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# Momentum, Value and Quality Investing in European Markets

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**ABSTRACT:**

This thesis examines the risk-adjusted performance of momentum, value and quality strategies as well as strategies that combine the selected strategies using different methods. The thesis aims to investigate if the previously documented anomalies present abnormal returns in the European market, and if the performance and abnormal returns can be improved by combining the individual factors together.

Earlier research on momentum, value and quality is abundant, but research combining the three factors into one using integrating, mixing and average rank methods is limited, and has provided mixed results. Majority of literature supports the view that integrating method of multifactor portfolio construction is the most efficient one, while alternate views argue that the results of the integrating method are not robust due to low diversification or data-snooping, or that the mixing method is superior due to lower transaction costs. A third alternative of average ranks is considered which could potentially have more robust results due to better diversification as well as lower transaction costs, as has been evidenced by previous literature. This thesis adds to the existing research by researching the gross profitability premium together with momentum and value, while also expanding the existing literature of momentum, value and quality combinations by expanding the time and data coverage to the European level.

First, the results are provided for each individual factor independently. In the second stage, the portfolios are sorted by size to investigate if any of the results are due to the size effect. In the third stage, the factors are combined pairwise by the three methods, and in the last stage, the three factors are combined using the three methods. The granular approach allows to examine if the three factors benefit from each other, and to what degree, and if the results are due to size effect. Previous literature has shown that factor portfolio abnormal returns are often greater among small firms but exist in other size groups as well.

Results show that momentum, value and quality strategies can generate abnormal returns, and beat the market with risk-adjusted performance. The individual single-factor strategies can be enhanced by incorporating other factors into the strategy either by integrating, mixing, or averaging the factors. The risk-adjusted performance is improved with even the simple mixing method, whereas the results can be improved even further by incorporating more elaborate combination methods depending on the investment objective. The different methods come with their own benefits and caveats, which are further discussed in the thesis. The multifactor portfolios have characteristics similar to those of single-factor portfolios, but generally have better risk-adjusted performance than the single-factor counterparts.

**KEYWORDS:** momentum, value, quality, strategies

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**Laskentatoimen ja rahoituksen laitos**

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**TIIVISTELMÄ:**

Tutkielman tarkoituksena on tutkia momentum, arvo- ja laatustrategioiden riskikorjattua suorituskykyä, sekä edellä mainittuja strategioita yhdistelevien monifaktoristrategioiden riskikorjattua suorituskykyä. Tutkielman tavoitteena on tutkia, mikäli nämä strategiat tuottavat epänormaaleja tuottoja Euroopan rahoitusmarkkinoilla, ja mikäli riskikorjattua suorituskykyä ja epänormaaleja tuottoja voidaan parantaa faktoreita yhdistämällä.

Momentum, arvo- ja laatu ovat kattavasti tutkittuja aiheita, mutta tutkimustieto niiden yhdistämisestä eri tavoin on rajattua, ja tulokset ovat olleet vaihtelevia. Suurin osa aiemmasta kirjallisuudesta tukee näkökantaa siitä, että integroiva menetelmä on tehokkain tapa yhdistää kaksi tai useampaa faktoria monifaktoriportfolioksi, mutta vastaväitteiden mukaan tapa ei tuota kestäviä tuloksia matalan hajautustason tai datalouhinnan vuoksi. Toisen näkökannan mukaan portfolioita sekoittava lähestymistapa on tehokkain tapa hajautuksen sekä matalien kaupankäyntikulujen takia. Tutkielmassa tutkitaan myös kolmatta lähestymistapaa, faktorien keskiarvoistamista, joka voi johtaa kestävämpiin tuloksiin hyvän hajautuksen ja matalalampien kaupankäyntikulujen takia, kuten aiempi tutkimus on osoittanut. Tämä tutkielma lisää kirjallisuuden kattavuutta tutkimalla momentum- ja arvopreemioita yhdessä bruttotuottavuus- eli laatupreemion kanssa samalla lisäten kirjallisuuden maantieteellistä kattavuutta Euroopan tasolle sekä lisäten ajallista kattavuutta.

Ensimmäisessä vaiheessa jokaista faktoria tutkitaan itsenäisesti. Toisessa vaiheessa faktoriportfoliot järjestetään koon mukaan ja arvioidaan johtuvatko tulokset otoksen yritysten pienestä koosta. Kolmannessa vaiheessa faktorit yhdistetään pareittain edellä mainituilla tavoilla. Seuraavassa vaiheessa kaikki kolme faktoria yhdistetään edellä mainituilla tavoilla, ja viimeisessä vaiheessa arvioidaan johtuvatko tulokset yritysten pienestä koosta. Vaiheittaisen lähestymistavan avulla voidaan tutkia, hyötyvätkö faktorit toisistaan, missä määrin, ja johtuvatko tulokset kokoilmiöstä. Aiempi tutkimus on osoittanut, että faktoriportfolioiden epänormaalit tuotot ovat suurempia pienempien yritysten keskuudessa, mutta epänormaaleja tuottoja on saavutettavissa myös muissa kokoluokissa.

Tulokset osoittavat, että momentum-, arvo- ja laatustrategiat voivat tuottaa epänormaaleja tuottoja, ja suoriutua markkinaa paremmin riskikorjatun suorituskyvyn perusteella. Yksittäisiä faktoristrategioita voidaan parantaa sisällyttämällä strategiaan muita faktoreita joko integroimalla, sekoittamalla tai keskiarvoistamalla faktoreita. Riskikorjattua suorituskykyä voi parantaa myös yksinkertaisimmalla sekoitusmenetelmällä, ja tuloksia voidaan parantaa muilla menetelmillä sijoitustavoitteen mukaan. Eri menetelmillä on omat hyötynsä ja haittansa, jotka ovat tutkielman keskustelun aiheena. Monifaktoriportfoliot vastaavat ominaisuuksiltaan yksifaktoriportfolioita, mutta niillä on pääsääntöisesti parempi riskikorjattu suorituskyky.

**KEYWORDS:** momentum, arvo, laatu, strategiat

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# 1 Introduction

## 1.1 Background

Investors seek to generate better returns than the benchmark market that their portfolio is compared to. The main way this is done is by looking for investment possibilities that generate the most excess returns. One of the main theories in finance is the efficient market hypothesis by Eugene F. Fama (1965). In short, it states that investors should not be able to beat the market consistently. In the short term, significant excess returns are possible, but in the long run these returns should not exceed the market return. There is varying evidence and documentation of anomalies that, when utilized, can beat the market.

One of the most significant anomalies is the momentum anomaly, which contradicts the most fundamental statement of the hypothesis: Future returns cannot be predicted by past returns. Originally formalized by Jegadeesh and Titman (1993), momentum investing involves going long in short term winners and going short in short term losers. Again, there is evidence in favor of and against the presence of the momentum anomaly. The specifications for momentum investing have changed several times since its inception, and new implementations are constantly developed to take advantage of the momentum anomaly. There is no sentiment behind why the momentum-anomaly persists, but the main idea is that investors will overvalue past winners beyond their efficient price.

Another mainstream investment strategy is the value strategy. One of the simplest and a standard measure of value is the book-to-market value of the stock, which is the book value of equity divided by the market value of equity. The long-short strategy involves going long in the stocks with the highest book-to-market ratios and going short in the ones with the lowest. Returns from value strategies have been commonly found to be negatively correlated with the returns of momentum strategies.

Quality investing has also been a strategy for investing for several investors. While the idea behind it is simple, to go long in the stocks that are perceived as high quality and go short in the ones with the lowest quality, the formulation is not trivial. The main reason for this is the measure of quality. There is no universal definition as to what quality is and several measures, or proxies, have been developed for it. While returns and valuations are easily quantifiable, the measure of quality is dependent on what the investors deem as quality and can theoretically be anything from fundamental values to the corporate strategy of the firm and can often be mixed with measures of value. Most common formulations for quality are the Grantham quality, Graham's G-Score, Greenblatt's Magic Formula, Sloan's accruals, Piotroski's F-Score and Novy-Marx's gross profitability. Some of these assign ranks or points to stocks, while others use more quantifiable measures. Quality in this thesis is defined as high gross profitability to total assets, following Novy-Marx (2013).

The existence of momentum and value premium has been previously widely studied, while the gross profitability premium is a relatively recent premium. The momentum premium was documented in 1993 by Jegadeesh and Titman, and value has its roots in the book by Graham and Dodd published in 1934, and gross profitability premium as quality was introduced by Novy-Marx in 2013. The book-to-market ratio is included as an explanatory risk factor in the Fama-French three- and five factor models, and the five-factor model also includes a factor like gross profitability, the operating profitability factor or robust-minus-weak. Momentum has been included as an explanatory factor in an augmented three-factor model, the Carhart four-factor model (1997). The models are widely known in the field of finance and as such there is already an abundance of studies related to the performance of the individual factors, or premiums, as well attempts to find new variations for the existing factors to increase the premiums related to the factors.

As the anomalies have previously been studied extensively, there is also an increasing interest in ETFs, mutual funds and hedge funds that seek to exploit these anomalies. More recently there have been several funds that aim to combine several different factors under one portfolio, not unlike in the objective of this thesis. These are more commonly known as smart beta funds.

## 1.2 Purpose of the study

The main purpose is to test these investment strategies in the European market, both independently and as multifactor portfolios, and as a combination of different strategies combining different criteria, and to evaluate their performances in terms of excess returns, abnormal returns as well as risk, and evaluate the risk-adjusted performance. The portfolios are formed following simple specifications to avoid any data mining.

In the traditional capital asset pricing model (CAPM) by Sharpe (1964) and Lintner (1965) the relation between an asset's expected return and systematic risk can be measured with market beta. Under this model, any abnormal returns generated by the strategies will produce a significant alpha in the regression model. As the value and profitability premiums are included in the Fama and French (2012) five-factor model, it will also be utilized to see if the combination of multiple factors will introduce any additional abnormal returns not accounted for by the factors in the model. The CAPM alpha would indicate if the portfolios were able to generate returns more than the benchmark index, while the Fama-French alpha would also indicate if the abnormal returns in excess of the benchmark index could be explained by the increase in exposure to the risk factors.

I will also divide both the single-factor and multifactor portfolio results to subsamples based on size to evaluate if the premiums found with these strategies are driven by the size effect, where small stocks would be responsible for generating the excess returns while also increasing the riskiness of the portfolio through exposure to small stocks.

The main contribution of this thesis is the application of different strategies using comparable methods, which allows for comparing the performance of different strategies on different markets. The novelty is the diversification using different strategies whose returns are previously documented to be negatively correlated or uncorrelated. To the author's knowledge this is the first comprehensive evaluation of momentum, value, and gross profitability together in the European market using three well-known but different methods for constructing multifactor portfolios.

This thesis follows the general subject of multifactor portfolio construction, with earlier literature on the subject provided by Clarke et al. (2016), who compare mixing and integrating methods in the U.S. market, Bender and Wang (2016), who compare mixing and integrating methods globally, Ghayur et al. (2018), who compare mixing and integrating methods in both developed and emerging markets, Chow et al. (2018), who compare mixing and integrating methods in the U.S., Grobys and Huhta-Halkola. (2019), who compare integrating, mixing and average rank methods in the Nordics, and more recently, Silvasti et al. (2021), who compare mixing and integrating methods in the Nordics. While previous literature has evaluated momentum, value and quality in context of multifactor portfolio construction, the literature has often combined even more factors e.g., low volatility, size and investment, and used extensive portfolio optimization to arrive at optimal structure of different portfolios, and focused on the factors either globally or in the U.S. Most commonly integrating and mixing methods have been pitted against each other, see Clarke et al., Bender and Wang, Ghayur et al., Chow et al., and Silvasti et al. Another common occurrence is combining momentum, value and low beta, as with Clarke et al. (who also include size), Bender and Wang (who also include quality), Chow et al. (who also include profitability and investment factors), and Silvasti et al. The previous literature can be expanded even further when focusing on combinations of momentum and value only, which have been studied by e.g., Asness et al. (2013), Fisher et al. (2016), and Grobys and Huhta-Halkola. Fisher et al. and Grobys and Huhta-Halkola also study the momentum and value factors with average ranking methods, which have previously not been studied as extensively.

This thesis differs from previous literature by providing a specific focus on the European market, while limiting the methodology to three replicable methods, and limiting the number of factors to three specific factors that have been previously well-documented and would potentially benefit from either known negative or positive correlations (i.e., value has a negative correlation to both momentum and quality, while momentum is positively correlated with quality). This aims to suppress the noise that could be caused by unknown factors in the mix to provide more robust results. This thesis also follows largely the research methodology of Grobys and Huhta-Halkola (2019) by evaluating the average rank method, and Silvasti et al. (2021) among others by pitting mixing and integrating methods against each other while effectively extending the research to the European level and providing results from the inclusion of the quality factor and long-short portfolios. Contrary to Bender and Wang (2016) and Ghayur et al. (2018), who evaluate the integrating and mixing methods using global portfolios, the results are specifically limited to the European level, as Fama and French (2012) find that the global factor models are not robust in explaining average returns, while Chow et al. (2018) find that integrating method is superior in the U.S. market when the set of stocks is limited enough. The novelty of the thesis and differences to previous literature can be condensed as follows: the previous literature focuses on multifactor portfolios either globally, in the U.S., or in the Nordics, and not specifically in Europe. The previous literature also focuses mostly on mixing and integrating methods, except for Fisher et al. (2016) in the U.S. and Grobys and Huhta-Halkola in the Nordics who also evaluate the average rank methods, though they also shift their focus away from the other methods. The third important aspect is that while momentum, value and quality have been studied together (see Bender and Wang, 2016; Chow et al., 2018), previous literature has included multiple other factors such as low-beta and investment factors in the mix, instead of providing a combination consisting purely and only of momentum, value, and quality.

## 1.3 Hypotheses

As the thesis evaluates three different investment strategies and their combinations, the first research question is if we can find any premiums related to the factors in the sample. Therefore, the first hypothesis is:

> H1: Stocks with high recent past performance, high book value to market value ratios and high gross profitability to total assets ratios are able to generate abnormal returns over the benchmark index.

The results are expected to show that the strategies generate excess returns over the market return and to be in line with previous findings (see e.g., Asness, 1997; Rouwenhorst, 1998; Fama & French, 1998; Griffin et al., 2003; Novy-Marx, 2013; Asness, Moskowitz & Pedersen, 2013; Novy-Marx, 2015; Walkshäusl, 2014; Frazzini & Pedersen 2014; Asness, Ilmanen et al., 2015). The results will also include various metrics of both risk characteristics of the portfolio as well as risk-adjusted performance, which will then be used in benchmarking the performance of the multifactor portfolios.

Given that it is possible that the results are driven by the small size effect, the second hypothesis is if abnormal returns can be found in other size groups:

> H2: Abnormal returns for single- and multifactor portfolios exist outside of the small stock universe.

It is expected that the abnormal returns are highest among the small stock universe, as has been previously found (see e.g., Fama & French, 2011; Fama & French, 2015; Novy-Marx, 2013; Asness et al., 2018).

The main hypothesis of the thesis is the interaction of the three factors when constructing multifactor portfolios:

H3: The risk-adjusted performance of the multifactor portfolios is different from single-signal portfolios.

The results are expected to be in line with previous research where the performance was improved for multifactor portfolios (see e.g., Fitzgibbons et al. 2017, Grobys et al. 2019). The performance improvement will be quantified based on abnormal returns increase, risk-adjusted performance measure increases in terms of Sharpe and Sortino ratio, as well as increase in monthly and maximum drawdown measures.

## 1.4 Structure of the study

In the following chapter efficient market hypothesis will be discussed as it is closely related to the hypotheses to be tested. The third chapter will focus on the investment strategies to be studied, as well as previous research on combining these strategies. Fourth chapter will introduce asset pricing models, most importantly the capital asset pricing model (CAPM), and the Fama-French five-factor model which will be used in this thesis to evaluate abnormal returns. A brief overview on other asset pricing models will also be provided. The fifth chapter will focus on the data used in the research, as well as the methodology for constructing the portfolios. Risk-adjusted performance measures will also be introduced that will be used to evaluate the performance of the portfolios. The results are discussed in chapter six and chapter seven will provide the conclusions of the thesis.

# 2 Efficient market hypothesis

This chapter will focus on efficient capital markets and efficient market research, while asset pricing models will be discussed further in the following chapter.

## 2.1 Efficient capital markets

*The primary role of capital markets is the allocation of ownership of the economy's capital stock* (Fama, 1970, p. 383). According to Fama, in an ideal situation, market pricing would give market participant accurate signals for production-investment decisions under the assumption that all available information is fully reflected in the price of a security. The basis for any financial theory is the concept of efficient markets. When all available information is fully reflected in prices of securities, the market is called efficient.

Fama (1970) introduced three levels of efficiency, along with three tests for market efficiency: the weak-form test for if only historical prices are reflected in the security price; the semi-strong form test for if publicly available information, in addition to historical prices, such as firm announcements e.g. earnings announcements and stock splits, is reflected in the security price, and the strong-form test for if certain individuals or groups have monopolistic information available to them, i.e. if prices adjust to information not available to all market participants, or insider information.

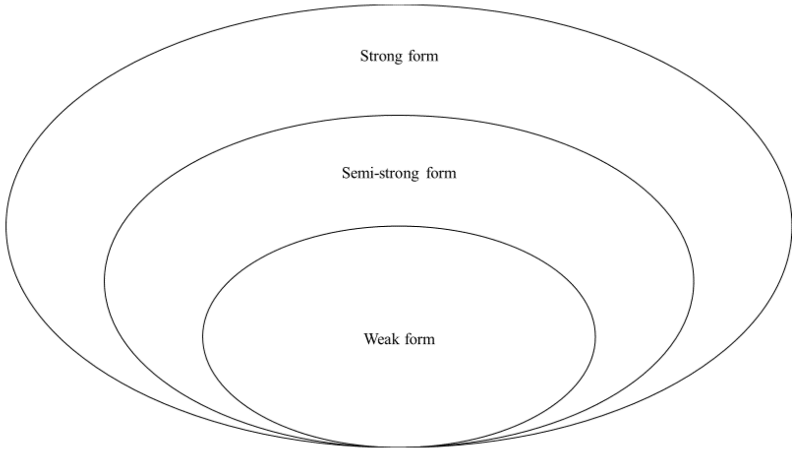


**Figure 1.** Three forms of the EMH

The three forms of efficient market hypothesis are illustrated in figure 1. The weak-form of market efficiency only includes the historical prices as information, the semi-strong form includes the weak-form as well as the publicly available information, while the strong form includes tests for both weak and semi-strong form, along with the private information, or information not available to all market participants.

Fama (1970) acknowledges that their main hypothesis is that *all* available information is reflected in the security prices, which presents an extreme null hypothesis and is not expected to be literally true. Instead, the different forms of efficiency and tests for efficiency allows for pinpointing where the market efficiency breaks down.

Fama (1970) also discusses three conditions that would positively affect the market adjustment to prices:

1. There are no transaction costs in trading securities.
2. All information is available for free for all market participants.
3. All agree on the implications of the currently available information to the current asset price and to the distribution of future prices.

## 2.2 Weak form

The test for weak form is a test if historical prices are reflected in the current price of a security. When the historical prices are properly reflected in the price, market is weakly efficient. Fama (1970) suggests that the weak form can be tested by examining the presence of serial correlation in the returns of the assets. The returns of assets should follow a random walk, i.e., they should be random and future returns cannot be predicted by looking at past returns. Fama compares thirty stocks from Dow Jones Industrial Average, with a period starting approximately from the end of 1957 and ending on September 26, 1962, finding no substantial linear dependence between lagged price changes or returns. Other studies have yielded similar results, e.g., Allen & Karjalainen (1995) could not find a dependence between past and future prices of S&P 500 index prices when accounting for a 1-day trading lag and trading costs.

Despite supporting evidence, there has also been evidence indicating that the conditions for the weak form are not fulfilled. Lo and McKinlay (1988) find positive autocorrelations in weekly returns by comparing portfolio returns for large and small capitalization stocks. They hypothesize that the autocorrelation is introduced by the less frequent trading of small capitalization stocks, which is amplified by the portfolio composition, as the portfolio is equally weighted instead of value weighted. Lo et al. (2000) find increased returns using technical analysis indicators such as head-and-shoulders and double-bottoms between 1962 and 1996 using NYSE, AMEX and Nasdaq stocks as a sample.

Jegadeesh (1990) finds significantly negative first-order serial correlation and significantly positive higher-order serial correlation for monthly U.S. stock prices. Jegadeesh and Titman (1993) find higher returns for stocks that have performed well in the past (three to twelve months prior to formation) and lower returns for stocks that have performed poorly during the same period. The strategy has since been dubbed “momentum” and will be discussed further in chapter 3. Momentum anomaly has since been vastly researched. As Jegadeesh and Titman find positive autocorrelation of returns over short- and medium term, De Bondt and Thaler (1985) find negative autocorrelation of returns over long term. In the contrarian strategy, stocks performing well over a long period (three to five years) have lower returns than those that have performed poorly over the same period). However, Jegadeesh and Titman also find that the momentum effect diminishes over the long term. De Bondt and Thaler suggest that the long-term reversal is resultant of overreaction of information to unexpected news, whereas Fama (1998) argues that overreaction to unexpected news is as common as underreaction. Fama also argues that the results are dependent on the methodology and are not robust.

When the market is weak form efficient, historical price information should be included in the current security prices. However, as evidenced by De Bondt and Thaler (1985) and Jegadeesh and Titman (1993), as well as several others following their research (see e.g., Asness, 1997; Asness et al., 2013; Bird & Whitaker, 2003), momentum strategies can generate excess and abnormal returns. As regular momentum strategies are purely based on historical price information, there is an argument that the market is not efficient. There have been attempts to explain momentum with increased risk, which would then support the argument that the market is weak form efficient. Fama and French (1996), however, are unable to explain momentum returns using the three-factor model, with others (see Chan et al., 1996; Asness et al., 1997) arguing for market inefficiency as the market is slow to react to all available information. Fama and French (2012) find that the five-factor model is able to explain momentum returns across markets, with the additional risk factors being able to explain momentum returns, and the increased risk of momentum strategies. Further explanations for momentum will be discussed in chapter 3.

## 2.3 Semi-strong form

Semi-strong form of efficiency is achieved when in addition to historical price information all publicly or obviously available information is included in the asset price.

If investors have access to such information, e.g., “*firm’s product line, quality of management, balance sheet composition, patents held, earnings forecast, and accounting practices*”, it is expected to be reflected in the asset price. (Bodie et al., 2014, p. 354; Fama 1970)

Semi-strong efficiency can be tested with event studies, where the reaction of the asset price is measured before, during and after events such as earnings announcements. Fama et al. (1969) studied if stock splits were correctly incorporated in asset prices after the event, finding supporting evidence for market efficiency, while noting that stock splits often have implicit information implying increased earnings prospects of the firm. Several studies with methodology similar to that of Fama et al. regarding public announcements have been conducted afterwards, with evidence supporting market efficiency. A review and discussion of these was also provided in Fama’s (1970) research.

Fundamental analysis should not be possible when the markets are semi-strong efficient. This can be extended to anomalies such as value and quality anomaly, i.e., firms with high book-to-market and gross profit to total assets ratios, which are dependent on the accounting values of firms, and therefore publicly available information. As with momentum, the reason behind anomalies such as value has been tried to explain with increased risk. For example, Fama and French (1992, 1993) argue that high book-to-market stocks are inherently riskier than low book-to-market stocks, as the book-to-market ratio acts as a proxy for undiversifiable risk. The other view, i.e., the behavioral view, contradicts the semi-strong form of market efficiency, as the premium associated with anomalies is not due to increased risk, but due to market inefficiency and mispricing (see e.g., Lakonishok et al., 1994; La Porta et al., 1997). An observation was made by Schwetz (2003) that the value anomaly, among other anomalies, has disappeared after research on the book-to-market ratio was published. This implies that market inefficiencies may have existed but have vanished as the publication of research findings cause the market to become more efficient, as practitioners exploit the anomaly to non-existence. The other explanation may be that the anomaly never existed but was a result of overfitting the data to find a predictable pattern. Further explanations for the value anomaly will be discussed in chapter 3.

## 2.4 Strong form

The strong form of market efficiency is achieved when information not publicly available is reflected in the asset prices, e.g., insider information. Niederhoffer and Osborne (1966) claim that NYSE specialists have been able to generate excess returns by using insider information regarding the information on unfulfilled limit orders placed on the exchange. Fama (1970) points out that while there is some evidence of the market not being fully efficient according to the strong form of market efficiency, it may not be advantageous for an average investor to expend resources finding the little-known information or identify the individuals or groups with the access to this information.

Sharpe (1966) approached the question by researching the returns of open-ended mutual funds. By generating abnormal returns, they argue that mutual fund managers have access to information the wider market does not have access to. Sharpe's findings indicate that the risk-adjusted performance (measured by Sharpe ratio) between mutual funds is largely the same, with the difference in returns arising from different objectives and risk profiles, as well as differences in expense ratios and leverage. Jensen (1968) finds that on average, mutual funds are not able to outperform a buy-and-hold market portfolio (measured by Jensen's alpha), and that there is not enough evidence that an individual mutual fund that did outperform did so due to information advantage instead of random chance.

While there is supporting evidence that the market may not be strong form efficient, there is also evidence provided by Sharpe (1966) and Jensen (1968) that attempting to utilize this information may not be cost-efficient from a fund management perspective, while Jensen (1968) also noted that the conclusions hold even when measured gross of management expenses. However, as evidenced by e.g., Bettis et al. (1997), who find that mimicking insider trades can generate abnormal returns, and Lakonishok and Lee (2001), who find that insider trading information, whether public or not, could be used to gain abnormal returns even when accounting for costs, as they find that insider trading activity can be used to predict future price movements.

# 3 Investment strategies

This chapter will discuss previous literature on investment strategies that are discussed in this thesis. The primary focus will be on momentum, value, and quality. While the scope of this review will be extensive, it is not exhaustive, and will focus more deeply on the most influential research.

## 3.1 Momentum

Contrarian strategy was originally developed by De Bondt and Thaler (1985). It is based on the view that individuals tend to overreact to information. This implies that one should go long on past losers and short on past winners, as the overreaction will be corrected soon after. It is based on a longer time horizon than the other strategies, as it uses the cumulative returns from past three to five years as the selection measure and holds these stocks for three to five years. In the three-year selection measure, and where the stocks are held for three years, the portfolio had excess returns of 19.6%.

Momentum has its roots in studies conducted by Jegadeesh (1990), who finds significantly negative first-order serial correlation in monthly stock returns and significantly positive higher-order serial correlation, with the twelfth month being particularly strong. This implies that the longer (up to twelve months) an asset has performed well, the more likely it is also to perform well in the following month.

Momentum as a strategy was originally developed as a counter to the contrarian strategies by Jegadeesh and Titman (1993). Following the study by Jegadeesh (1990), they tested momentum strategies by measuring cumulative returns from three to twelve months prior to the portfolio formation date and ranking these to winner and loser portfolios. The winner portfolio consists of the highest decile, measured by past performance, and the loser portfolio of the lowest decile. A second set of portfolios is also examined where a week is left between the portfolio formation date and the holding period start date to avoid bias from bid-ask spread, price pressure and lagged reaction effects. The most successful zero-cost portfolio is the one where the cumulative returns are measured from past twelve months skipping the last week and then held for three months, which yields 1.49% per month, or 17.88% annually.

Chan et al. (1996) find similar results with momentum measured by six months prior return and holding period ranging from six months to three years. They also confirm that the momentum effect seems to vanish after the first twelve months, as the returns from different deciles are approximately the same.

Grinblatt and Moskowitz (2004) find evidence of the momentum effect, but also measure the effect of consistency of past returns by counting the months of positive and negative returns during the momentum horizon. They find that consistent winners have double the premium compared to inconsistent winners. For the loser portfolios the consistency of losing does not yield similar results, which they attribute to tax-loss selling, which plays a larger role for the loser portfolios than for the winner portfolios. George and Hwang (2007) also find that momentum returns are at least partially due to tax loss selling in December, which is consistent with lower momentum-returns in Hong Kong and Japan, where tax-loss selling would not be possible.

Moskowitz and Grinblatt (1999) find industry momentum by calculating value weighted portfolio returns for industries instead of individual stocks, and then going long on the three winners and short on the three losers, instead of decile sorts of individual stocks. They find industry momentum to generate higher average returns than individual stock momentum for all horizons except the 12-1 horizon.

Whereas previous results are from the United States market, Asness et al. (1997) find momentum premiums in international country equity indices similar to momentum premiums of individual U. S. stocks. Chan et al. (2000) also find similar premiums in international country equity indices, with holding periods ranging from to 1 to 26 weeks.

Rouwenhorst (1998) finds momentum premiums in a sample of 12 European countries. Their methodology is similar to that of Jegadeesh and Titman (1993) with the momentum signal being measured from three to twelve months past return, and the holding period ranging from three to twelve months. They also construct momentum portfolios for each individual country, measuring 6-month past return and holding the portfolio for 6 months. They find significant momentum for all countries except Sweden.

Bird and Whitaker (2003, 2004) study momentum returns in Germany, France, Italy, Netherlands, Spain, Switzerland, and United Kingdom from January 1990 to June 2002 and find higher returns for past 6- and 12-month winners with holding periods ranging from 1 to 12 months, however, the results are significant only for Germany and United Kingdom at 5% level, with a 6-6 momentum strategy. For the entire sample and 12-1 strategy, they find increased returns for high momentum stocks at 10% significance level. While they find increased returns for all markets under study, they attribute the low significance to the small sample size.

Fama and French (2012) study firm size, value, and momentum in international stock markets, and find significant momentum in all regions except Japan. In accordance with earlier findings, they find a stronger momentum effect in small stocks. Asness, Moskowitz et al. (2013) have similar findings, finding significant momentum in everywhere but Japan, with the global sample generating 12.1% annual mean return.

While momentum has been mostly associated with stock returns, there is evidence of momentum being found across other asset classes. Asness, Moskowitz et al., (2013) find momentum premiums in equities, bonds, currencies, and commodities globally. Burnside et al. (2011) find momentum premiums in currencies, unexplained by additional risk, rare disasters, or the peso problem. Menkhoff et al. (2012) find momentum premiums in currencies, though the premiums are closely related to small currencies with high transaction costs, which would effectively account for up to 50% of the momentum returns. Barroso and Santa-Clara (2015) also find momentum returns unexplained by additional risk, arguing that momentum in currencies is an anomaly. Erb and Harvey (2006) find momentum in commodity futures. Liu and Tsyvinski (2018) and Liu et al. (2019) and Tzouvanas et al. (2019) find momentum premiums in cryptocurrencies, however, Grobys and Sapkota (2019) are unable to find momentum in cryptocurrencies.

Even though most momentum strategies are based on cross-section of the returns, an alternative is the time-series momentum by Moskowitz et al. (2012). The main difference to regular momentum strategies is that instead ranking assets relative to other assets, only the trend of a single asset is considered, i.e., only the sign of the look-back period return is relevant. Similar to regular momentum, Moskowitz et al. find that time-series momentum is strongest with a one-month holding period, while the strongest results are with a look-back period of 3-12 months, depending on the asset class. They find positive abnormal returns for commodity futures, equity index futures, bond futures as well as currency forwards.

Momentum has been a significant point of interest in finance research, but there is no clear consensus on the reason behind the momentum anomaly. The main drivers behind momentum have been hypothesized to be based on either irrational investors, causing mispricing (see e.g., Daniel & Titman, 1999), and additional risk, requiring a larger return for the additional risk carried (see e.g., Fama & French, 2012).

Daniel et al. (1998) propose that momentum is caused by biased self-attribution of investors, with investors overreacting to private information, e.g., their own analysis and interpretation of information, and underreacting to public information. The bias is fortified even further when the public information confirms the private information, but the bias is also strong against public information that contradicts the private information, as investors are overconfident. Hong and Stein (1999) argue that the opposite is true, and investors can be divided to “news watchers” and “momentum-traders" where the news watchers tend to underreact to private information in the short term, allowing momentum-traders to profit on the underreaction.

Daniel and Titman (1999) find that investor overconfidence is likely to cause momentum in stock prices. They find that momentum effect is stronger for firms with less available information, requiring more ambiguity in interpreting the available information. This is consistent with the fact that momentum stocks are often growth stocks, and with self-attribution bias theory of Daniel et al. (1998) as even more of the information available is based on private information.

Stambaugh et al. (2012, 2014) find that investor sentiment can explain the returns of several anomalies, including momentum. Long-short strategies exhibit higher average returns following periods with high investor sentiment. The returns of the short leg are significantly lower following high sentiment than low sentiment. The long leg, however, is largely unaffected by the sentiment.

Pastor and Stambaugh (2003) find that momentum returns are related to liquidity risk. Returns of illiquid stocks exceed those of liquid stocks by 7.5 percent annually even after adjusting for momentum, value and size factors, and the liquidity risk factor explains half of the momentum strategy returns over long term. Sadka (2006) finds similar results, contributing to the previous by arguing that the momentum premium consists of increased exposure to variable liquidity risk.

One of the most common arguments is that the momentum effect is caused by delayed reaction or overreaction by the market. Overreaction was also hypothesized and evidenced by De Bondt and Thaler (1985, 1987) for the contrarian strategy. Chan et al. (1996) finds similar results for the momentum effect, arguing that firms react slowly to earnings surprises, which causes both positive and negative drifts after the initial impact on the price. Following announcements will on average cause a similar surprise reaction in the stock prices. Their findings indicate that the momentum effect is caused by slow market reaction to new information. Chan et al. also argue that analysts are slow to update their forecasts.

Moskowitz and Grinblatt (1999) argue that momentum returns can be explained by industry-specific returns. After controlling for industry-specific momentum the momentum strategies for individual stocks are significantly less profitable. By subtracting the industry momentum return from each stock's individual return, the remaining return is 0.13% with a t-stat of 2.04, compared to the unadjusted return of 0.43% which is highly significant with a t-stat of 4.65. Fama-MacBeth regressions yield similar results, however, the industry momentum does not explain all momentum returns with the 12-1 momentum strategy. George and Hwang (2004) and Chordia and Shivakumar (2002) report similar findings regarding industry momentum.

Chordia and Shivakumar (2002) report similar findings as Moskowitz and Grinblatt (1999), however, they argue further that momentum and industry momentum are different anomalies, and whereas the momentum returns are explained by industry momentum returns, both the individual stock momentum returns, and industry momentum returns are explained by macroeconomic variables of dividend yield, default spread, term spread and yield on the three-month T-bill. The returns predicted by these variables is not significantly different from momentum returns.

George and Hwang (2004) find that the 52-week high price of a stock is a better predictor of the future returns than the past return, while also explaining the momentum returns with traders using the 52-week high price as an indicator of if the stock is over- or undervalued. By ranking stocks based on their current price relative to the 52-week high price, they construct high- and low relative price portfolios which consist of 30% with the highest ratio and 30% of the lowest ratio stocks. They then compare the returns of the relative price portfolio to momentum and industry momentum portfolio returns. The long-short portfolio returns of the momentum and industry momentum portfolios are similar to previous literature, whereas the 52-week high price return is slightly higher than the momentum return, and more than double that of the industry momentum return. When controlling for size and bid-ask bounce effects, the return of the relative price portfolio is more than double compared to momentum or industry momentum returns.

The long-horizon excess returns from momentum strategies seem to revert after three to five years. This is also consistent with the argument that momentum is caused by delayed overreaction by investors. Lee and Swaminathan (2000) develop a concept of "momentum life cycle" which describes an interaction between momentum, price reversals and trading volume. Stocks experience different cycles, varying from early-stage winners and losers to late-stage winners and losers. The stage is determined by the trading volume, where high volume winners and low volume losers are losing their momentum, whereas high volume losers and low volume winners are beginning to gain momentum.

Avramov et al. (2007, 2013) find a strong link between momentum and firm credit ratings. They find that extreme momentum decile portfolios consist mainly of high credit risk stocks, which generate both winner and loser returns. When high credit risk stocks are removed from the sample, the remaining momentum returns are statistically insignificant. As the improvement of financial performance for winner stocks and deterioration of loser stock is unexpected by the market, leading to earnings surprises and analyst forecast revisions.

Momentum strategies are subject to well-documented risk dubbed the "momentum crash", in which during sharp economic downturns the return of the loser portfolio will exceed that of the winner portfolio, effectively reversing the momentum and producing extreme drawdowns. The worst period for momentum strategy in the U.S. was in July to August of 1932 where a 12-1 momentum strategy would have yielded -60.98% and -74.36% monthly returns (Daniel & Moskowitz, 2016). More recently, in March to April of 2009 a 12-1 strategy would have yielded -30.54% and -45.52% monthly returns.

Assuming a generous 15% annual return afterwards it would still take almost 10 years to recover from a two-month loss. Moreover, momentum strategy suffers from high kurtosis as well as a negative skew, with a documented kurtosis of 18.24 and left skew of -2.47 (Barroso & Santa-Clara, 2015).

Daniel and Moskowitz (2016) present their key findings: There are relatively long periods over which momentum strategy experiences severe losses or crashes, with both crashes and extreme losses being clustered around certain periods. The crashes do not happen instantly but instead take place over multiple months. The worst momentum crashes occur in months when the two-year compounded market return is negative, but the contemporaneous market return is positive. They also find that the crashes are often not due to the long leg crashing, but instead of the short leg rallying.

Daniel and Moskowitz (2016) find that momentum portfolios have variable betas, with the loser portfolio often having a high beta during volatile, bear market periods. The winner portfolio may have a beta of above 2 during sudden market rises, but the loser portfolio beta could be even a 4 or 5. As the spread between the betas becomes negative and large during market upswings, the total return of the momentum portfolio becomes increasingly negative, as the loser portfolio has a more positive reaction to the market upswing. Similar findings were made previously by Grundy and Martin (2001), who find that during market declines the winner portfolio is likely to consist of low beta stocks, and the loser portfolio of high beta stocks, resulting in a negative beta for the portfolio.

Due to the extreme drawdown risks of the momentum strategy, attempts have been made to augment the momentum strategy to account time-varying market exposure of the strategy. Grundy and Martin (2001) were among the first to formulate a hedge against the time-varying market exposure, however, with a major caveat that it was not implementable ex-ante, as it is a forward-looking hedge. Despite this, by hedging the strategy against size and market factors, the variability of monthly returns decreases by 78.6%. Barroso and Santa-Clara (2015) then take the method further, by finding that the volatility of momentum portfolios is highly predictable and using realized daily variance of the momentum strategy to predict the future variance of the portfolio. The long-short portfolio is then scaled with the predicted volatility to arrive at a constant ex-ante volatility. They find that the Sharpe ratio is improved from 0.53 to 0.97, and excess kurtosis is reduced to 2.68, and left skew to -0.42. The worst monthly drawdown is improved to -28.40% from -78.96%, and maximum drawdown to -45.20% from -96.69%. The strategy also works outside of the U.S. as the results are improved in France, Germany, Japan, and the U. K.

Daniel and Moskowitz (2016) take the method further by determining the weightings of portfolios by forecasting the return and variance of the strategy, allowing for the objective of maximizing the Sharpe ratio. In contrast to the Barroso and Santa-Clara (2015) method, the volatility is not constant but variable. The dynamical weights of the momentum strategy approximately double the Sharpe ratio when compared to an unmanaged momentum portfolio, and the results are robust across markets, asset classes and time. Geczy and Samonov (2016) are able to replicate the results of both Barroso and Santa-Clara, and Daniel and Moskowitz. The performance of risk-managed momentum strategies has further been validated by Moireira and Muir (2017), Grobys (2017) and Grobys et al. (2018).

## 3.2 Value investing

Value investing has its roots in the book “Security Analysis” by Benjamin Graham and David Dodd (1934). The main idea behind value investing is that one should invest in undervalued “value firms”, firms that have a specific signal that indicates undervaluation, and sell overvalued firms. Value signal is usually determined by a ratio derived from the accounting values of the firm, with signals being previously constructed from ratios such as book-to-market (B/M), earnings-to-price (E/P), cashflow-to-price (CF/P), enterprise value to EBITDA (EV/EBITDA), dividends-to-price (D/P) or sales-to-price (S/P). While there are several ways to construct the value signal, arguably the most common signal is the book-to-market ratio, which compares the book value of equity to the firm's market value of equity. According to this signal value firms are firms whose intrinsic value is higher than their current market value and are fundamentally undervalued. As value can have many interpretations, for the purpose of this thesis, the terms value and growth will refer to high and low book-to-market ratios. Portfolios constructed using value measures among other are often called "smart betas" or "fundamental indices" but are not limited to these ratios (Asness, Frazzini, et al., 2015). In earlier literature it was common to lag the market value of equity by six months to prevent any look-ahead bias, or unwanted positions in momentum (Noxy-Marx, 2013), however, as suggested by Asness and Frazzini (2013), the view used to be reasonable, but is nowadays suboptimal. They suggest that only book value of equity should be lagged by six months to ensure the book value information is available to investors.

Early evidence of the book-to-market anomaly was reported by Stattman (1980), who finds a positive correlation between average returns and book-to-market ratios for U.S. stocks. Rosenberg et al. (1985) also find similar results. Lakonishok et al. (1994) find that stocks with high B/M or CF/P ratios generate higher average returns than ones with low ratios. The book-to-market ratio has been extensively researched by Fama and French (see 1992, 1993, 1996, 1998, 2006a, 2012, 2015, 2017, 2018, 2019). The book-to-market ratio is also included in the Fama-French factor models as an explanatory component.

Chan et al. (1991) provide international evidence of the value anomaly by finding a similar correlation in the Japanese stock markets as Stattman (1980) and Rosenberg et al (1985). Fama and French (1998) find significant value premiums in international markets, with high book-to-market portfolios having higher returns than low book-to-market portfolios by 7.68 percent per year.

Bird and Whitaker (2003, 2004) find value premiums in Europe, with value being measured with book-to-market and sales-to-price ratios, however, they fail to find a significant difference between the high and low value portfolio returns for all countries.

They attribute this partly to the small sample size for the countries. Despite this, the highest quintiles offer a robust return for all countries as well as the countries combined.

Asness et al. (2013) find value premiums in main international equity markets, and in addition to equity, they find similar value premiums in other asset classes as well. Cakici and Tan (2014) find significant value premiums in nine out of sixteen European countries, and in Australia, Hong Kong, Japan, New Zealand, Singapore and Canada. In the remaining European countries and United States, the value premium can be found but is not statistically significant at 5 percent level. At 10 percent significance level, value premium can be found in all countries except for Finland, Portugal and Spain, though value premium can also be found in Finland and Portugal for small stocks at 5 percent and 10 percent significance levels, respectively.

Pätäri and Leivo (2009) find evidence of value premiums in Finland with different value measures. Leivo and Pätäri (2009) find that the value premium can also be found for long-term holding periods in Finland. Davydov et al. (2016) also find similar premiums. Tikkanen and Äijö (2018) find value premiums in European markets with different value signals, and that the value premiums can be improved by combining with Piotroski's F-Score. Grobys and Huhta-Halkola (2019) find value premiums in the Nordic markets with book-to-market sorting, while providing evidence that the risk-adjusted returns can be increased by combining value with momentum.

Value has been found in other asset classes in addition to stocks. However, the definition of value in other asset classes is not as straightforward as it is for e.g., momentum, as it may be hard to define ratios such as book-to-market for other assets. Asness et al. (2013) overcome this by defining other value metrics, such as defining the book-value of bonds as the nominal cash flows discounted at inflation rate, and the price as the nominal cash flows discounted with yield-to-maturity of the bond. For commodities and exchange rates, the value ratio is the 5-year return of the commodity, or the 5-year exchange rate return considering local 3-month IBOR rate interest accruals. While the results for plain value applied to other asset classes vary a lot, when applied together with momentum the performance is improved and the results are similar to when combining momentum stocks with value stocks.

While the value premium has been researched comprehensively, and its existence has been confirmed on several different markets, there is no clear consensus on the reason behind the anomaly. The reasons behind the value anomaly have been argued to be like those of the momentum anomaly: high B/M stocks are either mispriced or carry more risk. As the existence of the value premium is contradicting with market efficiency (specifically the semi-strong form of market efficiency) Fama and French (1992, 1993) have argued that the value premium is a proxy for undiversifiable risk, like that of the size premium. They argue that value stocks are fundamentally riskier than growth stocks, and as such, should provide a higher expected return for the risk associated.

Griffin and Lemmon (2002) find a greater value premium for firms with high distress risk (measured by Ohlson's O-Score) arguing that firms with high distress risk have characteristics that make them more likely to be mispriced. Vassalou and Xing (2004) find correlation between default risk, size and value measures, stating that small firms and value firms have higher returns than big firms and growth firms only if they have higher default risk.

Petkova and Zhang (2005) study the time-varying risk patterns of value and growth stocks. They find that value stocks are riskier than growth stocks, but only during "bad times" when expected market risk premium is high. During "good times" value stocks are less risky than growth stocks. The conditional betas of value and growth stocks covary together with the expected market risk premium, with value having a positive covariance and growth a negative covariance with the expected market risk premium. Studying the performance of value and growth during recessions, they find evidence of timing impact on the return of the value strategy. Going in and out of recession, value returns increase faster than growth returns, but in the middle of recessions, growth stocks often have higher returns than value stocks. After recessions, the more depressed value stocks will earn higher returns than growth stocks, which have not been as depressed. Growth outperforming value supports the argument made by Lakonishok et al. (1994) that for value stocks to be fundamentally riskier than growth, they would have to underperform growth stocks frequently, and during times when marginal utility of wealth is high.

Hansen et al. (2008) find that long-run consumption risk can explain value returns. Malloy and Moskowitz (2009) along with Asness et al. (2013), Bansal et al. (2014) and Cakici and Tan (2014) report similar findings. Value has primarily a positive loading on future GDP or consumption growth, implying that value returns are dependent on the wider macroeconomic environment, and that value returns are lower prior to periods of low economic growth.

Numerous similar findings about the relation of value and growth stock returns to the future macroeconomic environment have been made. Low return on value strategies implies an incoming recession. Liew and Vassalou (1999) find that SMB and HML factors can predict future GDP growth. Similarly, Eleswarapu and Reinganum (2004) find that the wider stock market return is negatively correlated with the past returns of growth stocks. This supports the view that the value premium is indeed a compensation for added risk. Vassalou (2003) finds that a model that incorporates a factor for news about future GDP growth along with the market factor can explain expected returns as well as the Fama-French three-factor model. This implies that HML and SMB are proxies for low future GDP.

Asness et al. (2013) find that while macroeconomic risk variables can explain some of the value returns, a major contributing risk factor is the liquidity risk. Value performs poorly when the spread between 3-month U.S. treasury bills and 3-month LIBOR is high, which is a sign of a market environment where borrowing is difficult. Asness et al.

attribute this to the fact that value stocks are often stocks with either high leverage or stocks with poor recent performance.

The other view on the nature of value premium is the mispricing view, stating that market participants are not rational. Market participants tend to over-estimate the growth rate of growth companies, while underestimating the prospects of value companies. Value stocks have also been found to be equally or less risky than growth stocks, contradicting the risk premium theory (Lakonishok et al., 1994). Haugen and Baker (1996) find that the return from value among other factors cannot be attributed to any increase in risk, but instead mispricing of investors, as investors have inherent biases towards and against value and growth stocks.

La Porta (1996) finds that when sorting firms by their expected growth rate of earnings, stocks with low expected growth rates beat stocks with high expected growth rates by up to 20 percentage points. They also find evidence of markets being overly optimistic on the earnings of the high growth rate firms, while simultaneously being overly pessimistic on the earnings of the low growth rate firms. La Porta et al. (1997) find that most of the return difference between value and growth stocks is generated during earnings announcements, where earnings surprises are systematically more positive towards value stocks. However, this cannot be simply attributed to mispricing, but could also be attributed to differences in investor risk preferences.

In relation to the study by Griffin and Lemmon (2002), Campbell et al. (2008, 2011) find that while companies with high distress risk have high value factor loadings, they also have low returns and high standard deviation, contradicting the risk compensation hypothesis. Avramov et al. (2013) argue that value firms are high credit risk firms, where the high returns are realized after the firm survives the financial distress.

Ball et al. (2020) argue that the book-to-value ratio is not a proxy for the intrinsic value differential for firms, but instead works as a proxy for the underlying earnings yield. As the value factor returns have slowly been disappearing after 1990 in the U. S. market, they test their hypotheses that a) book-to-market is a proxy for the underlying earnings yield and b) retained earnings is a better proxy for the earnings yield. They show that before 1990 retained earnings and book-to-market ratios for individual firms in the U.S. market are highly correlated, which is why the book-to-market ratio was able to predict returns. However, after 1990 the correlation diminishes, along with the returns predicted by the book-to-market ratio. However, they show that the retained earnings still have predictive power, and argue that instead of intrinsic value, the book-to-market ratio represents earnings yield.

Israel et al. (2020) comment on the poor performance of value strategies, especially following the Global Financial Crisis. While they acknowledge that the performance of value strategies has significantly diminished, they find little to no merit for the reasons often given that value strategies would not work. They also argue that value-metrics still provide information about the expected performance of the stock, and that the value-metrics often have embedded information about the earnings expectations of a stock.

Maloney and Moskowitz (2021) investigate why value strategies have underperformed growth since the Global Financial Crisis. They do not find evidence indicating that value strategies have performed poorly because of the macroeconomic environment, or due to negative interest rate environment. They find weak links between long- and short-term interest rates for some value strategies. They conclude that the value strategy returns have diminished because of change in investor risk preference; value strategies often carry substantial drawdown risks, which are contemporarily valued differently than historically.

Arnott et al. (2021) have a different view on the underperformance or “death” of value strategies. They provide reasons why the anomaly would have ceased to exist: a) it never existed in the first place but was a result of data mining and overfitting, b) investor crowding has caused low or negative returns, and c) the factor may have been rendered useless due to structural changes in the market.  Given the long history of value strategies and wide research coverage, the data mining story seems unlikely. They argue that investor crowding would have led to valuation multiples to expand following value investor crowding, however, the opposite has happened, as value has become cheaper relative to growth. They, however, give some merit to the third option, as post-global financial crisis period has seen new large technological firms dominate the exchanges, while these stocks are also primarily growth stocks. However, they do not see this as a permanent change in the status of value and growth stocks. Instead, they argue that the strongest impact has been from the valuation of intangible assets in balance sheets of firms. When firms invest in R&D or intangible assets this is reflected immediately as a reduction of book-value of the firm. This has led to the diminishing of the value effect as firms have invested more in intangible assets after the GFC than they have historically. When accounting for investments in intangible assets, they find that the results are more robust, though the underperformance is still significant. Arnott et al. (2021) main conclusion is that while value strategies have been mostly unprofitable since 2007, the underperformance is not permanent and following the mean-reverting nature of book-to-market, they expect that the value effect will improve in performance.

Considering earlier literature, it can be concluded that a significant value premium has existed. However, it is possible that the value premium can no longer be found, but it is unknown if the absence of value premium is permanent or not. While the consensus is that it would be hard to exploit any value and growth stock by themselves, it would still be possible to extract information contained within the value factor and apply it together with other investment strategies.

## 3.3 Quality and profitability

Quality investing has no single quantifiable measure. Most common descriptions for quality are the Grantham quality, Graham's quality, Greenblatt's Magic Formula, Sloan's accruals, Piotroski's F-Score and Novy-Marx's gross profitability.

Jeremy Grantham's quality measure is "high return, stable return and low debt" GMO, 2004. Grantham rates companies as quality firms based on criteria of low leverage, high profitability, and low earnings volatility. While any direct quantifiability is hard to observe, and firms can only be ranked as being quality or not, Grantham's quality measure has been widely adopted to be used in various indices and as an overall guideline for measuring quality.

Benjamin Graham (2006) had five criteria for quality: adequate enterprise size, current ratio of two, net current assets that exceed long term debt, ten consecutive years of positive earnings, dividend record of uninterrupted payments for at least twenty years and EPS growth of at least one-third over the last ten years. Based on this, Novy-Marx (2015, p. 4) created a Graham G-Score of 1 to 5 based on the five quality-based criteria:

"This composite of Graham's five quality criteria gets one point if a firm's current ratio exceeds two, one point if net current assets exceed long term debt, one point if it has a ten year history of positive earnings, one point if it has a ten year history of returning cash to shareholders, and one point if its earnings-per-share are at least a third higher than they were 10 years ago"

Joel Greenblatt's Magic Formula is another well-known investment strategy. In his book "The Little Book that Beats the Market" (2006) he claims that the magic formula has beaten the S&P 500 96% of the time and has averaged an annual return of 30.8%. It is a combination of value and quality investing, as it is mainly based on two metrics: low relative costs and high returns on capital. Explicitly, the metrics are return on invested capital and earnings before interest and tax to enterprise value ratio (EBIT-to-EV). Stocks are ranked based on these two metrics and the ranks are then combined: stocks achieving the highest combined ranks will be selected. The Magic Formula excludes utilities and financial firms and consists of long-only positions. Davydov et al. (2016) find that the Magic Formula can outperform the market in the Finnish stock market.

Sloan's Accruals are based on the non-cash-based earnings and their ratio to total assets. Researched by Sloan in 1996, it is a widely known measure of quality. The accruals are accounting adjustments that reconcile the income statement values to those of operating cash flows. Sloan argues that stock prices do not reflect the non-cash-based earnings of the firm fully, which leads to mispricing. Instead, investors tend to focus on earnings, without fully reflecting the information contained in accruals and actual cash flows in asset prices until they begin to affect the current cash flows.

Haugen and Baker (1996) find that a firm's profitability, measured with return-on-equity and capital turnover, among others, is positively related to average returns. The results are robust when controlling for book-to-market. Similar findings are made by Cohen et al. (2002), who find that news about future cashflows of a firm are positively correlated with the return of the stock. Portfolios that have been formed based on news about cashflows have a beta close to zero, and significant alphas of 0.73-0.76% p.a. depending on the benchmark. Similar to Haugen and Baker they measure profitability with ROE.

Pastor and Veronesi (2003) find a relation between the uncertainty of profitability and book-to-market values. Book-to-market decreases with uncertainty about average profitability, with the decrease being larger for firms that pay no dividends. The uncertainty is mostly caused by short history as new firms do not have a long record of profitability. The implication is that new firms have generally lower book-to-market ratios, which then begin to increase as the firm matures.

Piotroski's (2000) F-score is another measure of quality that is based on the accounting values of firms. Piotroski's F-score is fundamentally a combination of previously mentioned strategies, and it uses binary measures to rank stocks. It includes nine different variables, and scores firms from zero to nine. The variables are positive net income, positive return on assets, positive operating cash flow in the current year, cash flow from operations being greater than net income, decreasing ratio of long-term debt, compared to the previous year, increasing current ratio, lack of stock dilution, increasing gross margin and increasing asset turnover ratio. The stocks are again ranked based on these binary variables, and firms with highest scores are selected.

Novy-Marx's (2013) gross profitability is another measure of quality. Noxy-Marx argues that profitability factors become more polluted the lower they are in the income statement and argues that the best proxy for profitability is gross profits-to-assets, effectively total revenues less the cost of goods sold scaled to total assets of the firm. Firms are then ranked by their gross profitability, and firms with high gross profitability are selected for a long portfolio, and firms with low gross profitability to the short portfolio, as with previous long-short portfolios. Novy-Marx finds that high gross-profitability stocks have a similar average return as value stocks (measured with book-to-market ratio), even though the strategy is implicitly based on growth. As Fama and French had been previously studying profitability along with investments (Fama & French, 2006a), Fama and French (2015) add operating profitability as one of the explanatory factors in their five-factor model. The main differences between Novy-Marx's quality and Fama-French's operating profitability are that operating profitability also includes income statements items of selling, general and administrative expenses as well as interest expenses, and Novy-Marx's quality also uses total assets to scale the quality measure, while operating profitability uses the book value of equity.

Ball et al. (2015) find that net income to total assets has similar results as Novy-Marx's gross profitability. Novy-Marx did not find this relation as they used the measure of net income to the book value of equity. Ball et al. (2016) find that both Sloan's accruals (1996) and Novy-Marx's (2013) gross-profitability have predictive power, with firms with low accruals outperforming ones with high accruals, and high profitability firms outperforming low profitability firms. They also augment Novy-Marx's gross-profitability with Sloan's accruals to develop a cash-based operating profitability measure, which outperforms both quality and accruals.

Asness et al. (2019, p. 35) define quality as a "*characteristic that investors should be willing to pay a higher price from*". They extend the previous profitability-based quality models by measuring quality with different types of profitability as well as measuring the growth rate of profitability. The profitability is the average of standardized ranks of gross profitability (GPOA), return-on-equity (ROE), return-on-assets (ROA), cash flow over assets (CFOA), gross margin (GMAR) and fraction of earnings composed of cash (equal to earnings minus accruals, ACC). They also include a definition of "safety", which is derived from return characteristics and fundamentals: low market beta, low volatility of profitability, low leverage, and low credit risk. They construct the quality-signal by taking the average rank of the three quality definitions. They find that quality stocks are not able to explain the stock prices, implicating that quality stocks are able to generate abnormal returns as well as improved risk-adjusted returns. In the U.S. sample, the long-short quintile portfolio is able to generate a monthly excess return of 0.42%, and 0.52% globally. Moreover, the returns cannot be explained by HML, SMB and UMD factors, with the four-factor model generating an alpha of 1.05% in the U.S. and 0.99% globally.

Hou et al. (2015) find that firms with high profitability or quality are able to generate abnormal returns. They study a wide range of profitability and quality measures among other anomalies and find that one half of the studied anomalies are unable to generate abnormal returns. They find that most anomaly returns can be explained by the investment and profitability factors. Most of the long-short portfolios sorted on profitability (e.g., ROE, F-score, gross profitability) benefit from improved Sharpe ratios.

Bouchad et al. (2018) find that the profitability anomaly is caused by "sticky analysts". The main three findings are based around the analyst expectations of the future profitability: analysts are too pessimistic of the future profits for firms with recent high profits, the profitability anomaly is stronger for firms that are followed by stickier analysts, and the profitability anomaly is stronger for firms with more persistent profits, i.e., have high past profitability in the long-term. They argue that the profitability anomaly is related to earnings momentum, as analysts and investors are slow to adopt new information. As the profitability of firms increase, the information is not adopted at the time but results in a drift towards the new level, as investors rely on earlier announcements.

Bouchaud et al. (2016) provide evidence for the behavioral view behind the cause of the quality anomaly. The story is similar to that of value and momentum anomalies: analysts systematically underestimate the future returns of high-quality firms while simultaneously overestimating the prospects of low-quality firms. They argue that the cause of mispricing may lie in the fact that analysts focus too much on other indicators, including momentum and book-to-market, and do not use other information available in the balance sheets. The behavioral view behind quality anomaly is also supported by the fact that the skew in quality returns is positive instead of negative, i.e., there is no similar risk of crashing as with other anomalies.

Quality and profitability are closely related and are usually considered to be synonymous. The main difference between various quality strategies is often only the numerator and denominator of the equation, where numerator is an income item from the income statement, and denominator is a balance sheet item. The views also differ slightly of what these items should represent: Novy-Marx (2013) argues that the item should be taken from as high as possible from the income statement to prevent any noise in the inputs, and the gross profitability should measure the profitability of assets. This is different from the view of e.g., Ball et al. (2015), who find that even the lowest item in the income statement has predictive power, while they also argue that an even better forecast would base the profitability in cash flow items instead of pure income statement items. The view of Fama and French (2015) differs slightly from that of Novy-Marx as they use the book value of equity in the equation, as in their view the explanatory factor is the profitability of equity. For this thesis, the quality strategy considered will be based on Novy-Marx's gross profitability.

## 3.4 Combining strategies

As different factors can be combined with different methods, the main methods considered are the integrating method, mixing method and average rank method. In the integrating method, the portfolio is constructed by selecting stocks which exhibit the chosen signals simultaneously, e.g., a stock that has high momentum and high value. In the mixing method, two portfolios are formed independently based on their exposure to the factors separately, e.g., a momentum portfolio and a value portfolio are formed. These two portfolios are then "mixed" together by assigning weights to each portfolio. In the average rank method, the stocks are ranked for both factors individually, and the average of these ranks is taken as the signal used in portfolio construction, e.g., an average rank portfolio can consist of stocks with extreme exposure to momentum and value, or a reasonable exposure to either factor.

Asness (1997) finds that while value and high momentum stocks generate higher average returns than growth and low momentum stocks, the spread between growth and value stocks combined with high momentum is not significant, with the winner portfolio return remaining largely the same for value and growth portfolios. For loser portfolios, the return is increasing with value. As the strategies are negatively correlated, high momentum portfolios have a bias towards growth stocks, and value portfolios have a bias towards low momentum stocks.

Asness et al. (2013) find that combining momentum and value by mixing the portfolios with 50/50 weights improves the return and Sharpe ratios of stock portfolios in main international markets. The improvement in return is modest, e.g., for continental Europe the individual returns of momentum and value of 5.3% and 12.1% are improved to a combined compounded annual return of 13.3%, but the individual Sharpe ratios are improved from 0.52 and 0.98 to a combined Sharpe ratio of 1.60. They attribute the improvement to the negative correlation of the two strategies, which reduces the standard deviation of the combination portfolio, while not having an impact on the return of the portfolio. In addition to stock selection, they find a similar improvement for other asset classes as well.

Asness, Frazzini et al. (2015) argue that profitability strategies should work well with value strategies, by removing the variation arising from low-quality value stocks. The Graham-Dodd (1934) original definition of value is also more in line with a combination of different value and profitability signals rather than a single signal. They also find that simple mixing portfolios of momentum, value and profitability have improved Sharpe ratios compared to any single signal portfolio. They attribute the increase in Sharpe ratio to the negative correlations between the three strategies, as momentum and profitability are closer to growth strategies than value strategies.

Bird and Whitaker (2004) combine momentum and value strategies in Germany, France, Netherlands, Spain, Switzerland and the United Kingdom between January 1990 and June 2002. They find that value strategy returns can be significantly improved by combining the book-to-market strategy with price momentum. The results are improved with both mixing and integrating techniques, and with holding periods ranging from 6 to 12 months. They find that when accounting for dispersion, or disagreement between analysts about the future earnings prospects of the company, the results can be improved even further by focusing on stocks with high dispersion. The results also indicate a small bias towards small capitalisation stocks, as the winner and value stocks have an average size decile rank of 3.56, and loser growth stocks have an average size decile rank of 5.67.

Tikkanen and Äijö (2018) use F-Score to screen European stocks included in value strategies to improve performance. They use measures of book-to-market, earnings-to-market, dividends-to-market, earnings before interest and taxes (along with depreciation and amortisation) to enterprise value, as well as Novy-Marx's gross-profitability. They find that performance is increased for all measures when screened with F-Score, though significance in alpha spreads between screening and no screening can only be found at 10% level for the dividend-to-market ratio. However, low F-score portfolios have significantly lower returns than high F-score returns, at 1% significance in alpha spread for all strategies expect for Novy-Marx's gross profitability. Tikkanen and Äijö hypothesize that the F-Score does not improve the gross profitability returns as gross-profitability itself is a quality-like measure, like the F-Score.

Fisher et al. (2016) find that value and momentum strategies perform better when the two factors are combined into one. The compound return and the risk-adjusted performance is improved for the multifactor portfolios, which are made following mixing and average rank methods. Another benefit of the multifactor portfolios is that the transaction costs are lower than for the single-factor portfolio, which increases the post-transaction cost performance of the portfolios.

Grobys and Huhta-Halkola (2019) compare the performance of integrating, mixing and average rank methods with momentum and value portfolios. They find that combining the two strategies improve both returns as well as the risk-adjusted returns. They find the average rank method to be superior in the Nordic market, though they note that the Sharpe ratio of the long-only average rank portfolio would be virtually the same as a simple long-only momentum portfolio, but the benefit would be realized through lower transaction costs as pointed by Fisher et al. (2016).

Fitzgibbons et al. (2017) compare two different methods of combining value and momentum: mixing, where a momentum portfolio is combined with a value portfolio with 50/50 weights, and integrating, where the selected stocks have both value and momentum signals. They find that both methods increase both raw returns and risk-adjusted returns, with integrating achieving better results. The main difference between the two methods is that integrating portfolios will have stocks with positive exposure to both signals, whereas the mixing portfolio has stocks with similar exposure to either one of the two signals. The integrating portfolio also requires less trading, improving trading efficiency and decreasing transaction costs, however, turnover savings are small compared to the improvement in return metrics such as information ratio, between the integrating and mixing portfolios. Though the integrating portfolio has better results on average, Fitzgibbons et al. find that the mixing portfolio can still outperform the integrating portfolio at times, notably at times when the underlying momentum and value stocks are performing poorly.

As the integrating portfolio has exposure to both signals in all stocks, the combined exposure for a single stock is always positive, whereas the mixing portfolio has exposure to both signals separately, and one stock may not necessarily have positive exposure to both signals. This implies that in the mixing portfolio where two strategies have negative correlation of returns, when the other signal is performing poorly, the other may compensate for it. As for the integrating portfolio, there is no such offset as all stocks will always have exposure to the poorly performing signal.

Clarke et al. (2016) compare the performance of integrating and mixing methods with momentum, value, size and low beta portfolios using 1000 common stocks in the U.S. equity market from 1968 to 2015. They find that integrating methods are more efficient in capturing the potential gain than individual factor portfolios that are mixed. They find that mixing sub portfolios can improve the Sharpe ratio by reducing the volatility of the composite portfolio, however, the average return is not improved when compared to the single factor portfolios. When integrating the stocks, the return is improved to 10.26% when compared to single factor best of 8.66%, and Sharpe ratio is improved to 0.672 from 0.512.

Bender and Wang (2016) also compare mixing and integrating portfolio construction methods with momentum, value, low volatility and quality portfolios from January 1993 to March 2015. The findings are similar to those of Clarke et al. (2016), whereby they find that mixing portfolios benefit mainly from improved risk-adjusted return, and integrating portfolios also benefit from improved raw returns. They only consider long-only portfolios with ranking multipliers resulting in overweighing the high-exposure stocks, and underweighting the low-exposure stocks, in a global stock universe, and the risk-adjusted return of the mixing portfolio fails to surpass the risk-adjusted return of the low-volatility portfolio. The integrating method is found to be superior to single-factor stocks and the mixing method.

Commenting primarily on the results of Bender and Wang (2016), Amenc et al. (2018) argue that the integrating method is not the superior method of constructing multifactor portfolios, as they argue that the returns of the integrating method are driven by the belief that there is a specific deterministic link between the factor exposures and returns. According to Amenc et al. the integrating method is too “fine-grain”, and the results are not likely to be robust, as using unstable stock-level information provides results that are likely to be biased by data-snooping and differences in risk.

Ghayur et al. (2018) compare integrating and mixing portfolio construction methods with momentum, value and quality portfolios from January 1979 to June 2016 in Russell 1000 stock universe as well as a global stock universe. As opposed to Bender and Wang (2016) they do not use size-based ranking multipliers but instead seek to have portfolios that have similar levels of exposure to individual factors. They find that mixing methods are able to improve the information ratios for low to moderate levels of factor exposure, however, high levels of factor exposure do not produce similar results, as the interaction effects are exceeded by high concentrations to individual stocks and stock-specific risks. With the integrating method high levels of factor exposure also generally improve the information ratios, with a few exceptions.

Chow et al. (2018) compare integrating and mixing portfolio construction methods with momentum, value, profitability, investment and low-beta portfolios in the U.S. market and developed markets. They find that integrating method is superior to mixing method when transaction costs are not accounted for, and when the set of stocks is limited enough. When accounting for transaction costs, the integrating method is still superior in terms of excess return and tracking error, however, integrating portfolios are beaten by the mixing portfolios in terms of information ratio. Chow et al. (2018) opine that mixing methods are generally superior as they are low-cost, and simpler to construct, whereas integrating portfolios would require investors that are able to tolerate significant volatility and tracking error related to the less diverse portfolios, and to be properly utilized would need a practitioner that would be able to take advantage of lower trading costs in the market.

Leippold and Rueegg (2018) analyze 26 possible combinations of momentum, value, robustness (or profitability), investment and low volatility with different portfolio construction methods: portfolios based on ranking terciles, the method presented by Bender and Wang (2016), and target-tracking error method proposed by Fitzgibbons et al. (2016), which targets to have an annual tracking error of 2%. Contrary to previous literature they do not find the integrating method to be superior when compared to the mixing method, but instead they find that the returns are not significantly different from each other, and risk-adjusted returns are not improved.

Silvasti et al. (2021) compare integrating and mixing portfolio construction methods with momentum, value and low-beta signals in the Nordic stock markets using long-only portfolios. They find that integrating methods are superior in both excess returns and risk-adjusted returns when compared to the mixing portfolios. The mixing portfolios fare better with drawdowns when compared to integrating portfolios. They also find that the improvement is not driven by small stocks as the results are based on the large-cap universe consisting of 30% of the largest stocks in the Nordics.

Israel et al. (2020) suggest that while value strategies have recently been less profitable, they still provide valuable information about the future earnings expectations of a stock.

They also state that while value as a standalone investment may not be as profitable as before, the negative correlations with both momentum and quality still offer powerful diversification benefits.

Israel et al. (2017) find that the integrating approach can also be used with long-short portfolios. By measuring the return of individual stocks that are either in the mixing portfolio, the integrating portfolio, or both portfolios, they find that stocks that are present in both portfolios have higher alphas, with integrated coming second. Long-short portfolios also have higher alphas than long-only portfolios.

The past literature is almost unanimous on the fact that combining multiple factors can generate superior results, but the literature is not so unanimous on what is the best way to combine the factors or signals together. Generally, integrating methods are shown to have better results, but one of the main arguments against it regardless of the results has been the high turnover, resulting in high transaction costs, and low liquidity from a limited pool of stocks, also resulting in high transaction costs as well as low diversification, and potentially high volatility and tracking errors. Most of the literature is focused on integrating and mixing methods, with little emphasis put on the average rank methodology, which was shown by Fisher et al. (2016) to be superior to the mixing method (as well as a method that closely resembles the integrating method) in the U.S. stock market, and by Grobys and Huhta-Halkola (2019) to be superior to both mixing and integrating method in the Nordic stock market. The average rank portfolio would potentially benefit from improved transaction costs when compared to the integrating portfolio, putting it on an equal footing with the mixing portfolio.

# 4 Asset pricing models

This chapter will focus on asset pricing models, with Capital Asset Pricing Model (CAPM) serving as the foundation, and then extended by Fama-French three, five and six factor models (1992, 2015, 2018). Another noteworthy model considered is the Carhart four factor model (1997) which is essentially the Fama-French three factor model supplemented with the momentum factor, which is also found in the Fama-French six factor model. The foundation of the asset pricing models is in the work of Markowitz (1952) which will be introduced briefly.

## 4.1 Modern portfolio theory

The modern portfolio theory is based on the work of Markowitz (1952), with the basic concept being that investors should seek to maximize the return of their portfolio with respect to the level of risk they are willing to accept, under the basic assumption that investors should consider expected return a desirable thing and the variance of return an undesirable thing. As one of the main assumptions is that investors are risk-averse by default, when given two portfolios with different levels of risk, investors will require a higher level of expected return for the portfolio with higher risk as a compensation for bearing the higher level of risk. According to Markowitz (1952) investors have a set of probability beliefs regarding the expected return from each investment as well as expected covariance for each pair of investments. Investor can then choose between different combinations of risk and return. Of these combinations the one with lowest variance for a given level of return, or highest return for a given level of variance determines the optimal portfolio. A main concept of the modern portfolio theory is that diversifying investments will lead to a lower level of risk, without lowering the level of returns. Instead of focusing on individual asset level risk and return relationships, portfolios of assets should be evaluated based on the interplay among all assets, as the resulting level of risk for the entire portfolio would be lower due to diversification (Markowitz 1952).

Important to the modern portfolio is the portfolio construction problem, which can be generalized to a case of many risky securities and a risk-free asset. The combinations of risky assets will produce the Minimum-Variance frontier, which represents the lowest attainable variance for a given portfolio expected return. The portfolios above the global minimum-variance portfolio (offering the lowest risk) are part of the "efficient frontier", i.e., portfolios that offer the best return for a given level of variance, while the portfolios below the minimum-variance portfolio are inefficient as other portfolios offer better return for the given risk level. Investor can then move along the efficient frontier to determine the expected return for their risk preference level. (Markowitz, 1952; Bodie et al., 2014).

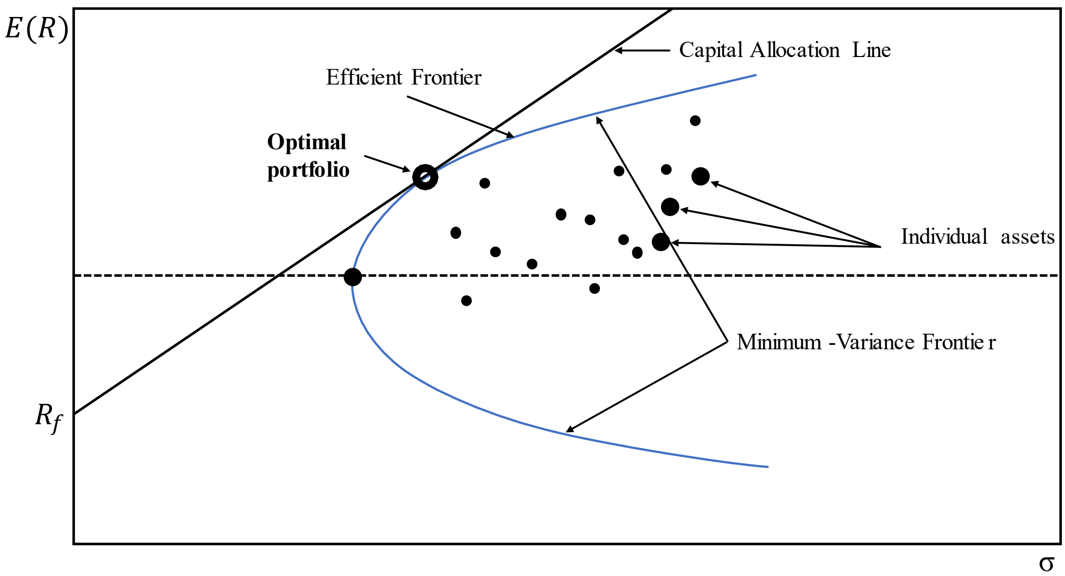


**Figure 2.** Optimal portfolio with a risk-free asset (Adapted from Bodie et al., 2014)

The optimal portfolio is determined by the steepest Capital Allocation Line, which represents the return from a combination of a risk-free asset (i.e., risk-free rate) and the portfolio of risky assets. This is theoretically the best possible way for portfolio construction, as it generates the highest possible return for a unit of risk (i.e., it has the highest Sharpe ratio).

## 4.2 Capital asset pricing model (CAPM)

CAPM is based on market equilibrium theory of asset prices under conditions of risk. The theory was derived by Sharpe (1964), Lintner (1965) and Mossin (1966) who derived the model independently of each other. Capital Asset Pricing Model itself is derived from the work of Markowitz (1952). CAPM is the formulation for the required rate of return of an asset based on its systematic risk. The capital asset pricing model contains a single factor, denoted beta, which is used to capture the asset's exposure to systematic, undiversifiable risk. The formula of CAPM is most often denoted as:

$$E(R_i) = R_f + \beta_i\left[E(R_m) - R_f\right] \quad (1)$$

Where $E(R_i)$ is the excess return of the asset or portfolio $i$

$R_f$ is the risk-free rate

$\beta_i$ is the exposure of the asset or portfolio $i$ to systematic risk, measured by the beta coefficient

$E(R_m)$ is the expected return on market portfolio.

The beta coefficient itself is derived from the covariance of the asset or portfolio $i$ to the market portfolio $m$:

$$\frac{cov(R_i, R_m)}{\sigma_m^2} \quad (2)$$

Alternatively, the asset's systematic risk is the slope parameter of the return of the asset regressed on the market return. As the beta measures the systematic risk, the higher the exposure of asset $i$ to the systematic risk, the higher return is required. Simply put, high beta stocks require high returns whereas low beta stocks require low returns. (Sharpe 1964.)

## 4.3 Three-factor model

While CAPM earned its place in portfolio theory, it has been evidenced that the beta coefficient fails to capture the risk premium entirely.

Banz (1981) finds that small stocks, measured by market capitalization, generate higher average returns than large stocks, even when adjusted for beta. Rosenberg et al. (1985) find that NYSE stocks with high book-to-market ratios generate higher average returns than those with low book-to-market ratios, also known as value vs. growth. Chan et al. (1991) find similar evidence in Japan.

While initially these findings were theorized to result from market inefficiency, where all information was not effectively included in the current asset prices, Fama and French (1993) argue that the size and value effects are caused by additional risk factors. They argue that the size and book-to-market ratios act as proxies to undiversifiable risk not captured by the CAPM. Building on this, they construct their famous three factor model, which has two additional factors in addition to beta: the small-minus-big (SMB, the size factor) and high-minus-low (HML, the value factor) factors. The two additional factors are constructed by ranking stocks by their market capitalization and book-to-market ratio independently. The size portfolio is then constructed by taking long a position in small firm portfolio and short position in the large firm portfolio (i.e., return of "small" portfolio minus return of "big" portfolio). The book-to-market or value portfolio is constructed in a similar manner, with long position in high book-to-market firm portfolio, and short position in the portfolio of firms with low book-to-market ratios. The three-factor model is based on time-series regression is as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left[(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + \epsilon_{it} \qquad (3)$$

Where $\alpha$ is the intersect of the regression

$R_m - R_f$ is the excess return on the market portfolio

$SMB_t$ is the return on the zero-cost size portfolio

$HML_t$ is the return on the zero-cost value portfolio

$\beta_i, s_i, h_i$ are the coefficients or loadings for market, size and value factors, respectively, for the asset or portfolio

$\epsilon_{it}$ is the zero-mean residual of the regression.

The beta is related to that of CAPM formula, whereas the additional two factors attempt to measure the additional risk that is carried by size and value stocks and priced by the market. The factors proxy for the additional distress risk arising from the value factor, and market covariation not captured by $\beta$ for the size factor (Fama and French, 1995). When the factor loadings capture all the variation in the expected returns, the intercept $a_i$ is zero for all assets.

Using the three-factor model to explain market anomalies, Fama and French (1996) find that other value signals such as earnings-to-price ratio (E/P) and cash-flow-to-price (CF/P) have a high factor loading on the value factor, explaining the higher returns generated by strategies implementing these ratios as the value signal. They also find that the three-factor model can explain the abnormal returns of contrarian strategy, with contrarian stocks often having high loadings on both size and value factors. In line with their previous findings, they find that long-term losers often behave like small, distressed firms. However, they find that the three-factor model is not explain the abnormal returns of momentum strategies.

## 4.4 Carhart four-factor model

The Carhart four-factor model was developed by Mark Carhart in 1995 for his PhD dissertation, and was used by Carhart in 1997 to study the performance of mutual funds. Carhart finds that mutual funds do not generate abnormal excess returns when accounting for the additional risk captured by the Fama-French three factor model with an additional risk factor based on one-year momentum. The expected return based on the four-factor model is as follows:

$$E(R_i) - R_f = \beta_i\left[E(R_m) - R_f\right] + s_i E(SMB) + h_i E(HML) + p_i E(PR1YR) \qquad (4)$$

Where $E(PR1YR)$ is the expected return on the zero-cost one-year momentum portfolio (also known as up-minus-down, UMD)

$p_i$ is the loading on the momentum factor

As the three-factor model was unable to explain the abnormal returns generated by momentum strategies, the Carhart four-factor model specifically employs an additional factor to capture the risk-adjusted returns resulting from momentum. Carhart (1997) finds that the four-factor model has more explanatory power than the CAPM or three-factor model.

## 4.5 Five-factor model

Novy-Marx (2013) finds evidence of firms with high gross profitability generating higher average returns than ones with low gross profitability. Aharoni et al. (2013) find that companies with less investments (i.e., are conservative) generate higher average returns than ones with high invstments (i.e., are aggressive). While Fama and French (2006a) had previously studied profitability and investments, considering these findings, Fama and French (2015) proposed a new, five-factor model. The model is essentially the three-factor model augmented with two additional factors: the profitability (robust-minus-weak, RMW) and investment (conservative-minus-aggressive, CMA) factors. While the Carhart four-factor model has more explanatory power introduced with the inclusion of the momentum factor, Fama and French (2015) opted to use alternative factors due to the factors being more consistent with the theory of market efficiency and rational pricing, whereas they argue that momentum could be treated as an anomaly left unexplained by different variations of the three- and five-factor models (Fama and French, 2018). As with the three-factor model factors, the additional factors are constructed using accounting information of firms: profitability is the operating profitability of the firm scaled to book value of equity, and investment is the growth rate of total assets between the previous fiscal year ($t-1$) and the one before ($t-2$). The assets are again ranked, and the factor returns are constructed with long-short portfolios, i.e., high profitability portfolio minus low profitability portfolio (RMW) and low investment portfolio minus high investment (CMA) portfolio. The five-factor model time-series regression equation is as follows:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \ & \beta_i\left[(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t \\ & + r_i RMW_t + c_i CMA_t + \epsilon_{it} \end{aligned} \tag{5}$$

Where $RMW_t$ is the return on the zero-cost profitability portfolio

$CMA_t$ is the return on the zero-cost investment portfolio

$r_i$, $c_i$ are the coefficients or loadings for profitability and investment factors, respectively, for the asset or portfolio

As with the three-factor portfolio, when the factor loadings capture all the variation in the expected returns, the intercept $a_i$ is zero for all assets. The return of a portfolio should therefore be explained by its exposure to the market, size, value, profitability and investment factors, which act as proxies to undiversifiable risk.

## 4.6 Six-factor model

As academia has been curious on the results of the five-factor model augmented with the momentum factor, Fama and French (2018) augmented their model with the momentum factor. Instead of being motivated by the rationality behind the momentum factor, they state that "*Our experience, however, is that readers are curious about how model performance changes when momentum factors are included".* According to Fama and French (2018) the momentum factor is not consistent with rational pricing and momentum can be considered an anomaly in the context of factor models. The regression equation for the six-factor model is as follows:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_i\left[(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t \\ + r_i RMW_t + c_i CMA_t + u_i UMD_t + \epsilon_{it} \end{aligned} \tag{6}$$

Where $UMD_t$ is the return on the zero-cost momentum portfolio

$u$ is the factor coefficient or loading on the momentum factor for the asset or portfolio

The UMD (up-minus-down) factor is constructed with a similar methodology as other Fama-French factors, with long positions in winners ("up") and short positions in losers ("down"). Fama and French (2018) find that momentum factors are important in explaining returns for portfolios formed on momentum, but do not bring any significant value to asset pricing models.

# 5 Data and methodology

## 5.1 Data

The sample consists of public companies from a sample of fifteen developed European markets. The markets included are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The sample countries are identical to that of Fama and French (2012) and Tikkanen and Äijö (2018).

**Table 1.** Descriptive statistics

Descriptive statistics for the sample

| | N | | | Average market cap, USD mil. |
|---|---|---|---|---|
| | Min | Average | Max | |
| Austria | 37 | 53 | 66 | 897 |
| Belgium | 55 | 86 | 108 | 1 789 |
| Denmark | 82 | 100 | 119 | 1 393 |
| Finland | 33 | 98 | 126 | 1 437 |
| France | 317 | 528 | 662 | 2 271 |
| Germany | 240 | 406 | 542 | 2 132 |
| Greece | 56 | 165 | 272 | 236 |
| Ireland | 27 | 33 | 39 | 1 082 |
| Italy | 104 | 176 | 260 | 1 755 |
| Netherlands | 74 | 111 | 149 | 3 221 |
| Norway | 46 | 126 | 175 | 992 |
| Portugal | 31 | 45 | 56 | 1 041 |
| Spain | 67 | 104 | 139 | 3 106 |
| Sweden | 23 | 175 | 469 | 1 468 |
| Switzerland | 119 | 158 | 183 | 4 174 |
| United Kingdom | 536 | 648 | 786 | 2 571 |

The return data is obtained from Thomson-Reuters Datastream database, along with accounting variables from Thomson-Reuters Worldscope database. The total return is measured using monthly total return indices for each of the sample firms, where the dividends are reinvested to the same stock. Monthly data for market capitalization with annual accounting data for book value of equity, total assets, net revenues, and cost of goods sold are used for calculating the book-to-market and gross profitability ratios. The data ranges from December 1991 to January 2019. Financial companies are excluded from the sample due to the different interpretation of their financial statements (see e.g., Fama and French, 1992; Piotroski, 2000; Asness et al. 2013). To control for possible illiquidity issues, the smallest 10% of companies are excluded from the sample (see e.g., Gray and Vogel 2012; Tikkanen and Äijö, 2018). All firms in the sample must have data available for calculating all the variables, otherwise they are excluded from the sample. All the stocks in the sample are also required to have the “Major Listing” flag. As issues with Datastream data have been previously identified, screenings following Ince and Porter (2006) are conducted on the data where extreme returns are removed. The delisting return of a stock is assumed to be zero.

As the portfolios formed are equally weighted, the STOXX Europe 600 equal weighted gross return index is used as the market portfolio. Following Tikkanen and Äijö (2018), the STOXX Europe 600 equal weighted net return index is used for the period before 2001, as the gross index is not available. This leads to underestimating the market return by the amount of withholding taxes paid on dividends over the period. Following Fama and French (2012) and Tikkanen and Äijö the 1-month U.S. T-bill rate is used as the risk-free rate and all returns are reported in U.S. dollars.

## 5.2 Portfolio and signal construction

For each month, the stocks are sorted into quintiles based on their signals (i.e., momentum, value, and quality). The portfolios are constructed using these signals with mixing, integrating and average ranking approaches, and rebalanced monthly, following previous literature (see e.g., Asness et al., 2013; Asness et al., 2014; Asness et al., 2015; Fisher et al., 2016; Grobys and Huhta-Halkola, 2019).

Following previous studies in value (see eg. Davydov et al., 2016; Walkshäusl 2017; Tikkanen and Äijö, 2018; Grobys and Huhta-Halkola, 2019) equally weighted portfolios are used in the empirical analysis.

### 5.2.1 Momentum signal

While the momentum signal can be constructed with different look-back and holding periods, the momentum signal in this thesis is constructed with previous 12-month cumulative raw returns, excluding the latest month's return. This is following Jegadeesh and Titman (1993), Fama and French (1996), Asness et al. (2013), Asness et al. (2015), and Grobys and Huhta-Halkola (2019). The latest month is skipped due to possible one-month return reversal caused by negative serial-correlation in monthly stock returns (Jegadeesh 1990). For the period t a firm must have return information from t-12 months, otherwise it is excluded from the sample.

### 5.2.2 Value signal

Book-to-market, or book value of equity divided by market value of equity is used as the value signal in this thesis. Book-to-market ratio is a commonly used measure of value (see e.g., Fama and French, 1992, 1993; Lakonishok et al., 1994; Fisher et al., (2016); Grobys and Huhta-Halkola, 2019). The book value of equity value is lagged by six months from the end of the calendar year, i.e., the book value of equity is updated annually at the end of June with the book value of equity from t-1. The market value of equity is updated monthly based on the current market capitalization, following Asness and Frazzini (2013). Firms with missing or negative book value of equity are excluded from the sample. While it is common to form the signals at the end of June based on either current market capitalization or six month lagged market capitalization (see e.g., Fama and French, 1992, 1993; Noxy-Marx, 2013) and the book value of equity from the end of the previous year with a holding period of 12 months, in this thesis the signals are constructed monthly as the momentum portfolios are also formed monthly.

### 5.2.3 Quality signal

While quality has several definitions with no single commonly used definition, in this thesis quality is defined with the measure of Novy-Marx's gross profitability. Quality is therefore calculated as total revenues less cost of goods sold, scaled to total assets of the firm. This is following the original definition by Novy-Marx (2013), with a similar factor used in the five-factor model by Fama and French (2015, 2017). Profitability in its various forms is a well-documented anomaly, and the purpose is to research the interaction of gross profitability, or quality, together with momentum and value stocks.

## 5.3 Risk-adjusted performance measures

Risk-adjusted performance is measured with Sharpe ratio and Sortino ratio. Sharpe ratio is a standard measure of portfolio performance. The Sharpe ratio is calculated by dividing the excess return of the portfolio with the standard deviation of the excess returns, which scales the return to the amount of risk, or volatility. Sharpe ratio is calculated as follows:

$$S_p = \frac{R_p - R_f}{\sigma_p} \tag{7}$$

Where $S_p$ is the Sharpe ratio of the portfolio

$R_p - R_f$ is the excess return of the portfolio

$\sigma_p$ is the standard deviation of the excess return of the portfolio

Following Tikkanen and Äijö (2018), the Israelsen (2005) modified Sharpe ratio will be used:

$$S_p = \frac{R_p - R_f}{\sigma_p^{\frac{ER}{|ER|}}} \tag{8}$$

Where $ER$ is equal to $R_p - R_f$

The difference to the original Sharpe ratio is that when the risk-premium is positive, the Sharpe remains the same, but in case of negative risk premiums, the standard deviation of excess return has an exponent corresponding to the expected return divided by the absolute value of the expected return. This will lead to more intuitive ranking, as higher Sharpe ratio will indicate higher risk-adjusted performance.

The significance of difference of two Sharpe ratios will be evaluated using the Ledoit-Wolf (2008) test and is based on circular block bootstrap method. Ledoit-Wolf test statistic is calculated with R package "PeerPerformance"[1] by Ardia and Boudt (2018).

Whereas the Sharpe ratio measures the overall risk-adjusted performance of the portfolio, it is also criticized for penalizing very high positive returns as they increase the standard deviation of the excess return (Goetzmann et al., 2007). Sortino ratio is utilized to measure the downside risk of the portfolio, as it considers only the deviation of returns below the minimum acceptable return (MAR). Following Tikkanen and Äijö (2018) the MAR is defined as the risk-free rate. The formula for the calculation of the Sortino ratio is as follows:

$$SR_p = \frac{R_p - MAR}{\sqrt{\frac{1}{n}\sum_{R_p<MAR}\left(R_p - MAR\right)^2}} \tag{9}$$

[1] https://CRAN.R-project.org/package=PeerPerformance

Where $SR_p$ is the Sortino ratio of the portfolio

$R_p - MAR$ is the return below the minimum acceptable return (effectively the excess return in this thesis)

$\sqrt{\frac{1}{n}\sum_{R_p<MAR}\left(R_p - MAR\right)^2}$ is the downside deviation of the return of the portfolio

The Fama-French (2015) five-factor model is used to measure abnormal returns in terms of alpha, and whether the excess return of the different portfolios can be explained with the five-factor model risk factors (market return, size, value, profitability, and investment). To avoid autocorrelation and heteroscedasticity, Newey and West (1987) standard errors with lags of four months are used in the regressions. The Fama-French factor returns are obtained from the data library of Kenneth French[2].

Following previous literature (see Leivo and Pätäri, 2011; Tikkanen and Äijö, 2018) the test statistics for differences in alphas will be calculated with an alpha spread test.

$$t = \frac{\alpha_i - \alpha_j}{\sqrt{SE^2_{\alpha_i} + SE^2_{\alpha_i}}} \tag{10}$$

Where $\alpha$ is the alpha of portfolio $i$ and $j$

$SE_\alpha$ is the standard error of the portfolios $i$ and $j$.

The degrees of freedom for the test statistic are based on the following calculation:

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$$v = \frac{\left(SE_{\alpha_i}^2 + SE_{\alpha_j}^2\right)^2}{\frac{SE_{\alpha_i}^4}{v_i} + \frac{SE_{\alpha_j}^4}{v_j}} \tag{11}$$

Where $v_i$ and $v_j$ are the degrees of freedom determined based on the number of time-series returns in samples $i$ and $j$, where $v = n - 1$

# 6 Results

The tables below present results for portfolios formed using different signals. Panels A present the portfolio return measures i.e., average excess returns, Fama-French (2015) five-factor alphas and betas along with risk-adjusted performance measures. Panels B present the characteristics of the portfolio in time-series averages for the momentum-signal (average raw return), value-signal (B/M), quality-signal (gross profitability) and size, and the average number of firms in the portfolio (n).

Following Fitzgibbons et al. (2017), there are two approaches to portfolio construction: the integrated approach where the styles are directly integrated into the main portfolio i.e., stocks which exhibit both signals simultaneously will be included in the portfolio, and the mixing approach where two style portfolios are formed independently, with the main portfolio consisting of the two portfolios with equal weights. Whereas Fitzgibbons et al. (2017) consider long-only portfolios, a long-short portfolio will be constructed with the high-signal being the long leg, and the low-signal being the short leg. Additionally, following Fisher et al. (2016) and Grobys and Huhta-Halkola (2019), the ranks of the three signals are combined and the average of the two or three ranks is used as a signal for portfolio formation as a third method.

Results are presented for each quintile, and the long-short portfolio consisting of the long top quintile and short bottom quintile. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

## 6.1 Single-signal portfolios

To determine if momentum, value and quality premiums can be observed in the sample, portfolios are first constructed using a single signal. First, the returns and portfolio characteristics are presented for the whole sample. The sample is then sorted based on size. Following Asness et al. (2013) and Tikkanen and Äijö (2018), firms are ranked based on their market capitalization in descending order. Large stocks are defined as those that account for 90% of the coverage of the sample for the given period, medium stocks are those that account cumulatively for the following 8%, while the remaining two percent are classified as small stocks.

### 6.1.1 Momentum returns

The table below presents results for momentum-sorted portfolios formed by ranking all stocks in the beginning of each calendar month by their cumulative 12-month raw returns, skipping the last month, with a holding period of one month. All stocks are equally weighted within a portfolio, and the portfolio is rebalanced monthly to maintain equal weights.

**Table 2.** Returns of momentum portfolios

Momentum portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the momentum portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the momentum signal. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratios are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.11 | 0.39 | 0.71** | 1.06*** | 1.64*** | 1.53*** |
| t | (0.23) | (1.10) | (2.26) | (3.49) | (4.84) | (5.18) |
| CAPM alpha (%) | -0.64*** | -0.20 | 0.18 | 0.56*** | 1.12*** | 1.75*** |
| t | (-3.36) | (-1.62) | (1.53) | (4.33) | (6.40) | (7.02) |
| Five factor alpha (%) | -0.32* | -0.24** | -0.02 | 0.32*** | 0.95*** | 1.27*** |
| t | (-1.66) | (-2.23) | (-0.17) | (3.07) | (6.01) | (4.43) |
| CAPM Beta | 1.10 | 0.89 | 0.78 | 0.73 | 0.77 | -0.33 |
| CAGR (%) | -1.45 | 3.15 | 7.52 | 12.18 | 19.84 | 18.60 |
| Std. (%) | 6.78 | 5.25 | 4.61 | 4.40 | 4.86 | 4.51 |
| Sharpe | 0.054 | 0.266 | 0.545 | 0.844 | 1.173 | 1.204 |
| Sortino | 0.079 | 0.378 | 0.796 | 1.310 | 1.933 | 1.836 |
| Worst monthly drawdown (%) | -29.31 | -28.78 | -26.48 | -23.35 | -21.65 | -27.24 |
| Maximum drawdown (%) | -77.25 | -65.62 | -59.85 | -54.91 | -51.30 | -47.01 |

| Panel B: Portfolio characteristics | | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
| 12-1 raw return (%) | -36.61 | -10.16 | 5.88 | 23.98 | 81.18 | 117.79 |
| B/M | 1.39 | 0.96 | 0.83 | 0.71 | 0.57 | -0.82 |
| Gross profitability | 0.36 | 0.39 | 0.41 | 0.43 | 0.45 | 0.09 |
| Size (USD mil.) | 734 | 2165 | 3106 | 3261 | 2218 | 1484 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The results provide positive evidence of correlation between past returns and excess returns, i.e., momentum effect. The portfolio consisting of past winners generates higher average returns compared to the past loser portfolio. The results are also improved as measured with risk-adjusted returns as the Sharpe and Sortino ratios improve with higher momentum. Overall, the performance of the high momentum portfolio is better than the low portfolio with virtually every metric. Though the performance is improved, there are periods where the low portfolio significantly outperforms the high portfolio. However, the worst monthly drawdown for the long-short portfolio is still improved compared to the long-only low portfolio, and only modestly worse than the long-only high portfolio, while the maximum drawdown is improved for the long-short portfolio compared to the long-only portfolios.

The results also indicate that the improved performance does not come at the cost of market risk, as the beta decreases almost monotonically with momentum, with the long-short portfolio having a negative beta of 0.33. Both CAPM and Fama-French five factor alphas also increase in a monotonical pattern, implying that the improved performance cannot be explained with increased market risk, or increased Fama-French risk-factors.

From the portfolio characteristics we can observe that high (low) momentum stocks are biased towards growth (value) stocks, implying a negative correlation between momentum and value. Momentum also seems to increase with higher market capitalization, implying that the momentum effect is not entirely driven by small firm effect.

### 6.1.2 Value returns

The table below presents results for portfolios sorted by book-to-market formed by ranking all stocks in the beginning of each calendar month by their book-to-market ratio at the end of the previous month, with a holding period of one month. All stocks are equally weighted within a portfolio, and the portfolio is rebalanced monthly to maintain equal weights.

**Table 3.** Returns of value portfolios

Value portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the value portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the value signal. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratios are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.69** | 0.69** | 0.68** | 0.74** | 1.10*** | 0.42* |
| t | (2.02) | (2.21) | (2.04) | (2.12) | (2.69) | (1.81) |
| CAPM alpha (%) | 0.13 | 0.15 | 0.12 | 0.16 | 0.46** | 0.33 |
| t | (0.93) | (1.50) | (0.97) | (1.24) | (2.54) | (1.51) |
| Five factor alpha (%) | 0.18 | 0.06 | -0.03 | 0.03 | 0.45*** | 0.27 |
| t | (1.44) | (0.74) | (-0.29) | (0.33) | (3.14) | (1.48) |
| CAPM Beta | 0.82 | 0.80 | 0.84 | 0.86 | 0.95 | 0.13 |
| CAGR (%) | 7.01 | 7.26 | 6.98 | 7.62 | 11.85 | 4.58 |
| Std. (%) | 4.93 | 4.69 | 4.92 | 5.04 | 5.77 | 2.96 |
| Sharpe | 0.492 | 0.523 | 0.490 | 0.515 | 0.661 | 0.481 |
| Sortino | 0.700 | 0.758 | 0.713 | 0.773 | 1.094 | 0.862 |
| Worst monthly drawdown (%) | -23.96 | -24.38 | -25.67 | -27.16 | -28.38 | -11.28 |
| Maximum drawdown (%) | -62.89 | -58.68 | -61.54 | -61.94 | -62.18 | -49.50 |

Panel B: Portfolio characteristics

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| 12–1 raw return (%) | 37.38 | 17.68 | 11.17 | 4.76 | -6.49 | -43.87 |
| B/M | 0.17 | 0.37 | 0.59 | 0.92 | 2.42 | 2.25 |
| Gross profitability | 0.60 | 0.46 | 0.38 | 0.33 | 0.27 | -0.33 |
| Size (USD mil.) | 3781 | 3406 | 2197 | 1482 | 621 | -3160 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The results provide positive evidence of correlation between the book-to-market ratio and excess returns, i.e., value effect. However, the excess return for the long-short portfolio is statistically significant only at 10% level. It can be noted that the lowest quintile does not have the lowest returns, but instead the excess returns are lowest for the third quintile, i.e., with firms that have a B/M ratio close to the median of the sample. The highest quintile still provides a monthly excess average return of 1.10%, significant at 1% level, whereas the other portfolios have lower excess returns.

A similar pattern with CAPM alphas can be observed as with excess returns, with the third quintile portfolio generating the lowest alpha of 0.12% and is not statistically significant. Only the highest quintile CAPM alpha is statistically significant at 5% level. The long-short portfolio does not generate a statistically significant CAPM alpha either. The results are similar with the Fama-French five factor alpha, where only the highest quintile generates a statistically significant alpha at 1% level. While the Fama-French alpha is not significant for the long-short portfolio, it is not surprising as the B/M ratio is already included as a factor in the Fama-French five factor regressions.

There are modest improvements with Sharpe and Sortino ratios between the lowest and highest quintile, indicating that the improved excess return is not entirely due to increased risk. The worst monthly drawdown is slightly worse for the highest quintile than it is for the lowest quintile, however, the maximum drawdown is improved slightly. Both the worst monthly drawdown and maximum drawdown are improved for the long-short portfolio, as the return pattern is quite similar for the extreme quintiles, dampening the overall impact of the extreme quintiles, which can also be observed in terms of lower standard deviation.

From the portfolio characteristics we can observe a similar bias as with momentum portfolios; high (low) B/M firms are biased towards low (high) momentum. While a relation between momentum and gross profitability could not be readily observed, a slight negative correlation between B/M and gross profitability can be observed. On the contrary to momentum portfolios, a negative relation between market capitalization and B/M values can be observed, with high B/M firms also having the lowest market capitalization in the sample, which implies that the value effect may be partially driven by the small firm size effect.

### 6.1.3 Quality returns

The table below presents results for quality-sorted portfolios formed by ranking all stocks in the beginning of each calendar month by their gross profitability at the end of the previous calendar year. As with book value of equity, at least six months lag is required for the gross profit and total assets that are derived from the balance sheet and income statement for the firm to ensure that the information is available to all investors. Therefore, the quality signal is calculated annually from period of July to June of the following year. All the stocks in the portfolio are equally weighted and should the composition of the portfolio change during the year due to e.g., stock being delisted the quality signals are recalculated and the portfolio is rebalanced to include quality stocks and equal weights.

**Table 4.** Returns of quality portfolios

Quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the quality signal. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratios are annualized. For portfolio characteristics the differential of high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.55 | 0.73** | 0.81** | 0.85*** | 0.97*** | 0.42*** |
| t | (1.51) | (2.11) | (2.34) | (2.59) | (2.87) | (3.59) |
| CAPM alpha (%) | -0.04 | 0.14 | 0.21* | 0.29*** | 0.42*** | 0.46*** |
| t | (-0.30) | (1.12) | (1.90) | (2.66) | (3.71) | (4.01) |
| Five factor alpha (%) | 0.02 | 0.09 | 0.14 | 0.14* | 0.29*** | 0.28*** |
| t | (0.16) | (0.85) | (1.62) | (1.80) | (3.64) | (2.66) |
| CAPM Beta | 0.87 | 0.86 | 0.88 | 0.84 | 0.81 | -0.06 |
| CAGR (%) | 5.03 | 7.42 | 8.48 | 9.20 | 10.79 | 4.96 |
| Std. (%) | 5.31 | 5.08 | 5.11 | 4.87 | 4.77 | 1.87 |
| Sharpe | 0.364 | 0.503 | 0.557 | 0.616 | 0.712 | 0.779 |
| Sortino | 0.533 | 0.742 | 0.828 | 0.925 | 1.101 | 1.283 |
| Worst monthly drawdown (%) | -27.06 | -26.32 | -26.61 | -24.89 | -24.67 | -7.77 |
| Maximum drawdown (%) | -62.16 | -60.88 | -60.84 | -59.68 | -60.58 | -17.11 |

Panel B: Portfolio characteristics

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| 12-1 raw return (%) | 9.22 | 11.76 | 13.29 | 14.09 | 16.00 | 6.78 |
| B/M | 1.26 | 1.08 | 0.85 | 0.71 | 0.56 | -0.70 |
| Gross profitability | 0.03 | 0.17 | 0.28 | 0.45 | 1.10 | 1.07 |
| Size (USD mil.) | 906 | 1994 | 2836 | 3269 | 2481 | 1575 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The results provide positive evidence of a relation between gross profitability and excess returns, with the excess returns increasing monotonically with gross profitability. The long-short portfolio generates an average excess return of 0.42% per month, which is statistically significant at 1% level. Both CAPM and Fama-French five factor alphas increase monotonically, with the high quintiles and long-short portfolios being statistically significant at 1% level. The Fama-French alpha for the long-short portfolio is

0.28% per month, despite the regressions already having a factor for profitability, although not in identical form as the quality signal.  A modest increase in risk-adjusted performance can be observed with monotonically increasing Sharpe and Sortino ratios for the quintile portfolios. The long-short portfolio benefits from greatly improved Sharpe and Sortino values, as both standard deviation and downside deviation for the long-short portfolio is lower than any of the quintile portfolios. The long-short portfolio also greatly benefits from the increased worst monthly drawdown and maximum drawdown metrics.

From the portfolio characteristics we can observe a relation between gross profitability and momentum, as the average 12-1 raw return increases as gross profitability increases. An inverse relation can be observed with gross profitability and B/M, where B/M decreases as gross profitability increases. Gross profitability also seems to be related to size, as market capitalization increases with gross profitability.

### 6.1.4 Portfolios sorted by size

As the results for the single-signal portfolios indicate a relation with size for all the signals, the portfolios are divided into subsamples based on their market capitalization. For each period, the firms are classified by size to small, medium, and large subsamples. Companies are ranked based on their market capitalization for the current period in descending order. Large stocks are defined as those that account for 90% of the market capitalization of the sample, medium stocks as those that account for the following 8 percentage points, and the remaining are defined as small stocks. The method is like that of Tikkanen and Äijö (2018) and Asness et al. (2013).

The table below reports the excess returns and Fama-French five factor loadings of the momentum portfolios sorted by size.

**Table 5.** Momentum portfolio returns sorted by size

Momentum portfolio returns sorted by size

The table below reports the monthly excess returns and Fama-French five factor loadings of the portfolios sorted by size and momentum. Stocks in the sample are ranked in descending order based on their market capitalization for each month. Large stocks account for 90% of the total market capitalization, medium stocks for the following 8% and small stocks the remaining 2%. Stocks in the subsample are then assigned to five quintile portfolios based on their ranking for the momentum signal. High - Low is the long/short portfolio composed of the extreme quintiles, and factor loadings are for the long/short portfolio

Panel A: Portfolio monthly excess returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Small | 0.11 | 0.24 | 0.65** | 1.01*** | 1.58*** | 1.47*** |
| t | (0.25) | (0.66) | (2.08) | (3.33) | (5.05) | (5.41) |
| Medium | 0.52 | 0.61* | 0.80** | 1.00*** | 1.43*** | 0.91*** |
| t | (1.24) | (1.73) | (2.42) | (3.09) | (4.20) | (3.78) |
| Large | 0.64* | 0.65** | 0.81*** | 0.96*** | 1.20*** | 0.55* |
| t | (1.72) | (2.13) | (2.87) | (3.28) | (3.76) | (1.90) |

Panel B: Portfolio factor loadings

| Portfolio | α | Rm - Rf | SMB | HML | CMA | RMW |
|---|---|---|---|---|---|---|
| Small | 1.26 %*** | -0.17** | -0.11 | -0.03 | 0.50* | 0.80*** |
| t | (5.45) | (-2.34) | (-0.86) | (-0.13) | (1.84) | (2.90) |
| Medium | 0.83 %*** | -0.15** | 0.04 | -0.21 | 0.31 | 0.60*** |
| t | (3.95) | (-2.23) | (0.34) | (-0.87) | (1.12) | (2.59) |
| Large | 0.35 % | -0.22*** | 0.26 | 0.00 | -0.01 | 0.96** |
| t | (1.16) | (-2.68) | (1.53) | (0.01) | (-0.03) | (2.50) |

The momentum effect is especially strong in the small sample, with a monthly average excess return of 1.47%, and monthly alpha of 1.26%, both statistically significant at 1% level. The momentum effect can also be found in the medium subsample, where the excess return is 0.91% with an alpha of 0.83%. As the alpha decreases with larger stocks, the profitability factor of the stocks also increases, explaining some of the decrease in alpha in addition to the decrease in excess returns. While a significant alpha cannot be found for the large subsample, it still has statistically significant excess returns. A statistically significant alpha can be found for the medium subsample.

The table below reports the excess returns and Fama-French factor loadings of the value portfolios sorted by size.

**Table 6.** Value portfolio returns sorted by size

Value portfolio returns sorted by size

The table below reports the monthly excess returns and Fama-French five factor loadings of the portfolios sorted by size and value. Stocks in the sample are ranked in descending order based on their market capitalization for each month. Large stocks account for 90% of the total market capitalization, medium stocks for the following 8% and small stocks the remaining 2%. Stocks in the subsample are then assigned to five quintile portfolios based on their ranking for the value signal. High - Low is the long/short portfolio composed of the extreme quintiles, and factor loadings are for the long-short portfolio

| Panel A: Portfolio monthly excess returns | | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
| Small | 0.48 | 0.59* | 0.60* | 0.75** | 1.18*** | 0.70*** |
| t | (1.49) | (1.86) | (1.81) | (2.17) | (2.96) | (3.44) |
| Medium | 0.73** | 0.69** | 0.81** | 0.90** | 1.24*** | 0.51** |
| t | (2.15) | (2.11) | (2.42) | (2.48) | (3.18) | (2.46) |
| Large | 0.77** | 0.79*** | 0.75** | 0.81** | 1.13*** | 0.36 |
| t | (2.59) | (2.89) | (2.53) | (2.56) | (3.20) | (1.63) |
| **Panel B: Portfolio factor loadings** | | | | | | |
| Portfolio | α | Rm - Rf | SMB | HML | CMA | RMW |
| Small | 0.69 %*** | 0.06 | 0.03 | 0.39*** | -0.13 | -0.41*** |
| t | (3.73) | (1.22) | (0.30) | (2.71) | (-0.75) | (-2.68) |
| Medium | 0.25 %* | 0.09*** | -0.01 | 0.66*** | 0.14 | -0.14 |
| t | (1.86) | (2.71) | (-0.23) | (5.52) | (1.01) | (-1.20) |
| Large | 0.04 % | 0.16*** | 0.01 | 0.78*** | 0.19 | -0.25 |
| t | (0.28) | (4.17) | (0.17) | (5.64) | (1.11) | (-1.24) |

Like the results with the momentum portfolios, the results indicate that the excess returns are stronger among small stocks. Whereas the returns for the high quintile are roughly the same for each of the size-sorted portfolios, the difference arises from the low quintile. The small-low portfolio generates a monthly average excess return of 0.48%, and the large-low portfolio generates a larger monthly excess return of 0.77%. The spread between high and low B/M firms is thus much lower among large firms. The findings with Fama-French alphas are similar; the small, long-short portfolio is able to generate a higher alpha than the large, long-short portfolio, but majority of the returns are captured by the HML factor. The results indicate that the intrinsic value of a stock has a more significant role within the small and medium stock universe.

The table below reports the excess returns and Fama-French factor loadings of quality portfolios sorted by size.

**Table 7.** Quality portfolio returns sorted by size

Quality portfolio returns sorted by size

The table below reports the monthly excess returns and Fama-French five factor loadings of the portfolios sorted by size and quality. Stocks in the sample are ranked in descending order based on their market capitalization for each month. Large stocks account for 90% of the total market capitalization, medium stocks for the following 8% and small stocks the remaining 2%. Stocks in the subsample are then assigned to five quintile portfolios based on their ranking for the quality signal. High - Low is the long/short portfolio composed of the extreme quintiles, and factor loadings are for the long-short portfolio.

Panel A: Portfolio monthly excess returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Small | 0.51 | 0.65* | 0.69** | 0.73** | 1.01*** | 0.50*** |
| t | (1.44) | (1.92) | (2.10) | (2.21) | (2.94) | (3.95) |
| Medium | 0.68* | 0.90** | 0.94*** | 0.87** | 0.97*** | 0.30** |
| t | (1.92) | (2.55) | (2.64) | (2.51) | (3.00) | (2.29) |
| Large | 0.78** | 0.83*** | 0.86*** | 0.92*** | 0.88*** | 0.10 |
| t | (2.48) | (2.62) | (2.66) | (3.21) | (3.20) | (0.86) |

Panel B: Portfolio factor loadings

| Portfolio | α | Rm - Rf | SMB | HML | CMA | RMW |
|---|---|---|---|---|---|---|
| Small | 0.42 %*** | -0.01 | 0.00 | -0.10 | 0.08 | 0.34*** |
| t | (3.65) | (-0.38) | (0.07) | (-1.22) | (0.71) | (3.34) |
| Medium | 0.18 % | -0.01 | 0.06 | -0.05 | -0.03 | 0.43*** |
| t | (1.50) | (-0.46) | (0.83) | (-0.56) | (-0.30) | (4.55) |
| Large | 0.13 % | -0.02 | -0.02 | -0.34*** | 0.18* | 0.21* |
| t | (1.10) | (-0.61) | (-0.33) | (-3.15) | (1.73) | (1.76) |

As with previous findings, the quality effect also seems to be stronger among small stocks. While the effect is not as substantial as with the momentum and value portfolios, the small, long-short portfolio is still able to generate a monthly excess return of 0.50%, with the large portfolio generating only one fifth of that amount at a monthly excess return of 0.10%. The excess return and alpha of the small portfolio are significant at 1% level, whereas no significance can be found for the large portfolio excess return at 10%

level. The RMW factor also no longer explains the returns of the portfolio, but instead the loading on the HML factor becomes negative and statistically significant. This is interesting as the opposite can be observed with the value portfolio, where small value stocks have a significant negative loading on the RMW factor, implying that there may be a connection between size, B/M and profitability. The results indicate that the gross profitability of a firm is a more significant factor for small and medium companies.

## 6.2 Two signal portfolios

Two-signal portfolios are formed using both integrating and mixing approaches, following Fitzgibbons et al. (2017). In the integrating approach, stocks which exhibit the given signals simultaneously will be chosen to the portfolio, whereas in the mixing approach the portfolios for the given signals are formed independently, and a mixing portfolio is formed by assigning equal weights to the sub-portfolios. In addition to mixing and integrating approaches, a third set of portfolios is formed based on average ranks following previous literature.

### 6.2.1 Momentum-value returns

The table 8 below presents results for portfolios formed by integrating both momentum and value signals. The portfolio consists of stocks that exhibit both given signals, e.g., winner-value portfolio will consist of stocks that have both the winner signal and the value signal, and loser-growth portfolio consists of stocks that exhibit both the loser signal and the growth signal.

**Table 8.** Integrated momentum-value portfolio returns

Integrated momentum-value portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the momentum-value portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the momentum and value signals simultaneously. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratios are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | -0.56 | 0.11 | 0.66* | 1.24*** | 1.95*** | 2.52*** |
| t | (-1.19) | (0.32) | (1.97) | (3.91) | (5.39) | (7.81) |
| CAPM alpha (%) | -1.24*** | -0.47*** | 0.12 | 0.75*** | 1.47*** | 2.71*** |
| t | (-5.13) | (-3.43) | (0.80) | (4.88) | (6.09) | (9.09) |
| Five factor alpha (%) | -0.88*** | -0.51*** | -0.12 | 0.46*** | 1.22*** | 2.10*** |
| t | (-3.63) | (-4.03) | (-1.00) | (4.09) | (5.90) | (7.40) |
| CAPM Beta | 1.00 | 0.86 | 0.80 | 0.72 | 0.72 | -0.28 |
| CAGR (%) | -9.16 | -0.24 | 6.75 | 14.49 | 24.11 | 32.65 |
| Std. | 6.88 | 5.20 | 4.82 | 4.51 | 5.18 | 5.16 |
| Sharpe | -0.001 | 0.076 | 0.486 | 0.955 | 1.288 | 1.688 |
| Sortino | -0.386 | 0.104 | 0.697 | 1.564 | 2.458 | 3.131 |
| Worst monthly drawdown (%) | -25.25 | -29.00 | -29.05 | -23.17 | -18.03 | -26.24 |
| Maximum drawdown (%) | -95.72 | -74.00 | -64.11 | -51.72 | -43.24 | -39.52 |

Panel B: Portfolio characteristics

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| 12-1 return (%) | -35.39 | -9.86 | 5.92 | 23.66 | 67.30 | 102.69 |
| B/M | 0.16 | 0.37 | 0.59 | 0.91 | 2.25 | 2.09 |
| Gross profitability | 0.50 | 0.48 | 0.38 | 0.31 | 0.26 | -0.24 |
| Size (USD mil.) | 1184 | 3284 | 2916 | 1884 | 487 | -697 |
| n | 56 | 87 | 112 | 92 | 46 | -10 |

The results provide positive evidence for the benefit of combining momentum and value signals. While the value effect in the sample is not as substantial as the momentum effect, a clear improvement can be found in excess returns, alphas and Sharpe ratios.

This, however, comes with the cost of increased risk in terms of standard deviation, while decreasing the worst monthly drawdown of the portfolio significantly, from -27.24% and -11.28% for the single-factor momentum and value portfolios, respectively, to the combined worst monthly drawdown of -26.24% of the integrated long-short portfolio, being slightly better than for the single-signal momentum portfolio. Despite some increase in risk, the performance of the portfolios is generally improved.

The high portfolio seems to have a bias towards small stocks, as the average market capitalization of the high portfolio is only 487 USD million, whereas the average market capitalization is significantly higher for other quintiles. This would increase the exposure of the long-short portfolio to size effect. The diversity of the portfolio is also greatly reduced; the average number of stocks in the portfolio is only 46 for each month for the highest quintile, and 56 for the smallest quintile.

The table 9 below presents results for portfolios formed by mixing single-signal momentum and value portfolios, by forming a portfolio that consists of 50% of stocks with momentum signal and 50% with value signal. Therefore, the high portfolio consists 50% of winner stocks, and 50% of value stocks, while the low portfolio consists of 50% of loser stocks, and 50% of growth stocks.

**Table 9.** Mixing momentum-value portfolio returns

Mixing momentum-value portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the mixed momentum-value portfolios. Stocks in the sample are assigned to separate five quintile portfolios based on their ranking for the momentum and value signal, which are then combined with 50/50 weights. High - Low is the long/short portfolio composed of the extreme quintiles. Sharpe and Sortino ratio are annualized.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.40 | 0.54 | 0.70** | 0.90*** | 1.37*** | 0.97*** |
| t | (1.02) | (1.64) | (2.15) | (2.78) | (3.84) | (8.71) |
| CAPM alpha (%) | -0.25* | -0.03 | 0.15 | 0.36*** | 0.79*** | 1.04*** |
| t | (-1.97) | (-0.25) | (1.28) | (2.97) | (5.41) | (9.16) |
| Five factor alpha (%) | -0.07 | -0.09 | -0.02 | 0.17** | 0.70*** | 0.77*** |
| t | (-0.70) | (-1.08) | (-0.24) | (2.02) | (6.57) | (9.48) |
| CAPM Beta | 0.96 | 0.84 | 0.81 | 0.79 | 0.86 | -0.10 |
| CAGR (%) | 2.89 | 5.23 | 7.26 | 9.92 | 15.95 | 12.17 |
| Std. (%) | 5.66 | 4.91 | 4.75 | 4.66 | 5.10 | 1.63 |
| Sharpe | 0.246 | 0.392 | 0.519 | 0.678 | 0.936 | 2.045 |
| Sortino | 0.352 | 0.561 | 0.755 | 1.028 | 1.530 | 4.927 |
| Worst monthly drawdown (%) | -26.64 | -26.58 | -26.08 | -25.26 | -25.01 | -5.85 |
| Maximum drawdown (%) | -65.77 | -62.27 | -60.70 | -58.39 | -56.91 | -11.25 |

The 50% split results in the portfolio being the average of the two single-signal portfolios in terms of the return metrics. While the mixed portfolio fails to outperform the single-signal momentum portfolios, the portfolio risk-adjusted performance is greatly improved, as the long-short portfolio generates an annual Sharpe of 2.045, and an annual Sortino of 4.927, as the standard deviation of the portfolio is reduced due to the interaction of the two portfolios, and the downside deviation of the portfolio diminishing close to zero. The maximum drawdown of the portfolio is extremely low at -11.25%, while worst monthly drawdown is only -5.85%. The results indicate that while the overall returns of the mixing portfolio are reduced compared to the single-factor momentum portfolio, the risk-adjusted performance is greatly improved, most likely owing to the negative correlation of returns between the momentum and value portfolios. Compared to the integrating portfolio, the portfolio diversity is also not as greatly compromised, as the portfolio consists of approximately double the number of stocks, with the only overlapping stocks being the ones that are included in the integrating portfolios.

The table 10 below presents the results for the momentum-value portfolio formed by taking the average of the ranks for the momentum and value signals. As the average of the ranks is taken, it is not necessary for a stock to have extreme exposure to both factors simultaneously, but a reasonable exposure to both factors.

**Table 10.** Average rank momentum-value portfolio returns

Average rank momentum portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the average rank momentum-value portfolios. Stocks in the sample are assigned to five quintile portfolios based on their average ranking for the momentum and value signals. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratios are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | -0.11 | 0.48 | 0.94** | 1.10*** | 1.49*** | 1.61*** |
| t | (-0.30) | (1.39) | (2.54) | (3.29) | (4.66) | (9.05) |
| CAPM alpha (%) | -0.73*** | -0.11 | 0.32** | 0.55*** | 0.99*** | 1.72*** |
| t | (-5.58) | (-1.05) | (2.57) | (4.02) | (6.40) | (9.68) |
| Five factor alpha (%) | -0.57*** | -0.15* | 0.33*** | 0.33*** | 0.74*** | 1.30*** |
| t | (-5.09) | (-1.80) | (3.16) | (3.40) | (7.16) | (10.42) |
| CAPM Beta | 0.92 | 0.88 | 0.93 | 0.80 | 0.75 | -0.17 |
| CAGR (%) | -3.04 | 4.32 | 10.02 | 12.47 | 18.00 | 20.58 |
| Std. (%) | 5.46 | 5.11 | 5.40 | 4.79 | 4.58 | 2.56 |
| Sharpe | 0.000 | 0.334 | 0.612 | 0.807 | 1.133 | 2.130 |
| Sortino | -0.096 | 0.475 | 0.941 | 1.239 | 1.925 | 5.081 |
| Worst monthly drawdown (%) | -26.24 | -27.58 | -27.10 | -25.74 | -22.90 | -8.51 |
| Maximum drawdown (%) | -81.91 | -63.98 | -62.58 | -59.44 | -50.73 | -18.26 |

| Panel B: Portfolio characteristics | | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
| 12-1 return (%) | -17.65 | -2.27 | 18.53 | 25.04 | 40.67 | 58.32 |
| B/M | 0.33 | 0.56 | 1.07 | 1.04 | 1.47 | 1.14 |
| Gross profitability | 0.51 | 0.46 | 0.41 | 0.36 | 0.30 | -0.21 |
| Size (USD mil.) | 2692 | 3168 | 2370 | 2046 | 1213 | -1479 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The results indicate an improvement in annual excess returns, alphas, and risk-adjusted performance metrics compared to single-factor portfolios. While the average rank long-short portfolio fails to outperform the integrating long-short portfolio in terms of excess and abnormal returns, the risk adjusted performance for the portfolio is greatly improved, with the Sharpe and Sortino ratios being even greater than with the mixing portfolio. Overall, the return performance of the average rank portfolio is like the integrating portfolio, but the risk-adjusted performance is like the mixing portfolio.

The average rank portfolio reasonably has overlaps with the integrating and mixing portfolio, as the average rank portfolio consists of stocks that either have average exposure to both factors or extreme exposure to one of the individual factors. Comparing the portfolio characteristics to the integrating approach, the momentum and value factors are not as extreme as for the integrating approach. Similarly, the size is the lowest for the highest quintile, however, the average market capitalization is still higher than with the integrating approach. An important contrast to the integrating approach is that the portfolio diversity is not compromised compared to the single-factor portfolios, as the average rank portfolios contain the same number of stocks as the single-factor portfolios.

### 6.2.2 Momentum-quality returns

The following table 11 presents results for portfolios formed by combining both momentum and quality signals. As previously, the portfolio consists of stocks that exhibit both given signals simultaneously.

**Table 11.** Integrating momentum-quality portfolio returns

Integrated momentum-quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the integrated momentum-quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the momentum and quality signals simultaneously. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | -0.02 | 0.43 | 0.70** | 1.15*** | 1.85*** | 1.87*** |
| t | (-0.03) | (1.18) | (2.17) | (3.83) | (5.54) | (6.39) |
| CAPM alpha (%) | -0.75*** | -0.17 | 0.15 | 0.65*** | 1.34*** | 2.10*** |
| t | (-3.37) | (-0.99) | (1.21) | (4.90) | (8.49) | (8.29) |
| Five factor alpha (%) | -0.33 | -0.23 | -0.08 | 0.38*** | 1.16*** | 1.49*** |
| t | (-1.51) | (-1.45) | (-0.72) | (3.63) | (8.85) | (5.55) |
| CAPM Beta | 1.09 | 0.88 | 0.81 | 0.74 | 0.76 | -0.33 |
| CAGR (%) | -3.19 | 3.46 | 7.24 | 13.31 | 22.97 | 23.22 |
| Std. (%) | 7.17 | 5.45 | 4.83 | 4.50 | 4.83 | 4.81 |
| Sharpe | 0.000 | 0.279 | 0.513 | 0.894 | 1.336 | 1.348 |
| Sortino | -0.011 | 0.395 | 0.741 | 1.382 | 2.285 | 2.319 |
| Worst monthly drawdown (%) | -31.14 | -30.31 | -28.47 | -22.41 | -22.94 | -17.42 |
| Maximum drawdown (%) | -82.78 | -64.93 | -59.34 | -53.77 | -51.53 | -35.69 |

Panel B: Portfolio characteristics

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| 12-1 return (%) | -38.88 | -10.17 | 5.90 | 23.95 | 78.69 | 117.57 |
| B/M | 1.71 | 1.13 | 0.82 | 0.58 | 0.37 | -1.34 |
| Gross profitability | 0.01 | 0.17 | 0.28 | 0.45 | 1.15 | 1.14 |
| Size (USD mil.) | 331 | 1965 | 3970 | 4529 | 2210 | 1879 |
| n | 134 | 104 | 104 | 106 | 115 | -19 |

The results are similar to that of the integrating momentum-value portfolios. The results are improved for every metric, with the monthly excess return improving by 34 basis points compared to the single-signal momentum portfolio, and the Fama-French alpha increasing by 22 basis points, with a modest improvement in risk-adjusted performance and drawdowns. While the performance is improved, the results are not as extreme as with the momentum-value portfolios.

Whereas the momentum and quality signals are stronger for the portfolios, a negative relation with the value signal can be observed, where the high portfolio is more biased towards growth stocks, whereas the low portfolio consists of value stocks. This is consistent with both momentum and quality stocks. The average market capitalization is also increasing with momentum and quality, which is also consistent with the individual factor portfolios. Overall, the largest difference in portfolio composition is the diversification of the portfolio. The portfolio is again less diverse than individual factor portfolios, with the highest quintile consisting of 115 stocks on average. While this is higher than for the momentum-value integrating portfolio, it is still much lower than for the single-signal portfolios.

The table 12 below presents results for mixing single-signal momentum and quality portfolios. As before the portfolio is constructed by having 50% of the long or high portfolio invested into stocks with high momentum, and 50% to stocks with high quality or profitability. Similarly, the short or low portfolio will consist 50% of stocks with low momentum, and 50% with low gross profitability.

**Table 12.** Mixing momentum-quality portfolio returns

Mixing momentum-quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the mixing momentum-quality portfolios. Stocks in the sample are assigned to separate five quintile portfolios based on their ranking for the momentum and quality signals, which are then combined with 50/50 weights. High - Low is the long/short portfolio composed of the extreme quintiles. Sharpe and Sortino ratio are annualized.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.33 | 0.56 | 0.76** | 0.96*** | 1.30*** | 0.98*** |
| t | (0.80) | (1.61) | (2.31) | (3.04) | (3.97) | (5.96) |
| CAPM alpha (%) | -0.34** | -0.03 | 0.20* | 0.42*** | 0.77*** | 1.11*** |
| t | (-2.24) | (-0.24) | (1.77) | (3.70) | (6.04) | (7.83) |
| Five factor alpha (%) | -0.15 | -0.08 | 0.06 | 0.23*** | 0.62*** | 0.77*** |
| t | (-1.18) | (-0.80) | (0.74) | (2.69) | (6.57) | (5.19) |
| CAPM Beta | 0.99 | 0.87 | 0.83 | 0.79 | 0.79 | -0.19 |
| CAGR (%) | 1.84 | 5.29 | 8.02 | 10.71 | 15.31 | 11.92 |
| Std. (%) | 5.96 | 5.13 | 4.84 | 4.60 | 4.70 | 2.60 |
| Sharpe | 0.192 | 0.385 | 0.554 | 0.730 | 0.970 | 1.302 |
| Sortino | 0.280 | 0.557 | 0.816 | 1.110 | 1.539 | 2.170 |
| Worst monthly drawdown (%) | -28.19 | -27.55 | -26.54 | -24.12 | -23.16 | -11.79 |
| Maximum drawdown (%) | -66.75 | -63.30 | -60.34 | -57.35 | -55.93 | -23.33 |

As with the momentum-value mixing portfolio, the average excess returns are approximately the average of the single-signal portfolios, while the risk-adjusted performance measures are improved. While the improvement is not as substantial as with the momentum-value mixing portfolio, an improvement in Sharpe ratio of 0.098 and an improvement in Sortino ratio of 0.334 can be observed. The worst monthly drawdown and maximum drawdowns are reduced to approximately half of the momentum portfolio drawdown measures, with a worst monthly drawdown of -11.79% versus -27.24% of the momentum long-short portfolio, and maximum drawdown of -23.33% versus -47.01% of the momentum long-short portfolio. Overall, the implications are largely the same as for the momentum-value mixing portfolio. The performance in terms of excess and abnormal returns is reduced, but the risk-adjusted performance and stability of returns is improved.

The following table 13 presents the results for the momentum-quality portfolio formed by taking the average of the ranks for the momentum and quality signals.

**Table 13.** Average rank momentum-quality portfolio returns

Average rank momentum portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the average rank momentum-quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their average ranking for the momentum and quality signals. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.15 | 0.52 | 0.76** | 1.03*** | 1.45*** | 1.30*** |
| t | (0.36) | (1.47) | (2.29) | (3.25) | (4.59) | (5.93) |
| CAPM alpha (%) | -0.53*** | -0.08 | 0.19* | 0.50*** | 0.94*** | 1.47*** |
| t | (-3.16) | (-0.64) | (1.73) | (4.05) | (7.30) | (7.81) |
| Five factor alpha (%) | -0.30* | -0.12 | 0.06 | 0.30*** | 0.74*** | 1.04*** |
| t | (-1.91) | (-1.23) | (0.80) | (3.33) | (7.15) | (5.30) |
| CAPM Beta | 1.01 | 0.88 | 0.84 | 0.78 | 0.75 | -0.26 |
| CAGR (%) | -0.48 | 4.71 | 7.98 | 11.63 | 17.44 | 15.91 |
| Std. (%) | 6.25 | 5.18 | 4.88 | 4.62 | 4.53 | 3.49 |
| Sharpe | 0.086 | 0.352 | 0.547 | 0.781 | 1.119 | 1.293 |
| Sortino | 0.123 | 0.509 | 0.816 | 1.189 | 1.813 | 2.153 |
| Worst monthly drawdown (%) | -30.27 | -27.32 | -25.43 | -24.40 | -22.14 | -16.02 |
| Maximum drawdown (%) | -72.27 | -62.82 | -59.78 | -58.09 | -53.29 | -30.76 |

Panel B: Portfolio characteristics

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| 12-1 return (%) | -25.36 | -5.72 | 13.45 | 27.45 | 54.48 | 79.84 |
| B/M | 1.46 | 1.05 | 0.83 | 0.65 | 0.47 | -0.99 |
| Gross profitability | 0.09 | 0.23 | 0.38 | 0.51 | 0.83 | 0.74 |
| Size (USD mil.) | 772 | 1896 | 2562 | 3170 | 3084 | 2312 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The average rank momentum-quality portfolio benefits from improved risk-adjusted performance, whereas there is no improvement in excess and abnormal return performance compared to the single-signal momentum portfolio, though the return performance is improved when comparing to the single-factor quality portfolio. The risk-adjusted performance compared to the single-signal momentum portfolio is improved in terms of Sharpe by 0.089 and in terms of Sortino by 0.317. The drawdowns are also smaller with the worst monthly drawdown increasing to 16.02 % and the maximum drawdown increasing to 30.76 %.

Again, a negative relation between the momentum-quality portfolio and B/M ratio can be observed, with the B/M decreasing monotonically with higher gross profitability and momentum. The size of the firms also increases monotonically with momentum and gross profitability, which is expected based on the single-signal portfolio results.

### 6.2.3 Value-quality returns

The table below presents results for portfolios formed by combining both value and quality signals. As previously, the portfolio consists of stocks that exhibit both given signals.

**Table 14.** Integrating value-quality returns

Integrated value-quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the integrated value-quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the value and quality signals simultaneously. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.12 | 0.53* | 0.68** | 0.81** | 1.30*** | 1.18*** |
| t | (0.30) | (1.71) | (1.99) | (2.31) | (2.92) | (3.30) |
| CAPM alpha (%) | -0.44* | 0.00 | 0.09 | 0.24 | 0.71*** | 1.15*** |
| t | (-1.91) | (-0.02) | (0.73) | (1.60) | (2.76) | (3.38) |
| Five factor alpha (%) | -0.34 | -0.07 | 0.00 | 0.01 | 0.45** | 0.79** |
| t | (-1.46) | (-0.64) | (-0.04) | (0.06) | (2.09) | (2.27) |
| CAPM Beta | 0.83 | 0.79 | 0.88 | 0.85 | 0.88 | 0.05 |
| CAGR (%) | -0.45 | 5.16 | 6.82 | 8.53 | 14.36 | 13.81 |
| Std. (%) | 5.64 | 4.81 | 5.15 | 5.12 | 5.95 | 4.43 |
| Sharpe | 0.074 | 0.393 | 0.466 | 0.558 | 0.745 | 0.900 |
| Sortino | 0.103 | 0.556 | 0.689 | 0.848 | 1.330 | 1.771 |
| Worst monthly drawdown (%) | -22.93 | -23.61 | -24.55 | -26.92 | -27.22 | -15.66 |
| Maximum drawdown (%) | -76.70 | -58.50 | -62.51 | -61.76 | -66.59 | -56.67 |

Panel B: Portfolio characteristics

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| 12-1 return (%) | 43.54 | 19.51 | 11.96 | 3.76 | -8.45 | -51.99 |
| B/M | 0.15 | 0.38 | 0.59 | 0.91 | 2.00 | 1.85 |
| Gross profitability | -0.05 | 0.17 | 0.28 | 0.45 | 0.96 | 0.38 |
| Size (USD mil) | 1287 | 2999 | 3103 | 1776 | 161 | -1126 |
| n | 72 | 89 | 111 | 92 | 49 | -23 |

The results provide positive evidence for the benefit of combining value and quality signals. Combining the two signals results in higher excess returns for the long-short portfolio, with improved risk-adjusted performance compared to the single-signal value portfolios, whereas the risk-adjusted performance is slightly lower than for the single-signal quality portfolios. While the long-short portfolio can generate a monthly CAPM alpha of 1.15% at 1% significance level, the five-factor monthly alpha is smaller at only 0.79% and is statistically significant only at 5% level. However, this is not surprising as value is a risk factor in the five-factor model, and the RMW factor in the five-factor model is closely related to the gross profitability factor.

The table below presents results for mixing single-signal value and quality portfolios. As before the portfolio is constructed by having 50% of the long or high portfolio invested into value stocks (or stocks with high B/M ratios), and 50% to stocks with high quality (or gross profitability). Similarly, the short or low portfolio will consist 50% of growth stocks (or stocks with low B/M ratios), and 50% with low quality or gross profitability.

**Table 15.** Mixing value-quality portfolio returns

Mixing value-quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the mixing value-quality portfolios. Stocks in the sample are assigned to separate five quintile portfolios based on their ranking for the value and quality signals, which are then combined with 50/50 weights. High - Low is the long/short portfolio composed of the extreme quintiles. Sharpe and Sortino ratio are annualized.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.62* | 0.71** | 0.75** | 0.80** | 1.04*** | 0.42*** |
| t | (1.79) | (2.17) | (2.20) | (2.36) | (2.82) | (3.49) |
| CAPM alpha (%) | 0.04 | 0.15 | 0.16 | 0.22* | 0.44*** | 0.40*** |
| t | (0.36) | (1.36) | (1.45) | (1.95) | (3.30) | (3.48) |
| Five factor alpha (%) | 0.10 | 0.07 | 0.06 | 0.09 | 0.37*** | 0.27*** |
| t | (0.98) | (0.88) | (0.69) | (1.08) | (3.78) | (2.62) |
| CAPM Beta | 0.85 | 0.83 | 0.86 | 0.85 | 0.88 | 0.04 |
| CAGR (%) | 6.08 | 7.36 | 7.74 | 8.43 | 11.40 | 5.02 |
| Std. | 5.03 | 4.85 | 5.00 | 4.93 | 5.18 | 1.46 |
| Sharpe | 0.434 | 0.516 | 0.526 | 0.568 | 0.697 | 0.984 |
| Sortino | 0.624 | 0.754 | 0.773 | 0.852 | 1.118 | 2.033 |
| Worst monthly drawdown (%) | -25.51 | -25.35 | -26.14 | -26.03 | -26.53 | -5.99 |
| Maximum drawdown (%) | -60.84 | -59.78 | -61.19 | -60.67 | -61.20 | -25.61 |

The results are comparable to the two previous mixing portfolios; the benefit of the mixing portfolio is realized through improved risk adjusted measures. The Sharpe and Sortino ratios are improved for the portfolio with the Sharpe ratio improving by 0.205 – 0.503 and Sortino by 0.750 - 1.171. The improvement in Sortino ratio is more substantial when compared to the single-signal value portfolio, as the downside for the portfolio is more greatly reduced, and the downside of the portfolio is quite like that of the single-signal quality portfolio, though there is still an improvement in the worst monthly drawdown, while the maximum drawdown is a bit worse.

The table below presents the results for the value-quality portfolio formed by taking the average of the ranks for the value and quality signals.

**Table 16.** Average rank value-quality portfolio returns

Average rank momentum portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the average rank value-quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their average ranking for the value and quality signals. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | 0.44 | 0.64* | 0.87** | 0.91*** | 1.05*** | 0.61*** |
| t | (1.29) | (1.94) | (2.52) | (2.61) | (2.79) | (3.28) |
| CAPM alpha (%) | -0.11 | 0.08 | 0.28** | 0.32** | 0.46*** | 0.57*** |
| t | (-0.79) | (0.71) | (2.58) | (2.49) | (3.00) | (3.25) |
| Five factor alpha (%) | -0.10 | 0.03 | 0.27*** | 0.19** | 0.29*** | 0.38** |
| t | (-0.76) | (0.38) | (3.05) | (2.08) | (2.77) | (2.39) |
| CAPM Beta | 0.82 | 0.83 | 0.87 | 0.88 | 0.87 | 0.05 |
| CAGR (%) | 3.88 | 6.46 | 9.25 | 9.82 | 11.54 | 7.22 |
| Std. (%) | 4.98 | 4.86 | 5.04 | 5.15 | 5.19 | 2.28 |
| Sharpe | 0.313 | 0.465 | 0.603 | 0.623 | 0.701 | 0.909 |
| Sortino | 0.435 | 0.666 | 0.913 | 0.962 | 1.135 | 1.780 |
| Worst monthly drawdown (%) | -25.36 | -24.62 | -26.03 | -27.19 | -26.36 | -9.84 |
| Maximum drawdown (%) | -61.48 | -60.29 | -59.79 | -60.13 | -62.08 | -36.32 |

| Panel B: Portfolio characteristics | | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
| 12-1 return (%) | 27.87 | 17.39 | 12.82 | 6.86 | -0.55 | -29.42 |
| B/M | 0.33 | 0.55 | 0.88 | 1.17 | 1.53 | 1.20 |
| Gross profitability | 0.12 | 0.26 | 0.48 | 0.51 | 0.67 | 0.55 |
| Size (USD mil.) | 2268 | 3305 | 2906 | 1989 | 1019 | -1249 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The average rank value-quality portfolio benefits from improved excess and abnormal return performance compared to the single-signal portfolios. The risk-adjusted performance is also improved, with an improvement in both Sharpe ratio and Sortino ratio, though the ratios are not improved as much as for the mixing portfolio. While the return performance is slightly better than for the mixing portfolio, the improvement comes with increased risk, and the average rank portfolio fails to beat the mixing portfolio in risk-adjusted performance. The average rank portfolio is able to generate a statistically significant monthly alpha of 0.38%, whereas the mixing portfolio has a lower annual alpha of 0.27%, while the integrating has a higher annual alpha of 0.79% but is not statistically significant. The risk-adjusted performance of the average rank portfolio is similar to the integrating portfolio, with some improvement in both drawdown metrics.

From the portfolio characteristics an inverse relation with momentum and size can be observed, with high value and high-quality firms being small firms with low momentum. This is consistent with previous findings that high momentum firms are large growth firms. Some of the returns may therefore be explained by the firm size effect.

## 6.3 Three signal portfolios

The table below presents results for portfolios formed by combining all the three signals. As with the portfolios, the portfolios will consist of stocks that exhibit all the three signals simultaneously, i.e., have the best fit across multiple factors. As the number of firms that exhibit all three signals simultaneously is low, the portfolios are formed using breakpoints of 40th and 60th percentiles instead of the 20th and 80th percentiles, as otherwise the portfolio would be extremely thin.

**Table 17.** Integrating momentum-value-quality portfolio returns

Integrated momentum-value-quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the integrated momentum-value-quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their ranking for the momentum, value and quality signals simultaneously. High - Low is the long/short portfolio composed of the stocks above 60th and below 40th percentiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between extreme quintiles is reported.

Panel A: Portfolio returns

| Portfolio | 1 | 2 | 3 | 4 | 5 | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | -0.74 | 0.01 | 0.63* | 1.42*** | 2.36*** | 2.24*** |
| t | (-1.39) | (0.03) | (1.80) | (4.51) | (4.07) | (9.78) |
| CAPM alpha (%) | -1.36*** | -0.55*** | 0.07 | 0.96*** | 1.94*** | 2.36*** |
| t | (-3.73) | (-2.70) | (0.43) | (4.98) | (3.91) | (9.95) |
| Five factor alpha (%) | -1.07*** | -0.67*** | -0.16 | 0.61*** | 1.57*** | 1.89*** |
| t | (-3.08) | (-3.00) | (-0.90) | (3.94) | (3.27) | (9.58) |
| CAPM Beta | 0.92 | 0.83 | 0.82 | 0.68 | 0.66 | -0.19 |
| CAGR (%) | -12.50 | -1.71 | 6.14 | 16.84 | 26.91 | 29.48 |
| Std. (%) | 8.54 | 5.59 | 5.22 | 4.81 | 8.35 | 3.47 |
| Sharpe | -0.002 | 0.006 | 0.429 | 1.020 | 0.952 | 2.200 |
| Sortino | -0.430 | 0.008 | 0.615 | 1.776 | 1.807 | 4.851 |
| Worst monthly drawdown (%) | -26.79 | -28.32 | -28.36 | -19.88 | -23.54 | -16.79 |
| Maximum drawdown (%) | -98.50 | -81.62 | -64.52 | -44.67 | -51.41 | -20.46 |

Panel B: Portfolio characteristics

| Portfolio | 1 | 2 | 3 | 4 | 5 | High - Low |
|---|---|---|---|---|---|---|
| 12-1 return (%) | -38.30 | -9.89 | 5.94 | 23.52 | 64.71 | 103.01 |
| B/M | 0.15 | 0.38 | 0.59 | 0.90 | 1.87 | 1.72 |
| Gross profitability | -0.10 | 0.17 | 0.28 | 0.45 | 0.94 | 1.04 |
| Size (USD mil.) | 449 | 2957 | 4166 | 2366 | 121 | -328 |
| n | 15 | 15 | 26 | 17 | 4 | -11 |

The results are positive, with the three signal long-short portfolio outperforming all other portfolios in terms of average excess returns except the integrating momentum-value portfolio. However, risk-adjusted measures in terms of both Sharpe and Sortino ratio are significantly improved. The performance is improved monotonically with nearly every metric, except for standard deviation, which is slightly higher than the single signal momentum portfolio. The most substantial improvement is for the long-short portfolio which has a Sharpe ratio of 2.200, and a Sortino ratio of 4.851, which are among the highest of all the portfolios. However, as with the two signal portfolios, the diversification of the portfolio is extremely low, as the number of firms that are both winners (losers), value (growth) firms, and high (low) profitability firms simultaneously is low. For individual quintile portfolios there are even months with no stocks in the portfolio. The number of stocks for the extreme quintiles is the lowest, with the third quintile having the highest amount.

From the portfolio characteristics we can observe that the momentum, value, and quality signals for the extreme quintiles are now also focused on the extreme observations in the sample, which is due to the extremely thin portfolio composition. The extreme quintiles are also both composed of small firms with similar average market capitalizations.

The table below presents the results for the three-signal mixing portfolio. Like the two-signal mixing portfolios, the high portfolio consists of stocks with high momentum, high B/M ratios, or high gross profitability, with each of the sub-portfolios having an equal weight in the composite portfolio.

**Table 18.** Mixing momentum-value-quality portfolio returns

| Mixing momentum-value-quality portfolio returns in the sample, January 1993 - December 2019 | | | | | | |
|---|---|---|---|---|---|---|
| The table below reports the returns of the mixing momentum-value-quality portfolios. Stocks in the sample are assigned to separate five quintile portfolios based on their ranking for the momentum, value and quality signals, which are then combined with 1/3 weights. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between high and low portfolio is reported. | | | | | | |
| Panel A: Portfolio returns | | | | | | |
| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
| Excess return (%) | 0.45 | 0.60* | 0.73** | 0.88*** | 1.24*** | 0.79*** |
| t | (1.19) | (1.80) | (2.22) | (2.73) | (3.56) | (9.61) |
| CAPM alpha (%) | -0.18 | 0.03 | 0.17 | 0.34*** | 0.67*** | 0.85*** |
| t | (-1.45) | (0.28) | (1.51) | (2.92) | (5.25) | (10.33) |
| Five factor alpha (%) | -0.04 | -0.03 | 0.03 | 0.16** | 0.56*** | 0.60*** |
| t | (-0.44) | (-0.38) | (0.40) | (2.01) | (6.50) | (10.11) |
| CAPM Beta | 0.93 | 0.85 | 0.83 | 0.81 | 0.85 | -0.09 |
| CAGR (%) | 3.63 | 5.96 | 7.68 | 9.69 | 14.24 | 9.81 |
| Std. (%) | 5.51 | 4.95 | 4.86 | 4.72 | 4.95 | 1.26 |
| Sharpe | 0.286 | 0.431 | 0.534 | 0.659 | 0.873 | 2.145 |
| Sortino | 0.411 | 0.624 | 0.782 | 0.995 | 1.401 | 5.301 |
| Worst monthly drawdown (%) | -26.78 | -26.49 | -26.25 | -25.14 | -24.90 | -4.85 |
| Maximum drawdown (%) | -64.09 | -61.81 | -60.74 | -58.82 | -58.02 | -8.63 |

The return performance for the mixing three signal portfolio is approximately the average of the three individual portfolios. As with the two signal portfolios, the three-signal portfolio does not outperform all the underlying single-signal portfolios in excess or abnormal return performance but has substantially increased risk-adjusted performance in terms of Sharpe and Sortino ratios, which are the best in the sample. Again, the downside of the portfolio is substantially reduced as the worst monthly drawdown and maximum drawdowns are extremely low at -4.85% and -8.63%, which are the best in the sample. Given the small positive correlation in returns with momentum and quality, and the negative correlation between value and both momentum and quality, the returns of the three portfolios have a combined profile where the downside is reduced for example during momentum crashes, but the upside return of the portfolio is also reduced, to the average of the three portfolios.

The table below presents the results for the three-signal portfolio formed by the average ranks of each underlying signal. Contrary to the integrating method, with the average rank method there will be no issues with thin portfolios, and extreme quintiles for the long-short portfolio are used as with other portfolios.

**Table 19.** Average rank momentum-value-quality portfolio

Average rank momentum-value-quality portfolio returns in the sample, January 1993 - December 2019

The table below reports the returns of the average rank momentum-value-quality portfolios. Stocks in the sample are assigned to five quintile portfolios based on their average ranking for the momentum, value and quality signals. High - Low is the long/short portfolio composed of the extreme quintiles. Panel B reports the time-series averages for each of the signals in addition to size and sample counts. Sharpe and Sortino ratio are annualized. For portfolio characteristics the differential between high and low portfolio is reported.

Panel A: Portfolio returns

| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
|---|---|---|---|---|---|---|
| Excess return (%) | -0.09 | 0.51 | 0.85** | 1.12*** | 1.51*** | 1.60*** |
| t | (-0.23) | (1.46) | (2.56) | (3.39) | (4.59) | (9.65) |
| CAPM alpha (%) | -0.72*** | -0.09 | 0.28** | 0.57*** | 0.99*** | 1.72*** |
| t | (-5.07) | (-0.84) | (2.58) | (4.61) | (6.84) | (10.41) |
| Five factor alpha (%) | -0.52*** | -0.07 | 0.19** | 0.37*** | 0.71*** | 1.23*** |
| t | (-4.45) | (-0.77) | (2.25) | (4.16) | (7.89) | (10.12) |
| CAPM Beta | 0.94 | 0.90 | 0.85 | 0.81 | 0.77 | -0.18 |
| CAGR (%) | -2.93 | 4.62 | 9.18 | 12.73 | 18.20 | 20.44 |
| Std. | 5.73 | 5.29 | 4.93 | 4.75 | 4.60 | 2.57 |
| Sharpe | 0.000 | 0.343 | 0.610 | 0.823 | 1.141 | 2.107 |
| Sortino | -0.072 | 0.495 | 0.916 | 1.283 | 1.926 | 5.165 |
| Worst monthly drawdown (%) | -28.29 | -26.99 | -25.85 | -25.12 | -23.31 | -10.02 |
| Maximum drawdown (%) | -77.61 | -62.71 | -59.69 | -58.49 | -54.56 | -16.46 |

| Panel B: Portfolio characteristics | | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | Low | 2 | 3 | 4 | High | High - Low |
| 12-1 return (%) | -13.94 | 1.81 | 11.60 | 23.04 | 41.80 | 55.74 |
| B/M | 0.66 | 0.92 | 0.87 | 0.92 | 1.11 | 0.45 |
| Gross profitability | 0.14 | 0.29 | 0.39 | 0.51 | 0.71 | 0.57 |
| Size (USD mil.) | 1596 | 2685 | 2893 | 2798 | 1514 | -82 |
| n | 496 | 497 | 497 | 497 | 497 | 1 |

The average rank three signal portfolio generates significant excess and abnormal returns but does not outperform all other portfolios, as it is outperformed by the integrating three signal portfolio and integrating momentum-value and momentum-quality portfolios. While the abnormal returns of the portfolio are slightly lower than for the single-signal momentum portfolio, the risk-adjusted performance is still significantly better than for any single-signal portfolio. If there would be constraints on short selling, the performance of the high quintile is approximately the same as it is for the single-signal high momentum portfolio, with minor improvements in drawdowns. As such there may be no additional performance improvement when considering enhancing a long-only momentum portfolio with the value and quality signals using average ranks.

As before, the average rank portfolios are not composed of quite as extreme momentum, value and quality signals as the single-signal or integrated portfolios, while there is a linear signal pattern with the quintiles. As the quintiles are now based on average ranks, the B/M value is approximately the same for the second to fourth quintile, while the momentum and quality signals improve in a more monotonical pattern. Again, the extreme quintiles are also composed of approximately the same sized stocks, with the average market capitalization being approximately the same for the extreme quintiles, while the quintiles between are more biased towards large stocks. This might be since the weight on small stocks is higher in the extreme quintiles, as value stocks are generally small stocks, while momentum stocks are generally large stocks.

## 6.4 Performance comparison

As the performance was improved when comparing the performance of single-signal portfolios to the multiple signal portfolios, the significance of the improvements should be quantified. The following table presents the results of the Ledoit-Wolf (2008) test of significance of the difference in Sharpe ratios, as well as alpha spread tests, based on Fama-French five factor model alphas. Each of the two and three factor portfolios is compared to the best single-signal long-short portfolio underlying the multiple signal portfolio, e.g., the momentum-value portfolios are compared to single signal momentum and value portfolios.

**Table 20.** Performance comparison

Performance comparison

The table below reports the comparison of multiple signal portfolios to single-signal portfolios. The table also reports the results of the Sharpe and alpha spread tests. The difference is compared to the best and worst of the related single-signal portfolios. The t-value on Sharpe spread test is based on Ledoit et al. (2008). Improvement compared to the best related single-factor portfolio is in **bold**. All figures are annualized if applicable.

| | Integrating | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| CAGR | **32.65** | **23.22** | **13.81** | **29.48** |
| Difference to best | 14.05 | 4.63 | 8.85 | 10.88 |
| Difference to worst | 28.07 | 18.26 | 9.23 | 24.90 |
| Std. | 17.88 | 16.65 | 15.35 | 12.03 |
| Difference to best | 7.64 | 10.16 | 8.86 | 5.54 |
| Difference to worst | 2.24 | 1.01 | 5.11 | -3.61 |
| Worst monthly drawdown | -26.24 | -17.42 | -15.66 | -16.79 |
| Difference to best | -14.96 | -9.65 | -7.89 | -9.01 |
| Difference to worst | 1.00 | 9.82 | -4.39 | 10.45 |
| Maximum drawdown | **-39.52** | -35.69 | -56.67 | -20.46 |
| Difference to best | 7.49 | -18.58 | -39.56 | -3.35 |
| Difference to worst | 9.98 | 11.32 | -7.17 | 29.04 |
| Sortino | **3.131** | **2.319** | **1.771** | **4.851** |
| Difference to best | 1.296 | 0.483 | 0.488 | 3.015 |
| Difference to worst | 2.269 | 1.036 | 0.909 | 3.989 |
| Sharpe | **1.688** | **1.348** | **0.900** | **2.200** |
| Difference to best | 0.485 | 0.144 | 0.121 | 0.996*** |
| t | (1.65) | (1.13) | (0.41) | (3.51) |
| Difference to worst | 1.207*** | 0.568** | 0.419 | 1.718*** |
| t | (4.74) | (2.71) | (0.64) | (4.62) |
| Alpha | **25.20** | **17.91** | **9.44** | **22.63** |
| Difference to best | 9.98** | 2.70 | 6.11 | 7.42* |
| t | (2.06) | (0.57) | (1.41) | (1.78) |
| Difference to worst | 21.98*** | 14.59*** | 6.22 | 19.41*** |
| t | (5.44) | (4.22) | (1.33) | (6.04) |

| Mixing | | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| CAGR | 12.17 | 11.92 | **5.02** | 9.81 |
| Difference to best | -6.43 | -6.67 | 0.06 | -8.79 |
| Difference to worst | 7.59 | 6.96 | 0.45 | 5.23 |
| Std. | **5.64** | 9.02 | **5.05** | **4.37** |
| Difference to best | -4.61 | 2.53 | -1.44 | -11.27 |
| Difference to worst | -48.54 | -45.16 | -30.43 | -18.10 |
| Worst monthly drawdown | **-5.85** | -11.79 | **-5.99** | **-4.85** |
| Difference to best | 5.43 | -4.02 | 1.79 | 2.92 |
| Difference to worst | 21.39 | 15.45 | 5.29 | 22.39 |
| Maximum drawdown | **-11.25** | -23.33 | -25.61 | **-8.63** |
| Difference to best | 35.76 | -6.22 | -8.51 | 8.48 |
| Difference to worst | 38.25 | 23.68 | 23.88 | 40.87 |
| Sortino | **4.927** | **2.170** | **2.033** | **5.301** |
| Difference to best | 3.091 | 0.335 | 0.750 | 3.465 |
| Difference to worst | 4.065 | 0.887 | 1.171 | 4.439 |
| Sharpe | **2.045** | **1.302** | **0.984** | **2.145** |
| Difference to best | 0.841*** | 0.099 | 0.205 | 0.942*** |
| t | (3.75) | (0.90) | (0.76) | (3.90) |
| Difference to worst | 1.563*** | 0.5230** | 0.5030*** | 1.664*** |
| t | (6.26) | (2.43) | (3.98) | (5.94) |
| Alpha | 9.22 | 9.27 | 3.27 | 7.25 |
| Difference to best | -6.00* | -5.95 | -0.05 | -7.96** |
| t | (-1.68) | (-1.53) | (-0.03) | (-2.27) |
| Difference to worst | 6.00** | 5.95*** | 0.05 | 3.93*** |
| t | (2.52) | (2.73) | (0.02) | (2.73) |

| Average rank | | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| CAGR | **20.58** | 15.91 | **7.22** | **20.44** |
| Difference to best | 1.99 | -2.69 | 2.25 | 1.84 |
| Difference to worst | 16.01 | 10.94 | 2.64 | 15.87 |
| Std. | **8.86** | 12.08 | 7.91 | 8.90 |
| Difference to best | -1.39 | 5.60 | 1.42 | 2.42 |
| Difference to worst | -45.32 | -42.10 | -27.58 | -45.27 |
| Worst monthly drawdown | **-8.51** | -16.02 | -9.84 | -10.02 |
| Difference to best | 2.76 | -8.24 | -2.07 | -2.24 |
| Difference to worst | 18.73 | 11.22 | 1.44 | 17.22 |
| Maximum drawdown | **-18.26** | -30.76 | -36.32 | **-16.46** |
| Difference to best | 28.75 | -13.66 | -19.21 | 0.65 |
| Difference to worst | 31.24 | 16.25 | 13.18 | 33.04 |
| Sortino | **5.081** | **2.153** | **1.780** | **5.165** |
| Difference to best | 3.245 | 0.317 | 0.497 | 3.330 |
| Difference to worst | 4.219 | 0.869 | 0.918 | 4.303 |
| Sharpe | **2.130** | **1.293** | **0.909** | **2.107** |
| Difference to best | 0.927*** | 0.090 | 0.129 | 0.904*** |
| t | (4.28) | (0.97) | (0.40) | (3.86) |
| Difference to worst | **1.649*** ** | **0.514** ** | **0.427*** ** | **1.626** ** |
| t | (6.44) | (2.33) | (3.29) | (5.75) |
| Alpha | **15.63** | 12.42 | **4.62** | **14.76** |
| Difference to best | 0.41 | -2.79 | 1.29 | 5.37 |
| t | (0.11) | (-0.67) | (0.56) | (1.44) |
| Difference to worst | 12.41*** | 9.10*** | 1.40 | 17.37*** |
| t | (4.69) | (3.42) | (0.48) | (6.63) |

The compounded returns are improved for almost all integrating and average rank portfolios. For integrating portfolios, the increased returns mostly come with increased volatility of returns, but for the average rank momentum-value portfolio and the three-signal portfolio the volatility is lower than for the single-signal portfolios. The mixing portfolios see lower returns, but the volatility is also greatly reduced. This leads to improved Sharpe and Sortino ratios for the mixing portfolios despite no improvement in returns, and the mixing three-signal portfolio has the highest Sortino ratio out of all portfolios. The ratios are similar regardless of the method used to construct the portfolio.

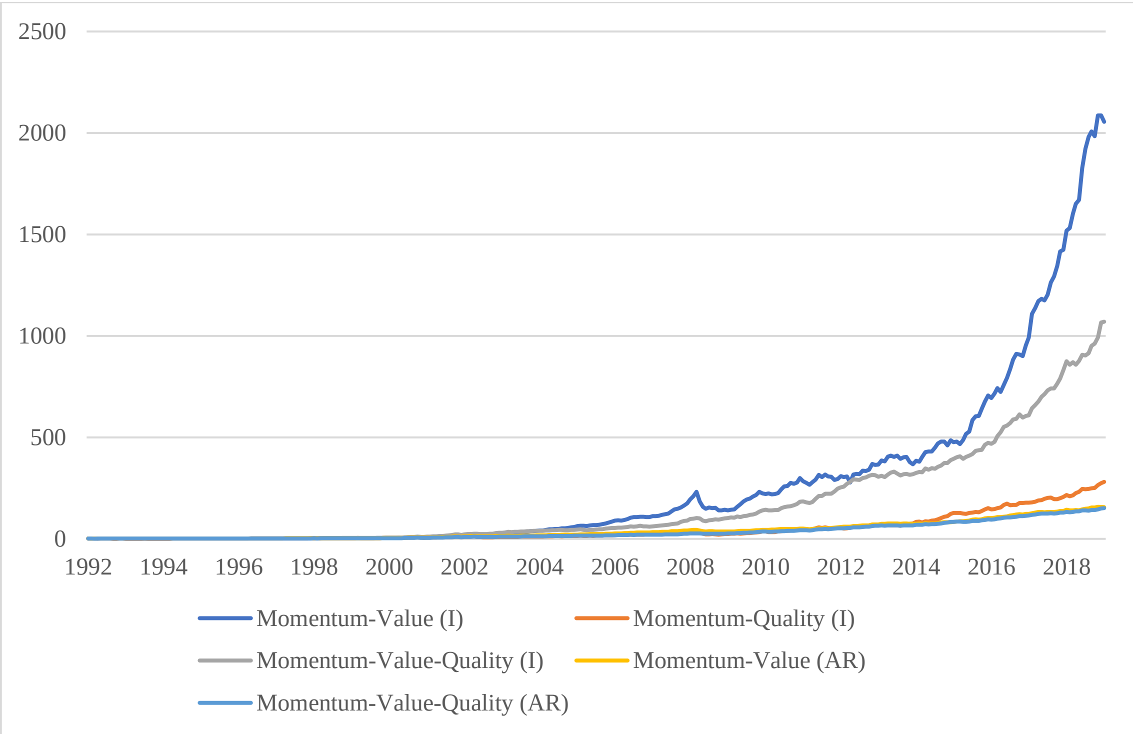


**Figure 3.** Cumulative returns of the top 5 portfolios

The integrating portfolios have generally worse drawdowns than single-signal portfolios, with the value-quality portfolio having even worse drawdowns than the value or quality portfolio. For the three-signal portfolio the drawdowns are slightly worse than for the single-signal portfolios. The mixing portfolios have slightly more variance in the drawdown metrics. The momentum-value and three-signal portfolios have significant improvements in drawdowns, whereas the drawdowns of the other portfolios are slightly worse. The results are similar with the average rank portfolio, where again the drawdowns for the momentum-value portfolio are improved, whereas the other portfolios are worse than the best single-signal portfolio but still better than the worst.

The Sharpe and Sortino ratios are improved across all portfolios. The integrating portfolios generally have higher excess returns, which contributes positively to both

Sharpe and Sortino ratios, despite the increase in volatility of returns. As the Sortino ratio increases more substantially the increase in deviation in returns is focused more on higher returns. The mixing portfolio has lower returns, but the standard deviation and downside deviation are both greatly reduced, which improves the Sharpe and Sortino ratios. For the average rank portfolio there is an increase of excess returns along with a slight increase in standard deviation, except for the momentum-value portfolio, which sees lower standard deviation of returns. The increase in returns is high enough to contribute positively to the Sharpe ratio. The Sortino ratios, however, see a substantial improvement, as the momentum-value portfolio Sortino ratio increases to 5.081 and the three-signal portfolio to 5.165.

While there is an improvement in Sharpe ratios, only the momentum-value (except for the integrating momentum-value portfolio) and three signal portfolios have a statistically significant difference in Sharpe ratio compared to the best single-signal portfolio. As the downside deviation is generally reduced across the portfolios, it is possible that the Sortino ratio spreads would be statistically significant, however, the Ledoit-Wolf (2008) test cannot be directly applied to Sortino ratios.

Improvements in five-factor alphas can be observed with multiple signal portfolios, however, these do not achieve statistical significance when compared to the best single-signal portfolio, apart from the integrating and average rank momentum-value and three-signal portfolios. This is likely since the alpha arising from momentum is already captured in the comparisons, and the improvement from the value and quality signals is more likely to be captured in HML and RMW factors. Momentum is also correlated with the RMW factor, which decreases any alpha arising from momentum stocks.

The three different methods of combining momentum, value and quality signals generate different results. The integrating method generates higher returns with higher risk; however, the risk-adjusted performance is still improved. The integrating method also suffers from increasingly thin portfolios as more signals are included, depending on the correlation of the signals. The mixing method allows for combining two different strategies in a simple manner, and if the returns of the two strategies are negatively correlated, it would offer hedge against volatility and downside risk of the portfolio. This manifests through the extremely high Sortino ratios. The average rank method allows to combine different signals as in the integrating method, but without the caveat of thin portfolios. While being second to the integrating portfolios in raw returns, the average rank portfolios have better risk-adjusted performance than the integrating counterparts.

Table 21 presents the factor loadings of the Fama-French five-factor model.

**Table 21.** Five-factor model regressions

Fama-French five-factor model regressions

The table below presents the results of Fama-French five-factor model regressions. The coefficient of alpha is expressed in percentages. T-statistics are in brackets below the coefficient. I, M and AR indicate Integrating, Mixing and Average Rank methods.

| | | α | Rm - Rf | SMB | HML | CMA | RMW |
|---|---|---|---|---|---|---|---|
| | | | | Integrating | | | |
| MV-I | Coef. | 2.10 %*** | -0.17** | 0.13 | 0.45* | 0.76*** | 0.73*** |
| | t | (7.40) | -(2.50) | (1.15) | (1.67) | (2.61) | (2.60) |
| MQ-I | Coef. | 1.49 %*** | -0.14** | -0.07 | -0.08 | 0.50 | 1.29*** |
| | t | (5.55) | -(1.97) | -(0.52) | -(0.37) | (1.83) | (4.41) |
| VQ-I | Coef. | 0.79 %** | 0.03 | 0.08 | 0.71*** | 0.00 | 0.41 |
| | t | (2.27) | (0.31) | (0.51) | (2.87) | (0.01) | (1.46) |
| MVQ-I | Coef. | 1.89 %*** | -0.10** | 0.06 | 0.35* | 0.46** | 0.67*** |
| | t | (9.58) | -(2.06) | (0.76) | (1.94) | (2.25) | (3.38) |
| | | | | Mixing | | | |
| MV-M | Coef. | 0.77 %*** | -0.06*** | 0.07 | 0.28*** | 0.25*** | 0.33*** |
| | t | (9.48) | -(2.80) | (1.40) | (3.23) | (2.66) | (3.10) |
| MQ-M | Coef. | 0.77 %*** | -0.08** | -0.03 | -0.07 | 0.28* | 0.73*** |
| | t | (5.19) | -(1.99) | -(0.42) | -(0.51) | (1.73) | (4.32) |
| VQ-M | Coef. | 0.27 %*** | 0.02 | 0.05 | 0.27*** | 0.06 | 0.08 |
| | t | (2.62) | (0.82) | (1.00) | (3.18) | (0.62) | (0.90) |
| MVQ-M | Coef. | 0.60 %*** | -0.04*** | 0.03 | 0.16*** | 0.20*** | 0.38*** |
| | t | (10.11) | -(2.60) | (0.90) | (3.01) | (3.00) | (5.14) |
| | | | | Average rank | | | |
| MV-AR | Coef. | 1.30 %*** | -0.12*** | 0.10 | 0.42*** | 0.37** | 0.51*** |
| | t | (10.42) | -(2.93) | (1.30) | (2.97) | (2.31) | (3.14) |
| MQ-AR | Coef. | 1.04 %*** | -0.12** | -0.08 | -0.06 | 0.35 | 0.96*** |
| | t | (5.30) | -(2.11) | -(0.83) | -(0.30) | (1.49) | (4.06) |
| VQ-AR | Coef. | 0.38 %** | 0.04 | 0.09 | 0.41*** | 0.12 | 0.10 |
| | t | (2.39) | (0.84) | (1.14) | (3.21) | (0.78) | (0.78) |
| MVQ-AR | Coef. | 1.23 %*** | -0.08** | 0.06 | 0.30*** | 0.44*** | 0.75*** |
| | t | (10.12) | -(2.49) | (0.89) | (2.63) | (3.36) | (4.98) |

Significant monthly alphas can be found for all the multi-signal portfolios. The lower alphas of the value-based portfolios are due to the positive loading on the HML factor, and lower alpha on the quality-based portfolios is primarily due to the high, positive loading on the RMW factor, except for the mixing and average rank value-quality portfolios. None of the portfolios have a significant loading on the SMB factor, as the long and short legs of each portfolio generally have similar loadings on the SMB factor, which reduces the overall exposure of the long-short portfolio to the size factor. While the five-factor model can explain some of the excess returns, all the excess returns are not captured by the risk-factors.

The table 22 below reports the excess returns and alphas of the different portfolios sorted by size.

**Table 22.** Multifactor portfolio returns sorted by size

Multifactor portfolio returns sorted by size

The table below reports the excess returns and Fama-French alphas of the portfolios sorted by size. Stocks in the sample are ranked in descending order based on their market capitalization for each month. Large stocks account for 90% of the total market capitalization, medium stocks for the following 8% and small stocks the remaining 2%. Portfolios using different signals and methods are constructed from the sorted subsamples.

Panel A: Integrating portfolio excess returns

| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
|---|---|---|---|---|
| Small | 2.34*** | 1.69*** | 1.35*** | 2.25*** |
| t | (6.15) | (5.60) | (4.03) | (10.28) |
| Medium | 1.40*** | 1.30*** | 1.25*** | 1.64*** |
| t | (3.62) | (4.64) | (3.47) | (5.90) |
| Large | 0.53 | 1.04*** | 1.01** | 1.19*** |
| t | (1.53) | (3.11) | (2.59) | (4.52) |

Panel B: Integrating portfolio alphas

| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
|---|---|---|---|---|
| Small | 2.18*** | 1.40*** | 1.26*** | 2.17*** |
| t | (5.95) | (5.01) | (3.70) | (11.89) |
| Medium | 1.21*** | 1.03*** | 0.83** | 1.26*** |
| t | (3.54) | (3.82) | (2.55) | (4.90) |
| Large | -0.20 | 0.88** | 0.81** | 0.75** |
| t | (-0.50) | (2.52) | (2.11) | (2.45) |

| Panel C: Mixing portfolio excess returns | | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| Small | 1.09*** | 0.99*** | 0.60*** | 0.89*** |
| t | (10.79) | (6.20) | (5.42) | (11.01) |
| Medium | 0.71*** | 0.61*** | 0.40*** | 0.57*** |
| t | (6.16) | (4.50) | (3.83) | (7.55) |
| Large | 0.46*** | 0.33** | 0.23** | 0.34*** |
| t | (4.08) | (2.11) | (2.12) | (4.69) |

| Panel D: Mixing portfolio alphas | | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| Small | 0.98*** | 0.84*** | 0.55*** | 0.79*** |
| t | (11.44) | (6.31) | (5.19) | (11.24) |
| Medium | 0.54*** | 0.51*** | 0.21*** | 0.42*** |
| t | (6.61) | (4.48) | (2.75) | (7.93) |
| Large | 0.42*** | 0.24* | 0.09 | 0.18*** |
| t | (4.05) | (1.68) | (0.82) | (2.60) |

| Panel E: Average rank portfolio excess returns | | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| Small | 1.78*** | 1.32*** | 0.89*** | 1.69*** |
| t | (10.95) | (6.30) | (5.72) | (11.90) |
| Medium | 1.13*** | 0.76*** | 0.66*** | 1.17*** |
| t | (6.14) | (4.31) | (3.72) | (7.42) |
| Large | 0.73*** | 0.50** | 0.36* | 0.67*** |
| t | (4.22) | (2.29) | (1.96) | (4.41) |

| Panel F: Average rank portfolio alphas | | | | |
|---|---|---|---|---|
| Portfolio | Momentum Value | Momentum Quality | Value Quality | Momentum Value Quality |
| Small | 1.60*** | 0.82*** | 0.82*** | 1.60*** |
| t | (13.30) | (5.58) | (5.58) | (13.30) |
| Medium | 0.85*** | 0.64*** | 0.33** | 0.85*** |
| t | (6.32) | (4.27) | (2.43) | (7.19) |
| Large | 0.38** | 0.40* | 0.20 | 0.36** |
| t | (2.52) | (1.85) | (1.09) | (2.45) |

Generally, the excess returns and abnormal returns are smaller for the medium and large portfolios, with the integrating portfolio having even negative alphas for the large stock portfolios. The portfolios are mostly able to generate statistically significant excess returns, except for the large, integrating momentum-value portfolio. The portfolios are also mostly able to generate statistically significant abnormal returns, except for large integrating momentum-value portfolio, large mixing value-quality portfolios, and large average rank value-quality portfolios.

While the performance is better for the small and medium stock portfolios, the large portfolio results are still mostly statistically significant, and it can be concluded that the portfolio performance improvement is not entirely based on the size effect. For the integrating portfolios, the inclusion of the third signal yields more consistent results across the subsamples, whereas no similar observation can be made for mixing or average rank portfolios. The large portfolio results should however be interpreted with caution, as the number of stocks in the sample is low, with an average of 52 stocks per single-factor quintile, and the integrating portfolio having even less.

# 7 Conclusions

The main motivation of this thesis was to study if the well-known momentum, value and quality effects could be improved by using the other effects as timing signals, and if the correlation relationship between the three signals would allow to improve the risk-adjusted performance when compared to the single-signal strategies utilizing momentum, value, and quality. As smart beta and multifactor investing is becoming more popular, the topic is as timely as ever.

The results show that while momentum effect is the most significant, value and quality strategies can beat the market in risk-adjusted performance. The results are in line with previous research, even though the signal construction methodology may differ from main previous research. The three different signals can be found across firms of different sizes. While the momentum, value and quality effects are strongest in the small stock universe, the effect can also be found among medium and large stocks, though in a smaller scale. This leads to the conclusion that the while the effects are partially driven by the small firm effect, it cannot be explained entirely by the size effect.

By utilizing multiple factors when constructing portfolios, investor can increase the risk-adjusted performance of their portfolio. How the portfolio performance is improved is largely dependent on the method. With the integrating approach, investors can limit their factor exposure only to the factors they want. This comes with the caveat that with low correlation between the factors the pool of available firms with exposure to both factors may become extremely small. With the mixing approach the investor can easily increase exposure to two or more factors without severely compromising the diversity of the portfolio, while allowing to benefit from low correlation between the portfolios. The risk-adjusted performance can therefore be improved, while there will be little to no additional abnormal returns. The average rank method allows to combine two or more different factors without compromising the diversity of the portfolio at all. By contrast to the integrating method, the average rank method is not limited to extreme exposure to multiple factors, but instead reasonable exposure to one or more factors.

This allows to improve the portfolio performance by increasing the returns of the portfolio as with the integrating approach, as well as allowing to benefit from low correlation of the underlying stocks, leading to even better risk-adjusted performance.

Overall, the risk-adjusted performance of the portfolios was generally greatly improved regardless of the method used to construct the portfolios. As there is more than one way to construct the portfolios, the constraints to the formation of the portfolio should be carefully considered, e.g., with short-selling constraints the focus should be on the better performing long-only portfolios, whereas the focus of this thesis has been on the long-short portfolios.

Transaction costs are not considered in this thesis, but arguably the transaction costs could be higher for single-factor portfolios, as was shown by Fisher et al. (2016) in the U.S. market. This would effectively improve the performance of the multifactor portfolios when compared to the single-factor portfolios. However, Fisher et al (2016) only consider mixing and average rank portfolios. The integrating method usually targets a very limited pool of stocks, which could potentially see higher transaction costs if the liquidity diminishes for single stocks.

The focus on this thesis has been on momentum, value and quality. Future research subject could be the different forms of momentum, value and quality, as the focus has now been on 12-1 return momentum, book-to-market value, and gross profitability as quality. For example, Barroso and Santa-Clara (2015) studied risk-managed momentum which could replace the traditional momentum as a factor in the multifactor portfolio, potentially improving the risk-adjusted performance even further. Book-to-market value is a common indicator for value, but there are also several others, e.g., cashflow-to-price, EV-to-price, dividends-to-price etc. which could very well replace the book-to-market ratio as the value signal.

Quality and profitability have also previously been a topic of interest, e.g., Ball et al. (2015, 2016) find that operating profitability is a more robust indicator of future performance, which they augment to cash-based operating profitability, which yields even better results. Another interesting measure is the quality measure by Asness, Frazzini et al. (2019), which breaks the quality measure into components of profitability, growth and safety. The quality measure itself is like a multifactor average rank portfolio consisting of stocks with signals for profitability, growth and safety.

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