered in this study. In instances where balance sheet information is unavailable the value of such account is set to zero mirroring Ball et al. (2015). In case the profitability measures cannot be computed with given data the company is excluded from the sample. Firstly, the gross profitability measure is calculated following Novy-Marx (2013) and is formed as follows:

(17) $$Gross\ profitability = \frac{Gross\ profits}{Book\ Value\ of\ Total\ Assets},$$

where gross profits are calculated by subtracting costs of goods sold from revenues. Book value of total assets are preferred as the deflator for gross profits due to the nature of gross profits being unaffected of leverage and interest payments (Novy Marx 2013). Gross profitability attempts to focus on the items of the income statement that are related to companies' current revenue (Ball et al. 2015). Novy-Marx (2013) finds that gross profitability measure seems to outperform other profitability used in the previous literature to measure profitability in the power of predicting the cross-section of expected returns and therefore the measure is selected to be considered also in this study.

Furthermore, Ball et al (2015) continue to focus on the income statement items that reflect the companies' current revenue and after re-examining gross profitability they suggest an alternative measure for profitability named operating profitability that seems to outperform gross profitability. The main difference to gross profitability is the accounting of selling, general and administrative expenditures (SG&A) excluding the research and development expenditures (R&D). Operating profitability represents the second measure for profitability in this study and is formed following Ball et al. (2015):

(18) $$Operating\ profitability = \frac{Gross\ profits - SG\&A - R\&D}{Book\ Value\ of\ Total\ Assets}$$

The third profitability measure in this study is cash-based operating profitability. This measure extends operating profitability by making it a cash-based measure. In order to do so accounting accruals must be excluded from operating profitability. The components in accounting that are considered to be accrual based are account receivables, changes in inventory and accounts payable. Ball et al. (2016) finds that cash-based operating profitability outperforms operating profitability and therefore it is taken into consideration also in this study. The cash-based operating profitability measure follows Ball et al. (2016) and is formed as follows:

(19) $$Cash\ operating\ profitability = \frac{Operating\ profitability - DAR - DI - IAP}{Book\ Value\ of\ Total\ Assets},$$

where

$DAR$ represents the decrease in account receivables

$ID$ equals to decrease in inventory and

$IAP$ stands for increase in accounts payable

In addition to profitability measures a momentum measure is needed to be able to form the combined portfolios. Following Bhootra (2018) this study constructs George and Hwang's (2004) 52-week high price as the momentum measure. 52-week high price refers to the highest closing price observed during the past 52-week time period. A higher value of the ratio suggests that the current price is closer to the 52-week price while a value of one indicates that the month-end price is the 52-week high price. This ratio is preferred since it does not experience long-term reversals unlike the traditional momentum theory of Jegadeesh and Titman (1993), and it can be views as an underreaction strategy similarly to gross profitability (Bhootra 2018). The calculation can be obtained as follows:

(19) $$52 - week\ high\ price = \frac{Current\ price}{52{-}week\ high\ price},$$

After the computation of profitability and momentum measures the combined portfolios can be formed. The portfolios are computed as equally weighted following

Davydov et al. (2016) and Tikkanen et al (2018). This is common when doing research in the Nordic stock markets since there exist large size deviations in terms of market capitalization. The portfolio returns are sorted based on profitability measures and the momentum measure once a year in June. Similarly, to Ball et al (2016) and Bhootra (2018) this lagging is done to ensure that the year-end information provided by the financial statements are reflected on the stock prices. This approach should minimize the risk of look-ahead bias in the observed results since the impact of the previous year's financial results should be already publicly available and reflected in prices.

The portfolios are then independently sorted into quintiles based on their profitability ratios and momentum ratios. Furthermore, all the portfolios are created as long-only and as long-short portfolios. Even though the smallest 10% of the stocks are eliminated from the dataset, when the combined portfolios are created the lowest tertile measured by market value is excluded from the stock universe. This is done to exclude the potentially illiquid stocks and to minimize the presence of smaller stocks in the universe since they might possess restrictions on the short selling. The single factor portfolios will be formed based on both the full stock universe and the limited stock universe in order to see how size affects the performance of the factors.

The performance of these combined portfolios are captured with four different measures. The results are then benchmarked against the combined Nordic market index and the performance of the single-factor momentum portfolio as well as the single-factor profitability portfolio. The risk-adjusted performance of the portfolios will be measured by Sharpe and Sortino ratios. Furthermore, the Capital Asset Pricing model and the Fama and French three factor model are used to measure the abnormal returns of the portfolios. The OLS regression to measure CAPM can be derived as follows:

(20) $R_{i,t} - r_f = \alpha_i + \beta_i(R_{m,t} - r_f) + \varepsilon_{i,t},$

Where

$R_{i,t}$ is the return on portfolio i at time t

$r_f$ represent the risk-free rate

$R_{m,t}$ is the return on market portfolio at time t

$\alpha_i$ represents the alpha (intercept) coefficient

$\beta_i$ is the beta (slope) coefficient

In addition to the capital asset pricing model the abnormal returns are measured by the Fama and French three factor model. The model can be formed as follows:

(21) $R_{i,t} - r_f = \alpha_i + \beta_1(R_{m,t} - r_f) + \beta_2 SML + \beta_3 HML + \varepsilon_{i,t},$

Where

$MKT$ is the market factor

$SML$ is the size factor (small minus big)

$HML$ is the value factor (high minus low)

# 7 Results

This section will present more detailed description of the stock universe and the portfolios formed based on the universe. In addition, it will cover the results obtained from the regression analysis for the single factor portfolios as well as the joint portfolios combined from momentum and profitability factors. These portfolios will be obtained as long-only and long-short and their performance will be analyzed. For all the regressions are Newey West estimator is used to adjust for heteroskedasticity and autocorrelation.

## 7.1 Summary statistics

The stock universe created in this study consists of stock traded in OMXH, OMXC, and OSEBX and OMXS. After the conditions discussed in the previous section are applied to the stock universe the sample used in this study is created. Table 1 describes the key statistics of the sample between years 1996 and 2020. As can be seen from table 1 the minimum number of stocks is 364 over the period and maximum number of stocks is 825. The number of observations is lower at the beginning of the sample period and the highest towards the end of the observation period signifying the growth of the Nordic stock markets over the examination period.

**Table 1. Descriptive statistics of the stock universe of Nordic stock markets**

| | Denmark | Finland | Norway | Sweden |
|---|---|---|---|---|
| Minimum number of stocks | 90 | 56 | 61 | 142 |
| Maximum number of stocks | 138 | 120 | 163 | 369 |
| Average number of stocks | 114 | 105 | 119 | 263 |
| Average market value in m'EUR | 1 401 | 1 638 | 1 005 | 892 |

The descriptive statistics in table 1 show that the average number of stocks is over doubled in Sweden compared to other Nordic countries. However, when measured by the average market value Finland is the biggest with an average market value of 1 638m€

and measured by average market value Sweden is the smallest with an average market value of 892m€. This is due to the nature of the Swedish stock markets since it has the most listed companies of the European Union thus most of them are considered small cap due to their market values. In addition, the market values of the Nordic stock markets are highly affected by individual companies. This is the case for example in Finland where a high proportion of the market value during the examination period comes from Nokia.

Furthermore, this dataset is divided into tertiles based on market value of the companies and the lowest tertile is excluded to create a second limited stock universe. This universe is used in the study the create the joint portfolios. The sample is chosen to avoid small stocks that could have liquidity issues or short-sale constraints. In addition, the single factor portfolios are also created with this limited stock universe that excludes the companies with the smallest market values hence for the single factor portfolios are observed via the full dataset and the limited dataset. The descriptive statistics of the limited stock universe are presented in table 2. It can be observed from the dataset that the average market value grows in the Danish companies from an average of 1 401m€ to 2 329m€. Similar behavior can be observed throughout the countries included in the sample. After the creation of these stock universes the following step is the formation of single factor portfolios.

**Table 2. Descriptive statistics of the limited stock universe of Nordic stock markets**

| | Denmark | Finland | Norway | Sweden |
|---|---|---|---|---|
| Minimum number of stocks | 55 | 38 | 48 | 97 |
| Maximum number of stocks | 79 | 91 | 131 | 246 |
| Average number of stocks | 66 | 74 | 87 | 172 |
| Average market value in m'EUR | 2 329 | 2 338 | 1 363 | 1 335 |

## 7.2 Momentum strategy

The empirical analysis is started by testing the presence of momentum strategy in the Nordic stock market sample. The stock universe is sorted into quintiles based on the value of their 52-week price ratio and the portfolios are obtained as equally weighted. The portfolios are rebalanced in June of every year. The panel A in table 3 presents the excess returns obtained alongside with the corresponding CAPM alphas for the full stock universe. As expected, the excess returns of the momentum portfolios are increasing as the 52-week ratio increases. The low momentum portfolio earns an excess return of -0.32 percent per month and a monthly alpha of -0.86 percent. The excess returns correspond to an annualized excess return of -4.61% with a statistical significance of 1%. The standard deviation is 25.8 percent and the maximum monthly drawdown during the examination period stands at 90 percent observed during the dotcom crash at the beginning of the 21st century. In addition, both Sharpe and Sortino ratios are negative for the low momentum portfolio.

The high portfolio earns an excess return of 1.03 percent per month while the t-statistic stands at 3.16. The CAPM alpha stands at a monthly 0.68 percent or 14.72 percent annually with a t-statistic of 2.75. Overall, the monthly spread of momentum strategies is an impressive 1.35 percent with t-statistics of 5.76. The CAPM alpha is even higher standing at a monthly 1.61 percent. Interestingly the long high momentum and short low momentum has a negative beta potentially suggesting an inverse relation to the market.

**Table 3. Results of momentum portfolios**

This table presents the results of the momentum portfolios' returns and the portfolio charasteristics. The companies are sorted into quintiles based on the gross profitability ratio at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French 3 factors alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Panel A: Portfolios sorted on momentum, 10% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,32 | 0,30 | 0,64* | 0,83** | 1,03*** | 1,35*** |
| | (-0,60) | (0,73) | (1,76) | (2,39) | (3,16) | (4,27) |
| CAPM $\alpha$ | -0,94*** | -0,20 | -0,20 | 0,44* | 0,68*** | 1,61*** |
| | (-2,62) | (-0,68) | (0,84) | (1,66) | (2,75) | (5,76) |
| CAPM $\beta$ | 0,65 | 0,52 | 0,42 | 0,41 | 0,37 | -0,28 |
| Annualised Stdev | | | | | | |
| Sharpe Ratio | -0,27 | 0,10 | 0,41 | 0,61 | 0,88 | 0,72 |
| Sortino Ratio | -0,27 | 0,09 | 0,37 | 0,54 | 0,83 | 0,64 |
| | | | | | | |
| Avg no of observations | 119 | 118 | 119 | 119 | 118 | 119 |
| Average 52-week ratio | 0,49 | 0,72 | 0,82 | 0,89 | 0,96 | |
| Average Market Value m€ | 391 | 887 | 1 170 | 1 604 | 1 714 | |
| Panel B: Portfolios sorted on momentum, further 30% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,13 | 0,26 | 0,68* | 0,79** | 1,07*** | 1,20*** |
| | (-0,60) | (0,73) | (1,76) | (2,39) | (3,16) | (4,27) |
| CAPM $\alpha$ | -0,83** | -0,26 | -0,26 | 0,36 | 0,67*** | 1,50*** |
| | (-2,32) | (-0,84) | (0,91) | (1,34) | (2,58) | (5,3) |
| CAPM $\beta$ | 0,73 | 0,55 | 0,45 | 0,45 | 0,42 | -0,32 |
| 3 factor model $\alpha$ | -0,76** | -0,25 | 0,22 | 0,36* | 0,68*** | 1,45*** |
| | (-2,55) | (-1,11) | (1,13) | (1,73) | (3,30) | (5,20) |
| Annualised Stdev | 0,23 | 0,19 | 0,17 | 0,16 | 0,15 | 0,18 |
| Sharpe Ratio | -0,22 | 0,07 | 0,43 | 0,53 | 0,83 | 0,62 |
| Sortino Ratio | -0,17 | 0,06 | 0,39 | 0,48 | 0,76 | 0,54 |
| | | | | | | |
| Avg no of observations | 80 | 79 | 79 | 79 | 79 | |
| Average MOM | 0,58 | 0,76 | 0,85 | 0,91 | 0,97 | |
| Average Market Value m€ | 1 032 | 1 397 | 1 830 | 2 194 | 2 145 | |

The momentum strategies’ results based on the stock universe excluding the bottom third of companies based on market value are presented panel B of the table 3. After excluding the smallest third of the companies based on the market value the regressions are rerun for the momentum strategies and in addition the Fama French alphas are included in the tables from the Fama and French three-factor model. The low momentum portfolio earns in this case a monthly excess return of -0.13 percent while the CAPM alpha is -0.83 percent with a t statistic of -2.32. The high momentum in this case earns an excess monthly return of 1.07 percent with an alpha of 0.67 percent while both of the results being significant at 1 percent level. The monthly spread of the momentum strategies is 1.20 percent. The momentum strategy generates statistically significant CAPM alphas in both the low and the high portfolios. Even though the alpha for low portfolio is slightly higher it also has more volatility as can be seen from the standard deviation. Therefore, it can be viewed as interesting that the high portfolio on the momentum strategy generates a monthly CAPM alpha of 0.67 percent by taking less risk and having on average bigger companies included in the portfolio measured by the average market value in the table. The three-factor model also provides similar information to CAPM alpha. Measured by the Fama and French alpha the low momentum portfolio earns an alpha of -1.10 percent, and the high momentum profitability earns a 0.51 percent alpha. So even after adding size and value factors the alpha is statistically significant.

Comparing to the results obtained with the full stock universe both the excess returns and CAPM alphas have decreased. The maximum monthly drawdown decreases in this sample both the high and low momentum portfolio compared to the stock universe where all stocks are included. The average market value is higher due to the smallest companies measured by market value being excluded. However, both the Sharpe and Sortino ratios decrease across the quintiles compared to the results from all stocks universe even though the dataset contains less of small companies hence the expectation could have been for these ratios to increase. Furthermore, a higher proportion of the momentum strategy spread is attributable to the low portfolio. In both samples the momentum strategy faces some crashes. These occur during the time period of extremely high market volatility for example during the financial crisis of 2007-2008 and have been documented also in earlier studies (see Daniel et al 2016; Grobys 2016). Overall, as expected the presence of momentum can be observed from both of the stock universes.

## 7.3 Gross profitability strategy

The gross profitability strategy is combined following Novy-Marx (2014) where the gross profitability is measured by the gross profits divided by the total assets. This variable is calculated for all the companies at the end of June and based on the gross profitability value they are sorted into quintiles. The results based on the complete stock universe are presented in panel A of table 4. The monthly excess returns for the low gross profitability are -0.25 percent however without statistical significance. The high gross profitability portfolio earns 0.91 percent excess returns with a t-statistic of 2.56 and the monthly spread for gross profitability is 1.17 percent. The monthly CAPM alpha is 0.48 (-0.75 percent) for high (low) portfolio. Observable from the table is that only the long-short portfolio receives a statistically significant excess returns and alphas at 1% level.

Further looking at the gross profitability of the stock universe where the smallest third of companies measured by their market value is excluded it is observable that the excess returns are decreasing compared to the full stock universe. The monthly excess results of the high gross profitability portfolio are though 0.71 percent and the equivalent CAPM alpha is 0.44 percent and a similar pattern of excess returns increasing with the gross profitability ratio can be observed from the table. The excess returns are more driven by the long side of the strategy. The Sharpe and Sortino ratios both slightly increase for the low portfolios compared to the full stock universe however they decrease for the high portfolios.

Once the operating profitability is tested with the three-factor model the alpha for the low portfolio corresponds to -0.61 percent with a t-statistic of -2.98 whereas the high portfolio receives a value of 0.50 percent with a t-statistic of 1.41. The only statistically significant alpha in the three-factor model comes from the low portfolio. The interesting result in table 5 is that in contradiction to Bhootra (2018) for both the CAPM alpha spread and the three-factor model alpha spread for gross profitability is more driven by the low portfolio than the high portfolio. This finding however is similar to Novy-Marx (2014) for the international evidence presented in the study where a higher proportion of the spread of the gross profitability alpha was driven by the low portfolio. However no persistent evidence can be found based on the three-factor model of the existence of gross profitability in the Nordic stock market in this study.

**Table 4. Results of gross profitability portfolios**

This table presents the results of the gross profitability portfolios' returns and the portfolio charasteristics. The companies are sorted into quintiles based on the gross profitability ratio at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French three-factor alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Panel A: Portfolios sorted on gross profitability, 10% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,25 | 0,43 | 0,61 | 0,77* | 0,91** | 1,17*** |
| | (-0,55) | (1,13) | (1,57) | (2,13) | (2,56) | (5,54) |
| CAPM $\alpha$ | -0,62* | -0,03 | -0,03 | 0,23 | 0,44* | 1,06*** |
| | (-1,89) | (-0,08) | (0,62) | (0,90) | (1,85) | (5,52) |
| CAPM $\beta$ | 0,52 | 0,46 | 0,48 | 0,45 | 0,46 | -0,06 |
| Annualised Stdev | 0,21 | 0,17 | 0,17 | 0,16 | 0,16 | 0,11 |
| Sharpe Ratio | -0,25 | 0,22 | 0,35 | 0,52 | 0,63 | 1,08 |
| Sortino Ratio | -0,23 | 0,20 | 0,32 | 0,48 | 0,62 | 1,17 |
| | | | | | | |
| Avg no of observations | 119 | 119 | 119 | 119 | 118 | |
| Average GPA | -0,05 | 0,13 | 0,24 | 0,37 | 0,74 | |
| Average Market Value m€ | 302 | 1 052 | 1 664 | 1 212 | 1 533 | |
| Panel B: Portfolios sorted on gross profitability, further 30% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,09 | 0,45 | 0,67* | 0,71* | 0,93** | 1,02*** |
| | (-0,19) | (1,11) | -1,70 | (1,89) | (2,54) | (5,52) |
| CAPM $\alpha$ | -0,62* | -0,03 | -0,03 | 0,23 | 0,44* | 1,06*** |
| | (-1,89) | (-0,08) | (0,62) | (0,90) | (1,85) | (5,52) |
| CAPM $\beta$ | 0,56 | 0,50 | 0,52 | 0,51 | 0,51 | -0,05 |
| 3-factor model $\alpha$ | -0,85*** | -0,28 | -0,06 | 0,03 | 0,28 | 1,13*** |
| | (-2,98) | (-1,10) | (-0,24) | 0,16 | 1,41 | 6,01 |
| Annualised Stdev | 0,21 | 0,19 | (0,18) | (0,17) | (0,17) | (0,10) |
| Sharpe Ratio | -0,16 | 0,21 | 0,37 | 0,43 | 0,60 | 0,99 |
| Sortino Ratio | -0,14 | 0,18 | 0,33 | 0,41 | 0,56 | 1,11 |
| | | | | | | |
| Avg no of observations | 79 | 79 | 79 | 79 | 78 | |
| Average GPA | 0,03 | 0,16 | 0,26 | 0,38 | 0,70 | |
| Average Market Value m€ | 681 | 1 700 | 2 167 | 1 812 | 2 240 | |

## 7.4 Operating profitability

The operating profitability ratio is computed according to Ball et al. (2015) at the end of June each year and furthermore sorted into quintiles based on the operating profitability ratio. The results based on the full stock universe are presented in table 5. The excess returns for the low operating profitability portfolio stands at -0.40 percent without being statistically significant whereas the CAPM alpha is -0.96 percent with a t-statistic of -2.85. The spread between the operating profitability strategies is 1.30 percent being significant at 1% level.

**Table 5. Results of operating profitability portfolios**

This table presents the results of the operating profitability portfolios' returns and the portfolio charasteristics. The companies are sorted into quintiles based on the gross profitability ratio at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French 3 factors alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Panel A: Portfolios sorted on operating profitability, 10% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,40 | 0,31 | 0,74** | 0,91** | 0,90** | 1,30*** |
| | (-0,79) | (0,84) | (2,06) | (2,52) | (2,49) | (5,75) |
| CAPM $\alpha$ | -0,96** | -0,11 | -0,11 | 0,47* | 0,48* | 1,44*** |
| | (-2,85) | (-0,38) | (1,18) | (1,84) | (1,89) | (7,21) |
| CAPM $\beta$ | 0,60 | 0,45 | 0,43 | 0,46 | 0,45 | -0,15 |
| Annualised Stdev | 0,24 | 0,17 | 0,16 | 0,16 | 0,16 | 0,14 |
| Sharpe Ratio | -0,32 | 0,14 | 0,50 | 0,62 | 0,64 | 0,96 |
| Sortino Ratio | -0,30 | 0,13 | 0,44 | 0,58 | 0,59 | 0,84 |
| | | | | | | |
| Avg no of observations | 119 | 119 | 119 | 119 | 118 | |
| Average OPA | -0,24 | 0,06 | 0,11 | 0,17 | 0,37 | |
| Average Market Value m€ | 424 | 863 | 1 332 | 1 597 | 1 547 | |
| | | | | | | |
| Panel B: Portfolios sorted on operating profitability, further 30% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,28 | 0,55 | 0,70* | 0,87** | 0,84** | 1,12*** |
| | (-0,55) | (1,44) | (1,87) | (2,32) | (2,24) | (5,2) |
| CAPM $\alpha$ | -0,88** | 0,08 | 0,08 | 0,39 | 0,36 | 1,24*** |
| | (-2,45) | (0,28) | (0,82) | (1,53) | (1,51) | (6,02) |
| CAPM $\beta$ | 0,62 | 0,50 | 0,48 | 0,50 | 0,50 | -0,13 |
| 3 factor model $\alpha$ | -1,08*** | -0,18 | 0,00 | 0,21 | 0,18 | 1,26*** |
| | (-3,43) | (-0,80) | (0,01) | (0,98) | (0,90) | (6,49) |
| Annualised Stdev | 0,23 | 0,18 | 0,18 | 0,17 | 0,17 | 0,12 |
| Sharpe Ratio | -0,26 | 0,28 | 0,41 | 0,55 | 0,55 | 0,88 |
| Sortino Ratio | -0,23 | 0,27 | 0,37 | 0,52 | 0,51 | 0,87 |
| | | | | | | |
| Avg no of observations | 79 | 79 | 79 | 79 | 78 | |
| Average GPA | -0,10 | 0,07 | 0,12 | 0,18 | 0,35 | |
| Average Market Value m€ | 987 | 1 342 | 1 858 | 2 120 | 2 291 | |

In the stock universe where the bottom third measured by market value is excluded the low operating profitability earns an excess return of -0.28 however it is not statistically significant as can be seen from Panel B of table 5. On the other hand, the high operating profitability achieves an excess return of 0.84 percent. The CAPM alpha is -0.88 for the low portfolio and statistically significant at 1 percent level. Moreover, the high portfolio earns a CAPM alpha of 0.36 however it is not statistically significant. The Fama and French alpha for the low portfolio stands at -1.08 percent and for the high portfolio at 0.36 percent. However, the high portfolio is not statistically significant. The excess returns of operating profitability strategy are more driven by the long side of the strategy supporting the findings of Ball et al (2015).

Similarly to the gross profitability it can be observed that the higher attribution to the operating profitability strategy's Fama and French alpha comes from the low portfolio whereas Ball et al (2015) finds that in their study operating profitability contributes equally on the long and the short side when tested on the US markets. The annualized standard deviation decreases as the operating profitability increases. The gross profitability and operating profitability both have similar annualized standard deviations and betas. This could be expected since both of them are profitability measures hence the characteristics of the portfolios created with both of the measures can be expected to be similar. The Fama and French three factor model results do not support the existence of operating profitability in the Nordic stock market in this study since only the low portfolio receives a statistically significant alpha.

## 7.5 Cash-based operating profitability

The last profitability measure constructed in this study is the cash-based operating profitability and it is constructed by following Ball et al. (2016). As for the other profitability measures the cash-based operating profitability ratio is calculated for each company at the end of June and then assigned into a quintile based on the value. Table

6 reports the results for cash-based operating profitability. Again, the low portfolios excess returns are not statistically significant but the excess returns from the high portfolio are significant on a 5 percent level. The CAPM alpha is 0.39 (-0.86) percent for the high (low) portfolio and significant at 10 percent (1 percent) level. Cash-based operating profitability has the lowest Sortino ratio of the profitability ratios.

**Table 6. Results of cash-based operating profitability portfolios**

This table presents the results of the cash-based operating profitability portfolios' returns and the portfolio charasteristics. The companies are sorted into quintiles based on the cash-based operating profitability ratio at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French 3 factors alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Panel A: Portfolios sorted on cash-based operating profitability, 10% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,29 | 0,43 | 0,69* | 0,81** | 0,83** | 1,12*** |
| | (-0,57) | (1,16) | (1,85) | (2,32) | (2,29) | (4,93) |
| CAPM $\alpha$ | -0,86** | 0,02 | 0,02 | 0,40 | 0,39 | 1,25*** |
| | (-2,51) | (0,06) | (0,92) | (1,52) | (1,60) | (6,43) |
| CAPM $\beta$ | 0,60 | 0,43 | 0,45 | 0,44 | 0,46 | -0,14 |
| Annualised Stdev | 0,24 | 0,16 | 0,17 | 0,16 | 0,16 | 0,13 |
| Sharpe Ratio | -0,26 | 0,24 | 0,43 | 0,56 | 0,58 | 0,85 |
| Sortino Ratio | -0,25 | 0,22 | 0,40 | 0,52 | 0,56 | 0,82 |
| | | | | | | |
| Avg no of observations | 119 | 118 | 119 | 119 | 118 | 119 |
| Average COPA | -0,18 | 0,06 | 0,12 | 0,18 | 0,39 | |
| Average Market Value m€ | 275 | 824 | 1 349 | 1 681 | 1 637 | |
| | | | | | | |
| Panel B: Portfolios sorted on cash-based operating profitability, further 30% of smallest companies excluded | | | | | | |
| Monthly excess returns | -0,19 | 0,50 | 0,76* | 0,83** | 0,78** | 0,97*** |
| | (-0,37) | (1,32) | (1,93) | -2,30 | (2,09) | (4,64) |
| CAPM $\alpha$ | -0,79** | 0,03 | 0,03 | 0,38 | 0,29 | 1,08*** |
| | (-2,19) | (0,12) | (0,93) | (1,42) | (1,26) | (5,40) |
| CAPM $\beta$ | 0,63 | 0,49 | 0,50 | 0,46 | 0,51 | -0,11 |
| 3 factor model $\alpha$ | -0,98*** | -0,20 | 0,02 | 0,16 | 0,13 | 1,11*** |
| | (-3,03) | (-0,88) | (0,09) | (0,78) | (0,63) | (5,71) |
| Annualised Stdev | 0,23 | 0,18 | 0,18 | 0,17 | 0,17 | 0,11 |
| Sharpe Ratio | -0,22 | 0,26 | 0,43 | 0,54 | 0,50 | 0,83 |
| Sortino Ratio | -0,18 | 0,24 | 0,39 | 0,51 | 0,47 | 0,91 |
| | | | | | | |
| Avg no of observations | 79 | 79 | 79 | 79 | 78 | |
| Average COPA | -0,07 | 0,07 | 0,12 | 0,19 | 0,37 | |
| Average Market Value m€ | 664 | 1 318 | 1 902 | 2 090 | 2 628 | |

The performance of cash-based operating profitability in the dataset excluding the lowest tertile of companies measured by market value is presented in panel B of table 6. The monthly excess returns are growing when moving from low portfolios towards the high portfolio in accordance with the earlier reported results in this study regarding gross profitability and operating profitability. The monthly excess returns for high (low) portfolio are 0.78 (-0.19) percent however only the high portfolio is statistically significant at 5 percent level. The CAPM alpha on the low profitability portfolio is -0.79 (t-statistic of -2.19) and for the high portfolio stands at 0.29 (t-statistic of 1.26). The high cash-based operating profitability is not statistically significant measured by the CAPM alpha. However, when turning the look towards the Fama and French alpha the high (low) portfolios earn a monthly alpha of 0.36 (-0.72). However as observed already with gross profitability and operating profitability neither cash-based operating profitability is able to survive from the three-factor model and is unable to generate statistically significant results.

Overall based on the results obtained from the dataset limiting out the smallest companies it can be observed that measured by monthly excess returns the gross profitability seems to outperform the other two profitability measures. The CAPM alpha is also only significant for the highest profitability portfolio and is insignificant for operating profitability as well as cash-based operating profitability. The CAPM beta values are extremely similar for all of the profitability measures without any significant deviations to one another similarly to the annualized standard deviations. The highest average market value is observed for the high cash-based operating profitability portfolio with an average market value of 2 622 m€. Based on the evidence proposed above it could be that the investor underreaction could be coming from the same source for both momentum and profitability strategies since for profitability and momentum strategies the higher contribution to the high-low spread can be attributed more to the low side of the strategy. Ball et al (2015) find that the Fama and French alphas of operating profitability outperform gross profitability whereas the result from this study suggests that the gross profitability CAPM alphas are higher. When the single factors are put to a test with the three-factor model the only one creating a significant alpha in the extreme portfolios is momentum strategy. Therefore, no statistically significant evidence can be concluded from the existence of the three profitability strategies.

## 7.6 Double sorted joint strategies

The primary objective of the study is to test the performance of a joint strategy formed from momentum and the selected three variables for profitability measuring for quality. In order to do that the stock universe omitting the lowest tertile of companies measured by the market value is utilized. This is done in order to exclude the smallest companies where short selling could be restricted and the stocks could be thinly traded. The companies in the sample are sorted independently into quintiles based on the measures for momentum and for profitability. The portfolios are rebalanced at the end of June each year making the holding period one year.

The joint strategies are formed as double sorted strategies forming a 5x5 matrix. This results in 25 portfolios for each strategy. The companies that get assigned to the highest quintile of the independent sort on momentum strategy and to the highest quintile of the independent sort on the profitability strategy will be in the 5,5 portfolio as presented in figure 5. Only accounting for the highest (5,5) and lowest (1,1) portfolios would result in thin portfolios. In order to account for that this study follows Silvasti et al (2021) and the 60$^{th}$ percentile is used as a limiter. This means that the companies that find strong signs of momentum and profitability and are assigned to either to the first or second quintile based on the independent sort will be included in the joint strategy. This is further highlighted in figure 5.

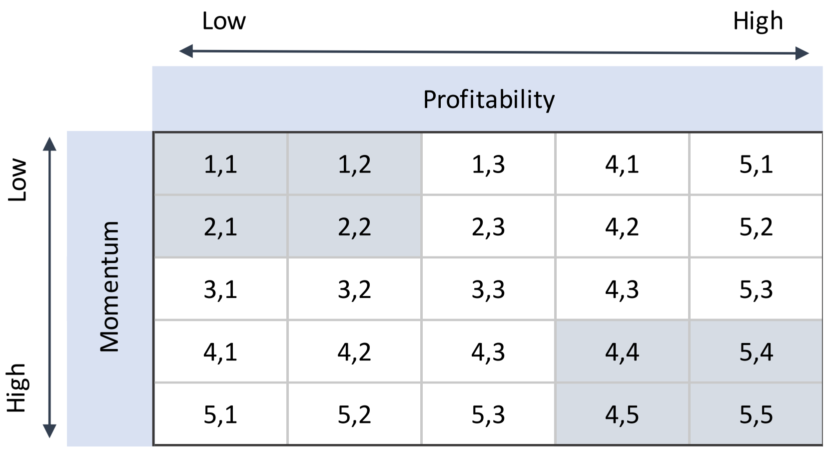


**Figure 6. Double-sorted portfolio strategy forming 25 portfolios based on independent sorts on Momentum and Profitability**

An interesting aspect to look at is also the correlation between profitability measures and momentum. The correlation matrix is presented in table 7 for the monthly excess returns on the long-short strategies and for the Nordic market index. A positive correlation means both strategies move towards the same direction and a negative correlation means they move to opposite directions. In the extreme correlation can be +/-1 meaning that the strategies move perfectly to the same direction. In the table 7 MOM H-L stands for momentum high-low, GPA H-L for Gross profitability (gross-profits to assets) high-low, OPA for operating profitability and COPA for cash-based operating profitability.

As expected, all the profitability figures are highly positively correlated with each other especially operating profitability and cash-based operating profitability since the latter one is an extension of the model used in the first one hence can be expected for the two strategies to be choosing similar companies to the high and low portfolios. The gross operating profitability seems to be the least correlated with momentum strategy out of the profitability strategies. The positive correlation is in accordance with findings from Novy-Marx (2014) since he finds that the gross profitability and momentum are orthogonal. In addition, it can be observed that all the high-low strategies are negatively correlated with the Nordic Market Index.

**Table 7.** Correlation matrix of the High-Low

| | *MOM H-L* | *GPA H-L* | *OPA H-L* | *COPA H-L* | *Nordic market index* |
|---|---|---|---|---|---|
| MOM H-L | 1,000 | | | | |
| GPA H-L | 0,479 | 1,000 | | | |
| OPA H-L | 0,634 | 0,709 | 1,000 | | |
| COPA H-L | 0,565 | 0,732 | 0,897 | 1,000 | |
| Nordic market index | -0,439 | -0,111 | -0,253 | -0,253 | 1,000 |

The results for the double sorted joint strategy for momentum and gross profitability is presented in table 8. The results are presented for the high portfolio, low portfolio and the high-low portfolio. The results show that the monthly excess return on the joint strategy is 1.11 percent for the high portfolio and -0.37 percent on the low portfolio. However only the high portfolio's excess returns are statistically significant at 1 percent level. The long-short strategy earns an excess monthly return of 1.48 percent (t-statistic of 3.05) corresponding to an annualized return of 17.8 percent. The CAPM alpha and the Fama and French alphas are statistically significant at 1 percent level for high, low and the high-low portfolios. The CAPM alpha is lower for the low portfolio than the Fama and French alpha.

The joint gross profitability and momentum strategy outperforms both the individual factor portfolios. The low portfolio has 28 basis points lower excess returns compared to the sole gross profitability low portfolio and 24 basis points compared to the low momentum strategy. For the joint strategy the high portfolio earns 40 basis points more than the sole gross profitability strategy and 4 basis points more than the sole momentum strategy indicating that a higher proportion of the strategy's excess returns come from momentum. As a long-only strategy the joint strategy therefore outperforms also the one factor strategies although the outperformance is only slight compared to the single-factor momentum strategy. The high-low strategy however beats the momentum strategy by 28 basis points. In all the three portfolios for the high, low and high-low the CAPM alphas and the Fama and French alphas are greater than for the one factor strategies. In addition, the CAPM alpha is statistically significant at 1 percent level, and apart from the high portfolio being statistically significant at 5 percent level on the three-factor model, the low and high-low portfolios are statistically significant at 1 percent level.

**Table 8.** Results of joint strategy on gross profitability and momentum portfolios

This table presents the results of th double sorted joint strategy portfolios' returns based on independent sorts on momentum and gross profitability and the portfolio charasteristics. The companies are sorted into quintiles based on the gross profitability and momentum ratios at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French three-factor alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | High | High - Low |
|---|---|---|---|
| Monthly excess returns | -0,37 | 1,11*** | 1,48*** |
| | (-0,69) | (3,05) | (4,91) |
| CAPM $\alpha$ | -0,99*** | 0,67*** | 1,66*** |
| | (-2,67) | (2,75) | (6,10) |
| CAPM $\beta$ | 0,66 | 0,46 | -0,20 |
| 3 factor model $\alpha$ | -1,28*** | 0,53** | 1,81** |
| | (-4,00) | (2,50) | (2,50) |
| Annualised Stdev | 0,25 | 0,16 | 0,16 |
| Sharpe Ratio | -0,30 | 0,81 | 0,98 |
| Sortino Ratio | -0,26 | 0,77 | 1,01 |
| | | | |
| Avg no of observations | 35 | 34 | |
| Average Market Value m€ | 920 | 2 533 | |

Furthermore, the joint strategy's performance is assessed in the figure 6 in comparison to the sole strategies and the Nordic market index. The figure shows that the joint strategy has been outperforming the single factor strategies as well as the index during most times. However, it has been lower than the market index during the end of the 20$^{th}$ century and surpassed the market index around mid 2001. After that it has been outperforming the markets however this figure shows that the strategy has suffered times when it has not been outperforming. The strongest performance of the strategy has been from 2018 onwards.

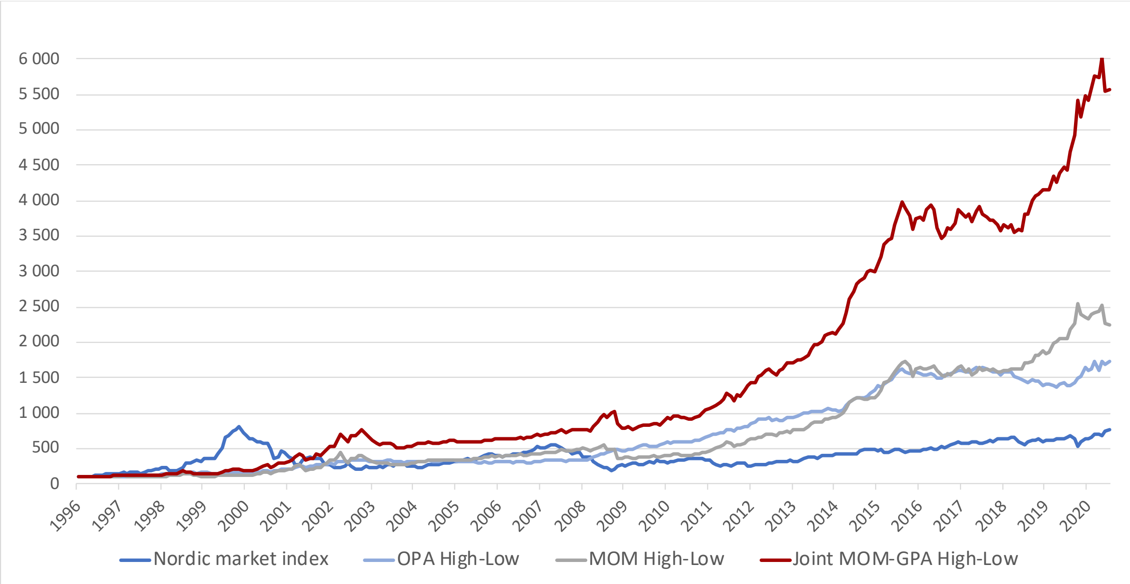


**Figure 7**. Performance of double sorted joint strategy on Momentum and Gross Profitability

The second joint portfolio created in this study is formed by double sorting on momentum and operating profitability. Similarly to joint gross profitability and momentum strategy the low, high and high-low results are presented in table 9. The low portfolio earns a monthly excess return of -0.24 percent however the result is not statistically significant. The high portfolio on the other hand earns a monthly excess return of 1.14 with a t-statistic of -3.11. The long-short strategy earns a monthly excess return of 1.38 percent corresponding to 16.4 percent annually. The CAPM alpha for the strategy is for the low portfolio -0.89 (t-statistic of -2.55) and for the high portfolio 0.71 (t-statistic of 2.71) making the alpha for the combined strategy to be 1.58 (t-statistic of 6.54) and hence being more driven by the short side of the strategy. The Fama and French alpha shows similar results to the CAPM alpha, the high portfolio receives an alpha of 0.55 percent whereas the low portfolio earns -1.15 percent both being statistically significant at 1 percent level.

**Table 9.** Results of joint strategy on operating profitability and momentum portfolios

This table presents the results of th double sorted joint strategy portfolios' returns based on independent sorts on momentum and operating profitability and the portfolio charasteristics. The companies are sorted into quintiles based on the operating profitability and momentum ratios at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French 3 factors alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | High | High - Low |
|---|---|---|---|
| Monthly excess returns | -0,24 | 1,14*** | 1,38*** |
| | (-0,47) | (3,11) | (5,01) |
| CAPM $\alpha$ | -0,89** | 0,71*** | 1,59*** |
| | (-2,55) | (2,71) | (6,34) |
| CAPM $\beta$ | 0,68 | 0,45 | -0,23 |
| 3 factor model $\alpha$ | -1,15*** | 0,55** | 1,70*** |
| | (-3,89) | (2,43) | (7,02) |
| Annualised Stdev | 0,68 | 0,45 | -0,23 |
| Sharpe Ratio | -0,24 | 0,85 | 0,88 |
| Sortino Ratio | -0,22 | 0,81 | 0,82 |
| | | | |
| Avg no of observations | 35 | 33 | |
| Average Market Value m€ | 851 | 2 709 | |

The joint strategy based on operating profitability and momentum creates smaller negative excess returns than the sole operating profitability portfolio on the low portfolios and it seems like the short side of the long-short strategy is driven more by the operating profitability than momentum. On the high portfolio the joint strategy exceeds the single factor momentum and operating portfolios by a monthly excess return spread of 7 basis points and 30 basis points, respectively. The high-low portfolio creates excess returns that are 18 basis points higher than the momentum strategy and 26 basis points higher than the sole operating profitability strategy. In addition, the joint strategy improves both the Sharpe ratio and Sortino ratio compared to the sole strategies. The joint strategy based on operating profitability seems to generate higher returns on the long side of the strategy compared to the joint strategy formed on the basis of gross profitability. It also receives a higher Sharpe and Sortino ratio than the joint strategy formed on gross profitability, so it seems to be the less risky option out of the two joint strategies. However, it loses to gross profitability in excess returns on the high-low portfolios due to the short side of the joint strategy formed on gross profitability.

Figure 6 demonstrates the performance of the joint strategy of momentum and operating profitability. The joint strategy formed on operating profitability and momentum has suffered from time-periods when it has not outperformed the market index, or the strategy based on purely operating profitability. The spread of joint strategy compared to the other strategies presented in the table below only started to widen after 2012. Prior to that it has been either slightly outperforming the other strategies or even underperformed compared to the other strategies, especially the single factor operating profitability portfolio. The figure also clearly shows that there is a high correlation with the single factor momentum portfolio and the joint strategy. The joint strategy does not seem to withstand the time comparison against the benchmark portfolios.

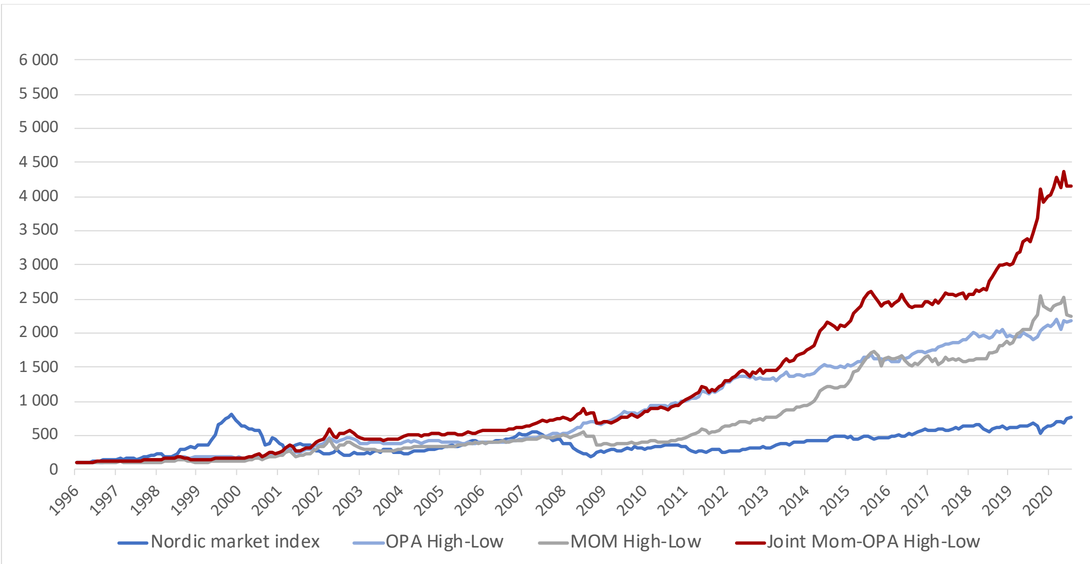


**Figure 8.** Performance of double sorted joint strategy on Momentum and Operating Profitability.

The last joint strategy is formed based on the double sort on momentum and cash-based operating profitability. The results of the joint strategy are reported in table 10. The monthly excess returns are statistically significant for the high portfolio and the long-short portfolio on 1 percent level being at 1.14 percent and 1.47 percent on a monthly basis. As for the other joint strategies based on profitability presented earlier the low portfolio of the joint strategy based on cash-based operating profitability is neither statistically significant. Both the CAPM alpha and Fama and French alphas are indicating similar results for all the portfolios, and they are all significant at one percent level apart from the Fama and French alpha for the high portfolio that is significant at 5 percent level. The high-low strategy's alpha both for the CAPM and Fama and French alpha seems to be driven more by the short side of the strategy.

**Table 10.** Results of joint strategy on cash-based operating profitability and momentum portfolios

This table presents the results of th double sorted joint strategy portfolios' returns based on independent sorts on momentum and cash-based operating profitability and the portfolio charasteristics. The companies are sorted into quintiles based on the cash-based operating profitability ratio at the end of June every month. The sample period covers from July 1996 to december 2020. The CAPM alphas and Fama and French 3 factors alphas are received from regressions and in addition the annualised standard deviation, sharpe ratio and sortino ratio are displayed. T-statistics are shown for regression results in parenthesis.

| | Low | High | High - Low |
|---|---|---|---|
| Monthly excess returns | -0,33 | 1,14*** | 1,47*** |
| | (-0,65) | (3,11) | (-8,79) |
| CAPM $\alpha$ | -0,96*** | 0,71*** | 1,67*** |
| | (-2,73) | (2,71) | (6,68) |
| CAPM $\beta$ | 0,67 | 0,45 | -0,22 |
| 3 factor model $\alpha$ | -1,21*** | 0,55** | 1,76*** |
| | (-3,98) | (2,43) | (7,23) |
| Annualised Stdev | 0,24 | 0,16 | 0,15 |
| Sharpe Ratio | -0,28 | 0,85 | 1,01 |
| Sortino Ratio | -0,25 | 0,81 | 1,01 |
| | | | |
| Avg no of observations | 35 | 33 | |
| Average Market Value m€ | 731 | 2953 | |

The strategy outperforms the sole cash-based operating profitability measured by the excess returns in all of the three portfolios. The spread between the excess returns on the high-low portfolio is a high 50 basis points and CAPM alpha and Fama and French alpha are also higher resulting in a spread of roughly 59 basis points on both alphas compared to the sole strategy. Compared to the single factor momentum portfolio the spread between the high-low portfolios is 27 basis points. For the high portfolio the joint strategy outperforms the single momentum and cash-based operating profitability by 7 basis points and 36 basis points, respectively.  The CAPM alpha and Fama and French alpha is also higher in the joint strategy compared to the pure momentum strategy. The long-short joint strategy seems to enhance the returns compared to the single factor strategies compiled from momentum and cash-based operating profitability.

The performance of the joint long-short strategy formed based on the cash-based operating profitability and momentum compared to the Nordic market index and the single factor strategies measured by excess returns is presented in figure 7. The behavior of the joint strategy measured by cash-based operating profitability mimics the performance of the joint strategy measured by gross operating profitability. The underperformance of the strategy is attributed to the end of the 20th century and since then it has over performed compared to the single factor strategies and the Nordic market index. As well, similarly to the joint strategy formed based on gross profitability, the gap between the joint strategy and the other benchmark portfolios starts to widen after 2011 and keeps on widening towards the end of the research period.

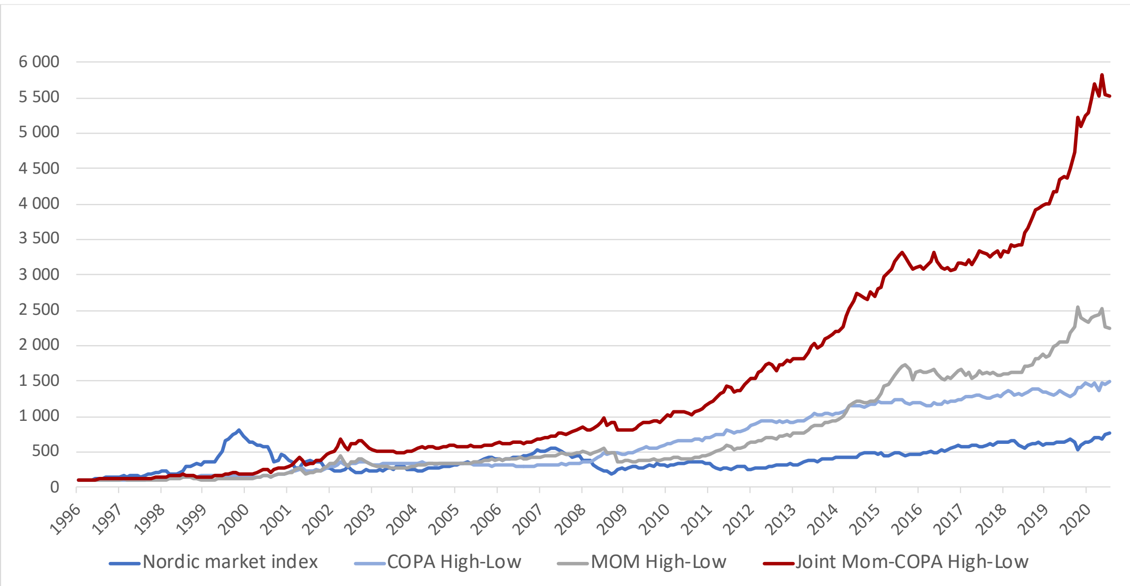


**Figure 9.** Performance of double sorted joint strategy on Momentum and Cash-based Operating Profitability.

The joint strategy on cash-based operating profitability seems to receive a rather identical excess return on the high portfolio to the joint strategy formed based on the operating profitability. On the long side of both of the joint strategies the CAPM alphas and the Fama French alphas are also extremely identical. It seems like both of the strategies on the long side are choosing very similar companies even though in cash-based operating profitability inventory and accounts payable are taken into account. The difference between the two joint strategies seems to come from the short side of the strategy. Based on the results of the joint strategies it seems like the combined strategy for the cash-based operating profitability is able to distinguish better the poor performing companies on the low side of the strategy since it generates 9 basis points more negative excess returns.

The table 11 represents the Fama and French three factor model factor loadings for each of the joint strategies formed based on profitability and momentum. For the joint strategy formed based on gross profitability the high-low portfolio is negative loaded with all the three factors. The joint strategy has a negative loading to the markets and small minus big factors in addition to the high minus low factor. This would imply that the combined strategy is a growth strategy since the loading to the high-low factor is negative however the result is statistically insignificant. In addition, based on the negative loading against the market factor it seems to offer hedge against the market. The small minus big factor loading is also negative for the long-short joint strategy meaning that the strategy performs well when big stocks are outperforming the small stocks. The long-short joint strategy formed on both momentum and operating profitability as well as momentum and cash-based operating profitability have very similar loadings to the factors as gross profitability. There is a negative correlation with the market factor and also with the size factor meaning that the strategy provides hedge against the markets and is tilted more towards being long on the big stocks and shorting the small stocks. However, the high minus low loading is not statistically significant for these joint strategies either.

**Table 11.** Results of Fama and French three-factor model

This table shows the results of the joint portfolios' returns on the Fama and French factors, market factor (MKT), the size factor (SML) and the value factor (HML) with t-statistics in parenthesis. The sample covers a time period from July 1996 to December 2020.

| | FF3 alphas and factor loadings | | | |
|---|---|---|---|---|
| | $\alpha$ | MKT | SMB | HML |
| | Panel A: Joint strategy on Momentum and Gross profitability | | | |
| Low | -1,28*** | 0,74*** | 1,11*** | 0,41** |
| | (-4.00) | (10,75) | (6,68) | (2,52) |
| High | 0,53** | 0,51*** | 0,66*** | 0,14* |
| | (2,50) | (9,34) | (5,85) | (1,81) |
| High - Low | 1,81*** | -0,24*** | -0,45*** | -0,27 |
| | (6,84) | (-3,46) | (-3,43) | (-1,48) |
| Panel B: Joint strategy on Momentum and Operating profitability | | | | |
| Low | -1,15*** | 0,75*** | 1,06*** | 0,33** |
| | (-3,89) | (10,30) | (5,96) | (2,13) |
| High | 0,55** | 0,49*** | 0,65*** | 0,22*** |
| | (2,43) | (9,44) | (5,89) | (3,17) |
| High - Low | 1,70*** | -0,26*** | -0,41*** | -0,11 |
| | (7,02) | (-4,02) | (-2,62) | (-0,72) |
| Panel C: Joint strategy on Momentum and Cash operating profitability | | | | |
| Low | -1,21*** | 0,74*** | 1,00*** | 0,34** |
| | (-3,98) | (10,43) | (5,78) | (2,09) |
| High | 0,55** | 0,50*** | 0,65*** | 0,22*** |
| | (2,43) | (9,44) | (5,89) | (3,17) |
| High - Low | 1,76*** | -0,24*** | -0,35** | -0,12 |
| | (7,28) | (-3,88) | (-2,31) | (-0,72) |

Overall seems like the long-short joint portfolio based on operating profitability and momentum seems to generate the lowest returns in the sample. The long-short joint portfolios using gross profitability or cash-based operating profitability measures combined with momentum seem to generate very similar excess returns. However, the difference is that on the gross profitability a higher proportion comes from the short side of the strategy than on the cash-based operating profitability. Measured by the Sharpe ratio the joint long-short strategy on cash-based operating profitability indicates the highest results out of the three long-short joint portfolios and seems to have the least risk. When looking at the Sortino ratio both of the strategies receive a value of 1.01 indicating a similar downside risk on both of the portfolios. All three of the combined strategies carried out as long short outperform the Nordic market index and the single factor strategies measured by the three profitability measures and momentum. The results provide evidence that by combining profitability as a quality measure to the momentum strategy increases the Sharpe ratio and especially the Sortino ratio by nearly doubling it compared to the performance of the sole momentum strategy.

# 8 Conclusions

The purpose of this study was to first test the single factor strategies based on quality, measured by three different profitability ratios, and momentum in the Nordic stock markets from period 1996 to 2020. The earlier research has suggested that using momentum as a strategy creates abnormal returns and similar findings have been done for gross profitability, operating profitability and cash operating profitability. The purpose being contributing to the growing literature on quality by focusing on the Nordic stock market. The excess returns of the single factors in this study were compared against a benchmark index that was created as an equally weighted average from the returns of the Nordic stock markets. The single-factor strategy based on momentum measure of 52-week high ratio generated statistically significant excess returns on the high side of the strategy however the short-side returns were not statistically significant. The CAPM alpha was although significant on the short-side of the strategy and the tree-factor model results were significant on both of the extreme portfolios. Overall based on the results of the study momentum strategy creates significant excess returns.

The excess returns for gross profitability are statistically significant mainly on the high portfolios and the high minus low portfolio. In addition, the results for the single factor models with capital asset pricing model found evidence from risk-adjusted abnormal returns for gross profitability on the high and low portfolios. However, when looked further at the portfolios using the three-factor model the alphas only the low portfolio maintained statistically significant abnormal returns. Uniformly to Novy-Marx (2014) study on international evidence that the higher proportion of the high minus low portfolio's alpha is driven by the short-side of the strategy. However, it contradicts the findings of Bhootra (2018) from the US stock markets. The same single factor portfolios are also created for operating profitability and cash-based operating profitability. The results for operating profitability and cash-operating profitability suggest similarly that the spread between the high-low portfolio is more driven by the short side of the strategy being consistent with Ball et al (2015;2016).

Furthermore, the joint strategies based on quality, measured by profitability, and momentum are examined in order to see if a combined strategy enhances the performance of the strategies. The joint strategy based on momentum and gross profitability does provide excess returns in the Nordic stock markets. The returns of the joint long-short strategy are more dispersed towards the short-side of the strategy. Similar results are found for the operating profitability and cash-based operating profitability however the magnitude of the excess returns of the joint strategies on momentum and operating profitability are less significant and this strategy performs the worst out of the joint strategies. The excess returns of joint strategy formed on cash-based operating profitability results in similar results than the joint strategy formed with momentum and gross profitability and seems like both of these measures earn very similar excess returns in the Nordic stock market over the observed time period.

Combining the momentum and profitability strategy does increase the Sharpe and Sortino ratio compared to the single- momentum strategy. The ratios are similar to the single-factor strategies formed based on profitability ratios. Still, they provide excess returns compared to the single-factor profitability ratios. Therefore, the joint strategy offers a better Sortino and Sharpe ratio than momentum strategy while providing greater excess returns than the single-factor profitability ratios. This does provide evidence that combining quality and momentum together can help finding weak performing and unprofitable stocks to short and finding stocks that have performed well in the past but can also be considered as quality stocks.

The long-short strategies based on the joint gross-profitability ratio and momentum as well as cash-based operating profitability and momentum result in the highest excess returns when executed as long-short strategy, buying the stocks in the long portfolio and shorting the stocks in the low portfolio. This is consistent with the findings of Bhootra (2018). The potential limitation in the execution of the strategy can arise from the possibility of individual investors to enter into short positions. The joint strategies based on gross-profitability and cash-based operating profitability could though be also implemented as long-only strategies however the excess returns in that strategy were only moderate when compared to the returns on single-factor momentum strategy. When the joint-strategies were observed over the sample period the indication is that there have been times in the late 20$^{th}$ century when the strategy was underperforming compared to the Nordic market index.

A possibility for future research could be to try and combine the momentum and quality measures with a third factor like value on the Nordic stock market since the combined strategy based on joint momentum and quality is negatively loaded with the value factor. The possibility to further also expand the quality and momentum observed together with different measures for quality could be a possibility to dive into in the future research.

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