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Long-Term Return Reversal and Fundamental Strength

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ABSTRACT:

Past return-based strategies, such as reversal and momentum, have been widely discussed in academic papers. In reversal strategies, such as long-term return reversal which was first presented by De Bondt and Thaler (1985), past stock price movements in one direction are expected to reverse to opposite direction in the future. Instead of focusing only on simple long-term return reversals, the purpose of this study is to examine whether fundamental strength-based sorting can enhance the performance of the long-term reversal strategy. Firms' fundamental strength is measured with Piotroski's (2000) FSCORE, which consists of nine variables measuring firms' profitability, leverage/liquidity, and operational efficiency. This study is motivated by the expectation errors framework presented by Piotroski and So (2012), who find that value/growth-strategy's returns are concentrated in portfolios with incongruent expectations implied by firms' FSCORE and book-to-market multiples. This study combines FSCORE with past return performance instead of pricing multiples. The hypothesis is, that reversals are strongest with high (low) fundamental strength stocks with the lowest (highest) past return performance.

The portfolios are formed by double sorting. First, the stocks are sorted to non-overlapping quartile portfolios based on the past 36 months returns, with ranking and holding periods being three years. Thereafter the winner and loser quartiles are sorted to high and low fundamental portfolios based on firms' individual FSCORE-values. The returns for each three-year fundamental reversal portfolios are calculated as value-weighted compound returns. Traditionally equal-weighted returns have been used widely in empirical finance, but value-weighted returns are used here to have more credible results, as suggested by Hou, Xue and Zhang (2018). Risk-adjusted return performance of the strategies is measured using Sharpe (1966) and Sortino (1994) ratios. It is also examined, whether the returns of the fundamental reversal strategies are explained by the common risk factors of Fama and French (2018) three-, five-, and six-factor models.

As hypothesized, long-term past losers with high fundamental strength have stronger reversals than past losers with low fundamental strength. On the other hand, similar return reversals are not observed with past winners. FSCORE-based fundamental analysis can help to enhance future risk-adjusted returns, as past winners and losers with high fundamental strength have better risk-adjusted performance than the low fundamental counterparts. The returns of the fundamental reversal strategies are explained by the common risk factors, when the three-factor model is augmented with investment and profitability factors. In factor loading level, past losers are characterized as having conservative capital expenditures, whereas past winners tend to have aggressive capital expenditures. The results of the study are affected by survivorship bias, as the data includes only the stocks included in the S&P 1500 index at the time of collecting the data.

KEYWORDS: FSCORE, return reversal, fundamental strength, fundamental analysis, contrarian

Contents

Figures

Tables

1   Introduction

Investment strategies based on past returns of stocks, such as reversal and momentum, have been widely discussed in past academic studies. In its basic form the discussion of past return-based phenomena focuses on efficient market hypothesis (Fama, 1970), and whether these strategies go against the weak form of the hypothesis or whether these phenomena are explained by the common risk factors. In reversal, also known as contrarian strategies, past stock price movements in one direction are expected to reverse to the opposite direction in a certain time period. The phenomenon of long-term stock price reversals was presented by De Bondt and Thaler (1985), who suggest that stocks with worst past returns outperform stocks with highest past returns with approximately 25% in the subsequent three years. In their study the stocks with the poorest past return performance are called "losers", whereas the stocks with the best past long-term performance are called "winners". Similar reversals are also found on short-term monthly periods (Jegadeesh, 1990), but the focus of this study is in long-term reversals.

In this paper the long-term reversal strategy is understood as a contrarian strategy which focuses solely on past long-term returns of securities. In the wider perspective, similar stock characteristics can be captured with other contrarian strategies such as value strategies, where the goal is to find undervalued value stocks and overvalued glamour stocks by using pricing multiples, such as price-to-book and price-to-earnings. Whether using simply past returns or accounting multiples, the behavioral explanation for these anomalies is suggested to be related to investors' overreaction, which drives the stock prices to non-rational levels and thus drives these contrarian strategies to outperform the market. (Lakonishok, Shleifer, & Vishny, 1994) Opposite to behavioral explanations, long-term reversals have been explained by risk-based theories. For instance, Fama and French (1996) are able to explain long-term return reversals with the three-factor asset pricing model. Moreover, Yaqiong (2012) questions the whole phenomenon of long-term reversals, as the return reversals are reported to occur only during the month of January.

Instead of focusing only on simple long-term reversal strategies, this study examines the role of fundamental strength in long-term reversals, and whether fundamental strength-based sorts can enhance the performance of the return reversal strategies. Firms' fundamental strength is measured with Piotroski's (2000) FSCORE. FSCORE is an accounting-based aggregate score, which classifies each firm based on their fundamental strength. Based on nine signals, FSCORE measures firms' profitability, change in financial leverage/liquidity and change in operational efficiency. Originally, Piotroski (2000) uses FSCORE to enhance the returns of a value strategy which buys high book-to-market value stocks. Later Piotroski and So (2012) suggest that value/glamour strategy's returns are highest with the stocks that have incongruent expectations implied by FSCORE and book-to-market multiple. Those findings are suggested to be due to investors' systematic expectation errors.

In this study the expectation errors are hypothesised to be found by using only past long-term returns instead of pricing multiples. As FSCORE has shown ability to enhance the returns of various investment strategies, it is interesting to see whether it can sort the future winners out of past loser stocks and future losers out of past winners simply by using past returns instead of pricing multiples. To the writer's best knowledge, empirical tests combining firms' fundamental strength and long-term return reversals have not been done in the past. To decrease the role of microcap stocks, and to better capture the investors' wealth effect as suggested by Fama (1998), the portfolios formed in this study are value-weighted. As shown by Hou, Xue, and Zhang (2018), portfolio weighting can influence the returns of various anomalies, and replacing equal-weighting with value-weighting can make the empirical results more credible.

1.1 Previous studies

After the publication of the original study by De Bondt and Thaler (1985), long-term return reversals and investor behavior-related explanation for the anomaly have been examined and challenged in various papers. Opposite to overreaction hypothesis, the

phenomenon is linked to seasonality and firm size, as studies show that it is focused on small firms in the month of January, whereas outside January the reversal returns disappear. (Zarowin, 1990; Yaqiong, 2012) Also, Grinblatt and Moskowitz (2004) and George and Hwang (2007) link long-term reversal to stock market seasonality and suggest that locked-in capital gains and tax loss selling are the main drivers for loser stock reversals. By using the three-factor model, Fama and French (1996) explain the returns of long-term reversals with positive size and value factors, meaning that past long-term losers are riskier due to smaller firm size and higher financial distress. Garcia-Feijoo and Jensen (2014) add, that monetary conditions play an important role in explaining the reversals. Opposing results have been found from international markets, as Wu, Li, and Hamill (2012) find that low and middle priced past losers gain significant abnormal returns in U.K stock markets after adjusting to common risk factors of the three-factor model, with the results generally supporting the overreaction hypothesis. Similarly, the evidence by Galariotis (2012) in French stock markets is supportive of overreaction hypothesis.

Piotroski and So (2012) find, that combining another type of contrarian strategy, book-to-market ratio-based value strategy, with FSCORE-based fundamental strength sorting enhances significantly the performance of the value strategy of buying high book-to-market stocks and selling low book-to-market stocks. Piotroski and So (2012) and Walkshäusl (2017) link this phenomenon to investors' expectation errors, as the value/glamour returns are statistically and economically significant with firms where expectations implied by current fundamental strength and book-to-market ratios are incongruent. Tikkanen and Äijö (2018) test the FSCORE-based sorting with several value strategies and find that the FSCORE enhances the performance of all the value strategies analyzed in the study. In addition to value strategies, FSCORE is also able to enhance the returns of other strategies, such as momentum (Chen, Lee, & Shih, 2016; Turtle & Wang, 2017; Ahmed & Safdar, 2018; Walkshäusl, 2019) and short-term reversal strategies (Zhu, Sun, & Chen, 2019).

1.2   Purpose of the study and intended contribution

Previous studies of return reversal strategies focus mainly on past returns, and fundamentals of the firms do not gain attention. The purpose of this study is to measure the impact of fundamental analysis in the form of FSCORE on the long-term return reversal strategy. As a comprehensive metric of firms' profitability, leverage/liquidity and operating efficiency, FSCORE is chosen as the measure of firms' fundamental strength. Whereas Piotroski (2000) and Piotroski and So (2012) combine FSCORE and book-to-market to sort firms into portfolios, here the portfolios are simply double sorted with FSCORE and past compounded returns. Moreover, past long-term returns can possibly work as a similar proxy of expectation errors as book-to-market and other pricing multiples used in the previous studies.

Intended contribution of this study is to find, whether fundamental analysis can enhance the performance of the long-term reversal strategy. Following the expectation errors framework, it is interesting to see whether high fundamental strength (high FSCORE) companies with poor past returns outperform companies with low FSCORE and poor past performance. Similarly, the study can show whether low fundamental strength winners perform worse than high fundamental winners. Motivating results are found by Zhu et al. (2019) with short-term return reversals, as they find that a strategy that buys past one-month losers with strong fundamentals and sells past winners with weak fundamentals outperforms other short-term reversal strategies examined in the study. In addition, as it is apparent that January returns play a role in simple long-term reversals, it is interesting to see how fundamental strength-based sorting affects the role of January returns in the long-term reversal strategy.

1.3   Research hypotheses

The first hypothesis of the study is built around the expectation errors framework of Piotroski and So (2012), which is also tested by Walkshäusl (2017) in European stock

markets. These studies conclude that the future revisions are concentrated on firms which have incongruent expectations between current pricing multiples and fundamental strength. As mentioned, here long-term past return performance of stocks is expected to mimic the expectations implied by book-to-market ratio. The expectations for this study, adapted from the expectation errors framework by Piotroski and So (2012) are presented in the following table:

Table 1. Expectations framework.

	Highest long-term past returns	Mediocre past returns	Lowest long-term past returns
Low FSCORE	Incongruent expectations	Ambiguous	Congruent expectations
Middle FSCORE	Ambiguous	Congruent expectations	Ambiguous
High FSCORE	Congruent expectations	Ambiguous	Incongruent expectations

Interpreting Table 1, the strongest reversals are expected to occur in the upper-left and bottom-right corners of the matrix, which have incongruent expectations implied by past long-term returns and fundamental strength. The middle portfolios with ambiguous expectations are not examined in this study. Similar ground for the hypothesis is provided by Zhu et al. (2019) in short-term monthly return reversals, as they find that monthly return reversals are higher with past losers (winners) that have strong (weak) fundamentals. Moreover, Ahmed and Safdar (2018) and Walkshäusl (2019) find reversals in momentum returns with firms that have incongruent past performance and fundamental strength. Following the findings from previous studies, the first hypothesis for this study is the following:

H1: Firms with incongruent past long-term returns and fundamental strength are expected to have stronger long-term reversals than firms with congruent past returns and fundamental strength.

The second hypothesis tests how the strategies fare against the common risk factors. In specific, strategies are tested with the common risk factors of Fama and French (2018) three- , five-, and six-factor models. If the hypothesis holds, the returns are explained by known risk factors, and the fundamental strength-adjusted long-term reversal strategies do not gain abnormal returns. The hypothesis is motivated by Fama and French (1996), who explain the unconditional long-term return reversals with the three-factor model. In the second hypothesis, the FSCORE sorted reversal strategies are called the fundamental long-term reversal strategies. The second hypothesis is the following:

H2: Returns of the fundamental long-term reversal strategies are explained by common risk factors.

1.4   Limitations

The returns of the portfolios examined in this study are affected by survivorship bias, as this study includes only the stocks that were included in the S&P 1500 index at the time of collecting the data. This can create upward bias to the returns of the portfolios, as stocks that have been delisted from the index due to reasons such as financial distress and acquisitions are not considered in the portfolio formation. In long-term return reversal studies, survivorship bias is reported to decrease the sample size by 10 to 20 percent, in cases where portfolios are formed only of stocks that have available returns for the whole three-year holding period (Loughran & Ritter, 1996; Kothari & Warner, 1997). In this study the character of survivorship bias is different, as the effect is increasing towards the older portfolios as the dropouts are not considered.

One consequence of including only the stocks that were included in the index at the time of collecting the data is that the analysis is limited to quartile past-return portfolios. This is due to reason that some of the portfolios would become unreliably small with more extreme portfolio formations. In addition, this study does not consider trading costs and

taxes, which is not highly problematic as portfolio turnover is low, and thus the strategies included require infrequent trading due to long holding periods.

1.5   Structure of the study

This paper is organized as follows. Chapter 2 presents the theoretical background related to the subject of the paper, by reviewing the theories regarding market efficiency and common asset pricing models. In Chapter 3, the phenomenon of long-term return reversals is reviewed, which is followed by the review of studies about fundamental strength, with the focus on studies regarding FSCORE and similar metrics. Chapter 4 presents the data and methodology used in this study. In Chapter 5 the results of the study are reported and analyzed, and Chapter 6 concludes the paper.

2 Theoretical background

This chapter reviews the theories and models which are related to the subject of the paper. First, the theory of market efficiency is reviewed in Chapter 2.1. Thereafter the main asset pricing models are presented in Chapters 2.2-2.6.

2.1 Market efficiency

According to Fama (1970, p. 383), capital market's main function is to allocate the ownership of the capital stock in the economy. In the efficient markets, security prices contain all available information enabling firms and investors to make decisions on resource allocation with accurate signals of prices. The discussion of market efficiency is important for this paper, as it analyzes investment strategy based on the past return performance and available financial statement information of stocks, which should be reflected by the prices.

The efficient market hypothesis can be separated to three levels based on the form of market efficiency, which are weak, semi-strong, and strong form. The weak and semi-strong forms are closely related to the subject of this paper. In weak form of market efficiency, information subset is the past returns of securities. When the weak form of market efficiency holds, investors cannot use historical return information to make profitable future trades. In the more restrictive semi-strong form of market efficiency, security prices reflect all publicly available information, for instance annual earnings announcements. In the most restrictive form of market efficiency, strong form, all available information is reflected in prices. That means that even private information that is not accessed by all market participants, such as corporate insiders' information, would be reflected in the prices. (Fama, 1970) Fama (1970, p. 415) concludes, that weak and semi-strong forms of market efficiency are strongly supported, whereas strong form is suggested to be a benchmark for analyzing possible inefficiencies in markets.

In a re-evaluation study, Fama (1991) addresses that many anomalies have emerged in the academic literature since the original publication of the efficient market hypothesis, and that the strongest version of market efficiency is false due to information and trading costs. The original hypothesis suggests that the costs of trading and information are always zero. In a more economically robust, although weaker form of efficiency, the profits of exploiting information do not exceed the costs of information and the arbitrage trading that is needed to exploit the inefficiencies (Jensen, 1978). Also, Fama (1991) argues that the true level of market efficiency can be impossible to infer precisely due to joint-hypothesis problem, which means that the market efficiency needs to be tested together with an asset-pricing model. This creates a situation, where it is ambiguous to separate whether abnormal returns are due to market inefficiency or due to a bad-model problem.

Fama (1998) further addresses the issues with unavoidable bad-model problem when analyzing anomalies which are based on long-term returns. Fama (1998, p. 285) argues, that all models that seek to describe average returns have problems, but that the bad-model problems are more serious in longer time horizons. The reason behind is that the volatility of the returns does not grow as fast with the return horizon as the model's errors with expected returns. Also, many anomalies are seen fragile, as changes to the methodology of the certain model can cause abnormal returns to disappear, which is a strong indication that the anomaly does not provide evidence against market efficiency. Fragility of many anomalies is later supported by Hou et al. (2018), who replicate a wide section of 452 anomalies in their study. They find that after controlling for micro-caps and using value-weighted returns instead of equal-weighted returns, most of the anomalies do not replicate properly and thus are not robust. To gain more credible results, this paper uses value-weighted returns.

Opposed to the efficient market hypothesis, investor behavior-based models have emerged, which base their hypotheses on psychological evidence and models (Barberis, Shleifer, & Vishny, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998). The behavior-based models are also important for this paper, as long-term return reversals have a

significant role in them. Barberis et al. (1998) present investor sentiment-based model, which is based on investor overreaction and underreaction. In their model, sophisticated investors gain abnormal returns by exploiting investor sentiment. The model proposes that investors give too much attention to the strength of new information such as earnings announcements, and simultaneously not enough attention for information's statistical weight. In their model, investors systematically underreact to news announcements in a short time horizon up to one year. This systematical underreaction leads to slow incorporation of information to prices. On the other hand, the model proposes that investors overreact to consistent series of information in a longer period of around three to five years, in both positive and negative information cases. In their model, continuous good or bad news drive prices to non-rational levels, which eventually leads to mean reversion.

Instead of building their model on specific psychological models, Hong and Stein (1999) generate a model which is based on gradual diffusion of information across the population. In their model, a short-term underreaction to information and continuance of returns eventually leads to overreaction and return reversals in long-term time horizons. They conclude, that under- and overreactions should be more prevalent with firms that are small and have low-analyst coverage, in other words in stocks with slower diffusion of information.

Fama (1998) argues that efficient market hypothesis is robust against behavioral models of long-term underreaction and overreaction to information. In fact, pure chance is given as an explanation for such anomalies, as the occurrence of these anomalies is roughly even and both post-event reversal and continuance of abnormal returns are almost evenly frequent. In other words, chance can create deviations in both directions in the expected abnormal returns of zero in the efficient capital markets. In addition, Fama (1998, p. 285) argues that behavioral models, such as the model by Barberis et al. (1998), explain the returns poorly outside the anomalies which they are designed to explain.

2.2 Dividend discount model

To find investment opportunities and to price equities, one of the most well-known tools is the dividend discount model (DDM). Gaining its fundamental ideas from a book by Williams (1938), the model derives the price of stock, or its intrinsic value, as the discounted present value of all its expected future dividends. The model assumes, that dividends are paid into perpetuity. (Bodie, Kane, & Marcus, 2011, p. 588) The dividend discount model can be depicted with the following formula (Bodie, Kane, & Marcus, 2011, pp. 586-588):

$$V_0 = \frac{D_1}{1+k} + \frac{D_2}{(1+k)^2} + \frac{D_3}{(1+k)^3} + \cdots \tag{1}$$

where V_0 = intrinsic value of the stock

D = received dividend

k = required rate of return

In practice, assessing dividends to the perpetuity is complicated, and therefore the original model has later been modified to have more practical value. Gordon and Shapiro (1956) simplify the assessment of future dividends by the concept of estimated constant growth rate, at which the future dividends are expected to grow. This constant-growth dividend discount model, also known as the Gordon model, can be presented with the following equation (Bodie, Kane, & Marcus, 2011, p. 589):

$$V_0 = \frac{D_1}{k-g} \tag{2}$$

where V_0 = intrinsic value of the stock

D_1 = dividend paid at year one

k = required rate of return

g = growth rate of the dividends

Gordon and Shapiro (1956) conclude, that the condition for the model to hold is that the growth rate of the dividends *g* is lower than the required rate of return *k*. If the condition does not hold, the intrinsic value of the stock would be infinite. The fundamental implications of the constant-growth DDM are, that the value of an equity is higher when either the required rate of return is lower, the expected dividend is higher, or when the growth rate of dividend increases (Bodie, Kane, & Marcus, 2011, p. 590).

2.3 Capital asset pricing model

The relationship between risk and returns is an interesting puzzle in finance, and many asset-pricing models have been created to explain the relation between the two. One of the most well-known asset pricing models is the Capital Asset Pricing Model (CAPM) originally created by Sharpe (1964) and Lintner (1965), which is also a basis or inspiration for many subsequent pricing models. The model is based on the assumptions of the market model, also known as the modern portfolio theory by Markowitz (1952). The CAPM predicts that the assets' expected excess returns are in a positive linear relation to their systematic risk. The systematic risk of an asset is implied by its beta (β), and in its traditional form the asset is supposed to have relatively higher expected excess return with higher beta due to its higher systematic risk. According to the model, the asset's expected excess returns should be strictly proportional to its beta. (Black, Jensen, & Scholes, 1972) The expected return of a stock and its relation to beta can be expressed with the following formula (Bodie, Kane, & Marcus, 2011, pp. 282, 293):

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \tag{3}$$

where $E(R_i)$ = expected return of the security i

R_f = risk-free rate

β_i = the beta coefficient of the security i

$E(R_m)$ = expected return of the market portfolio m

The traditional CAPM has certain assumptions, which are listed below (Black et al. 1972, pp. 1971-1972):

1. All investors can choose the portfolio on the basis of mean and variance, therefore using portfolio selection model (Markowitz, 1952).
2. Investors do not pay taxes or transaction costs.
3. Investors have homogeneous views and expectations, meaning that they share the same parameters on the returns of securities in joint probability distributions.
4. All investors can lend or borrow at a risk-free interest rate.

The traditional form of the CAPM is not consistent in the empirical tests. Evidence by Black et al. (1972) show, that low-beta securities have positive intercepts and high-beta securities have negative intercepts, which is contrary to traditional theory, as low (high)-beta securities have higher (lower) returns than what the model suggests. Also, not consistent with the prediction of the model, the intercept and the slope of the CAPM vary throughout the different time periods. Roll (1977) concludes, that valid testing of CAPM is impossible due to presupposition that the true market portfolio is known, as the correct test would use a market portfolio that includes all individual assets.

2.4 Three-factor model

Continuing from the patterns left unexplained by the CAPM, Fama and French (1993) explain the average returns of securities with the three-factor model. Combining evidence from various studies, Fama and French (1992) seek to explain the cross-section of average returns with beta, size as market capitalization, earnings-to-price-multiple, leverage, and book-to-market equity-multiple. In addition to conclusion that the positive relation between beta and average stock returns is not found, they find that especially

the combination of size and book-to-market have a strong role in explaining average re-turns, which also absorb the roles of earnings to price-multiple and leverage. The results mean, that instead of the risk of equities being one dimensional, there are multiple aspects of risk with affect the equities.

Fama and French (1993) continue the tests with time-series regressions and have strong evidence that in addition to excess market return factor, size and book-to-market factors explain well the variations in average stock returns. Size and book-to-market equity are linked to be proxies that capture the risk of common stocks, as high book-to-market firms tend to be financially distressed and to have bad prospects and low earnings on assets, whereas low book-to-market equity firms tend to have persistently high earnings. Size is also linked to risk via earnings, as small firms tend to be riskier than big firms due to more unstable earnings.

In the three-factor model, the size factor, known as SMB (small minus big), mimics the risk related to size by calculating the difference of average returns of portfolios of rela-tively small market capitalization stocks and portfolios of relatively large market capital-ization stocks with approximately matching weighted-average book-to-market equity. The book-to market equity risk factor, known as HML (high minus low), is measured by calculating the difference of average returns of two high book-to-market portfolios with large and small market capitalization stocks and two low book-to-market portfolios with approximately matching weighted-average size. (Fama & French, 1993) The three-factor model can be expressed with the following time-series regression equation (Fama & French, 2015, p. 2):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad (4)$$

where R_{it} = return on portfolio i for time t

R_{Ft} = risk-free return

R_{Mt} = return on the value-weighted market portfolio

SMB_t = risk factor related to size

HML_t = risk factor related to book-to-market equity

e_{it} = zero-mean residual

In a case that the intercept a_i is zero in the equation (4), the variation in expected returns is explained by the factors b_i, s_i, and h_i. Fama and French (1996) report, that the three-factor model does well on explaining the risk of stock returns and shows ability to explain investment anomalies. Interestingly, long-term return reversals are explained with the three-factor model, as HML and SMB slopes tend to be positive on stocks with poor long-term past performance and thus these stocks tend to have higher average returns in the future due to higher financial distress and smaller size. On the other hand, stocks with high long-term past performance tend to have low returns in the future and negative slope on HML risk factor, indicating of low financial distress.

2.5 Five-factor model

Even though the three-factor model is an improvement from CAPM in explaining the average stock returns, studies have reported anomalies which the model has difficulties to explain. Evidence from Titman, Wei and Xie (2004) show, that abnormal investment expenditures and future stock returns have a negative relation which is not explained by size and book-to-market risk factors. Firms with the highest addition to the level of capital expenditure tend to have gained positive returns in the past but gain lower returns up to next five years. As firms that have higher increases of capital expenditures are characterized by higher past returns and lower future returns, Titman et al. (2004) test the robustness of the results by controlling for long-term reversal of returns. They find that capital expenditures are independent of the return reversal effect but suggest that the reversal effect might be caused by the level of capital expenditures.

Also, Novy-Marx (2013) finds that the three-factor model is unable to capture the effect of firms' profitability in the cross section of average returns. Although having higher

valuation ratios, more profitable firms, proxied by gross profits-to-assets, tend to have significantly higher returns than firms with low profitability. In fact, profitability has approximately as high role in explaining the cross section of average returns as value factor, and profitability explains well a wide array of investment anomalies and strategies, especially anomalies which relate to earnings. Also, the returns of value strategies increase significantly when controlled for profitability. The results of Novy-Marx (2013) confront the original interpretation of value premium by Fama and French (1993), as value returns are not driven by financial distress, as value firms with higher profitability have higher returns than unprofitable value firms. These findings are also important from the aspect of this study, as firm profitability is one of the main dimensions of FSCORE, and FSCORE works as a leading indicator of firms' future profitability as suggested by Piotroski (2000).

Due to inability to capture the effects of investment and profitability in variation of average returns, Fama and French (2015) augment the three-factor model with profitability and investment factors. Profitability, known as RMW (robust minus weak), is measured by calculating the difference between stock portfolios with robust and weak operating profitability. Investment, known as CMA (conservative minus aggressive), is the difference between stock portfolios of low and high investment firms, where investment is measured as change in the total assets. As the value factor HML, the factors for profitability and investment can be interpreted as the averages of the factor portfolios for small and large market capitalization stocks. Positive exposures to profitability and investment factors mean that these stocks tend to be profitable firms with conservative capital expenditures, whereas negative slopes for these factors indicate relatively low profitability and aggressive capital expenditures. The five-factor model can be expressed with the following equation (Fama & French, 2015, p. 3):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + \qquad (5)$$
$$r_i RMW_t + c_i CMA_t + e_{it}$$

Where in addition to equation (4):

RMW_t = risk factor related to profitability

CMA_t = risk factor related to investment

As in the three-factor model, the intercept α_i measures the abnormal return for a port-folio *i*. One might ask, what is the rationale behind the decision to augment the three-factor model with profitability and investment, as there are also other puzzles in explain-ing the variation of stock returns. Fama and French (2015) explain the choice of profita-bility and investment with theoretical assumptions, as the use of these factors is based on a derivation of the dividend discount model by Miller and Modigliani (1961).

Generally, the five-factor model fares better than the three-factor model, capturing more anomalies and explaining better the variation in expected returns. Interestingly, augmenting the three-factor model with profitability and investment makes the value factor (HML) redundant, at least in U.S stock markets. On the other hand, the five-factor model has problems in the smallest size quintile portfolios with sorts on accruals, where the model does worse than the three-factor model. In addition, the five-factor model continues to fail in explaining momentum, which is reviewed in the next subchapter. (Fama & French, 2016)

2.6 Six-factor model

One puzzling phenomenon for the asset pricing models has been momentum effect. Jegadeesh and Titman (1993) find, that simply buying past winners and selling past losers gain significant abnormal returns. For instance, the effect is strong with six-month for-mation and holding periods, with the returns dissipating 12 months after the portfolio formation. A strategy of buying past winners and selling past losers gains positive returns for all but the first month during a 12-month holding period. In the later studies, the momentum effect of returns is found on international markets for instance by Fama and French (2012) and Asness, Moskowitz, and Pedersen (2013), with an exception of Japa-nese markets. As one of the suggestions to explain the phenomenon, Jegadeesh and

Titman (1993) suggest, that the phenomenon is linked to behavioral bias, with investors underreacting to information about firms' short-term prospects.

The explanation for the momentum anomaly is under debate, with risk- and behavior-based explanations suggested for the phenomenon. Generally supportive of underreaction based hypothesis by Jegadeesh and Titman (1993), Hong, Lim, and Stein (2000) base their hypothesis on the gradual information diffusion model of Hong and Stein (1999) and use firm size and analyst coverage as the proxies for the model. They find that momentum strategies' profitability declines significantly as the market capitalization increases. Also, momentum returns tend to be higher with firms that have low analyst coverage.

From a risk-based perspective, Pastor and Stambaugh (2003) create a market wide liquidity-based factor, "liquidity beta", to measure stocks' sensitivities to changes in aggregate liquidity. They find that liquidity, measured with stocks' daily returns and volume, has an important role in asset pricing. The spread between expected returns with the extreme decile portfolios gain abnormal annual returns of approximately 7.50% between the high liquidity beta portfolio and low liquidity beta portfolio, when controlling for the market, size, value, and momentum factors. Interestingly, a factor for liquidity risk explains about 50% of abnormal returns for momentum during the 34-year period used in the study. They conclude that the momentum strategy becomes less tempting when liquidity risk-based portfolio spreads are available, but do not successfully explain the whole phenomenon of momentum returns. Regardless of the specific explanation for the phenomenon, and as momentum is highly robust in out-of-sample tests and across asset classes as shown by Asness, Moskowitz and Pedersen (2013), Fama and French (2018) augment the five-factor model with momentum to form the six-factor model, which can be expressed with the following equation:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + \qquad (6)$$
$$r_i RMW_t + c_i CMA_t + m_i UMD_t + e_{it}$$

Where in addition to equation (5):

UMD_t = risk factor related to momentum

Momentum factor UMD (up minus down) is updated monthly by forming the portfolios based on average returns from months t-12 to t-2 with the portfolios being formed at the end of month t-1. In a similar fashion as value (HML), profitability (RMW), and investment (CMA) factors, momentum factor (UMD) is formed with spread portfolios by subtracting the average return on the two low past return portfolios of small and large market capitalization equities from the average return on the two high past return portfolios with approximately matching weighted-average size. In this paper the three-, five- and six-factor models are all used in explaining the returns of long-term reversal portfolios with fundamental strength-based sorts.

Whereas profitability and investment factors go under the umbrella theory of dividend discount model, momentum factor is more complicated for the finance theory. Fama and French (2018) raise the concern of using seemingly robust anomalies such as momentum in the asset-pricing models, as without a clear explanation for such a phenomenon a question can be raised about the persistence of the patterns in the future. Also, although the momentum factor is used in the six-factor model, Fama and French (2018) suggest to limit the use of factors to such which are explained by theoretical models.

3   Literature review

This chapter reviews the phenomenon of long-term return reversals in Chapter 3.1. Chapter also presents various explanations for the phenomenon. In Chapter 3.2, the studies regarding the concept of fundamental strength and fundamental scores are reviewed.

3.1   Long-term return reversals

In investing, overreactions can be explained as biased expectations of future earnings of stocks. For instance, people can become excessively pessimistic about certain stocks' future after a company repeatedly presents bad earnings reports. When in time the firm presents better than expected numbers, the stock reverts. On the other hand, people can also become overly optimistic with certain stocks, which eventually revert as the firms cannot fulfill the expectations. (De Bondt & Thaler, 1985) The main thesis in the paper from De Bondt and Thaler (1985) is, that if there is systematical overreaction in the markets, it can be observed by using only past return patterns instead of accounting data.

Without going in specific to find the explanation behind the possible overreactions, De Bondt and Thaler (1985) conduct an empirical study by using monthly cumulative excess returns in U.S stock market, and suggest that by focusing on the most extreme returns of preceding five years, the stocks with poorest past returns, named as the loser stocks, outperform the market in the next three to five years after the portfolio formation. Simultaneously the stocks with the most extreme positive past returns, named as the winner stocks, perform worse than the market. De Bondt and Thaler (1985) find, that in a subsequent three-year period, the past loser stocks have approximately 25% higher returns than the past winner stocks. Also, according to their hypothesis, the more extreme the past returns, the higher is the subsequent reversal of the stock. These findings are linked to investors' overreaction.

Two years later in the follow-up study De Bondt and Thaler (1987) continue to find similar systematic price reversals. By using accounting information, they also find that prior extreme stock returns predict later reversals in firm's earnings, which indicates market inefficiency in recognizing mean reversion in future earnings of firms, being consistent with overreaction hypothesis. At the same time, the results cannot be primarily explained by the alternative hypotheses, which are the firm size effect or CAPM beta based-risk measurement. As in their previous study, unusually high returns in January are observed, especially for the past losers. In fact, most of the reversals occur during Januaries. De Bondt and Thaler (1987) link investors' tax motivated trading as a possible explanation for the unusually high January returns.

Conrad and Kaul (1998) analyze various return-based investment strategies in U.S stock markets and find long-term return reversals with holding periods from 18 to 36 months only partly profitable. Profitability of long-term reversals is statistically significant only on the subperiod of 1926-1947, and it is linked to severe and unusual price movements during the period. They argue that instead of time-series patterns of individual stocks, the cross-sectional variance in the mean returns of stocks is a major factor in generating the profitability of reversal strategies, and due to this reason the statistically significant returns disappear for other periods.

Opposite to investor overreaction hypothesis, there are seasonality and risk-based explanations for long-term reversals. Zarowin (1990) re-examines the overreaction hypothesis and finds that three-year period reversals presented by De Bondt and Thaler (1985; 1987) are due to size differences between winners and losers, as loser stocks tend to be smaller. When the size is controlled, losers outperform past winners only in January. Fama and French (1996) extend this analysis and explain the returns of long-term reversals with the three-factor model. They find that past loser stocks tend to be relatively smaller and financially distressed and have on average higher future returns, whereas winners are relatively strong stocks with negative slopes on book-to-market factor and

low future returns. During the period from 1963 to 1993, long-term reversals exist up to five years, when using past 60 to 13 months returns in the formation. When the year before the formation is included, the winners gain higher returns than the losers due to continuation of short-term returns.

Grinblatt and Moskowitz (2004) link long-term reversals to seasonality and tax-loss selling and argue that due to these reasons long-term reversal returns are driven by January effect. George and Hwang (2007) also challenge overreaction hypothesis with tax-based hypothesis with samples from U.S and Hong Kong. In U.S stock markets, they attribute the loser stock reversals to tax-loss selling in December, whereas the reversals for winners are attributed to capital gains lock-in. Opposite to U.S, Hong Kong does not have capital gain taxes and the reversals disappear for winners and loser in every month including January, therefore strengthening the evidence for tax-based hypothesis. Also, Yaqiong (2012) analyses U.S stock markets between 1926 and 2009 and suggests that the returns of long-term return reversals are not due to investor overreaction and are rather largely non-existent. He suggests that long-term reversals are economically and statistically significant only in January with small firms, whereas negative return autocorrelations associated with long-term reversal returns are not robust outside January. As in the study by Fama and French (1996), the strategy differs from the original De Bondt and Thaler (1985) strategy, as there is one-year gap between portfolio formation and holding period.

In accordance with risk-based hypothesis, Garcia-Feijoo and Jensen (2014) link long-term reversals to monetary conditions and in more specific to firms' funding and to its constraints. The results suggest that the reversal returns of past losers are driven by improved monetary conditions, during which liquidity increases, and risk aversion of investors is reduced. In their analysis the prices of loser stocks of preceding five years reverse only during expansive monetary environment, with the reversals existing even outside January during those conditions. In turn, restrictive monetary environment affects negatively the firms which have relatively less access to funding, and which are more

dependent on external funding. The strongest reversals for loser stocks are obtained with small sized and financially distressed companies in line with risk-based explanations by Fama and French (1996). On the other hand, the return reversals for winner stocks occur only during restrictive monetary conditions, as the small sized and financially distressed past winners struggle the most during those conditions. The results of the study support the theory of time variation in risk and risk premium.

Long-term reversals are also examined in international markets. Baytas and Cakici (1999) analyze past return performance in U.S and in six other industrialized countries using holding period returns instead of cumulated abnormal returns. In addition, they analyze price and size-based strategies which do not consider the past return performance. The price-based strategy buys stocks with lowest prices, and sells stocks with the highest prices, whereas size portfolios sort the stocks to groups based on their market capitalization. Excluding U.S, they find evidence of overreaction and long-term return reversals are generally profitable with three-year arbitrage portfolios, which buys winners and sells losers. Baytas and Cakici (1999) suggest, that past performance based long-term reversal returns for winners and losers are partly explained by price and size effects. For example, the loser stocks are usually low priced and low market value companies. Their study finds that long-term strategies based on size and price outperform the long-term return reversal strategy, especially in the case of latter.

Wu et al. (2012) analyze, whether long-term reversal returns are concentrated on low-priced stocks. Using data from UK stock markets from 1970 to 2009, return reversals are found in low, middle, and high price levels for the past five-year losers and winners. The reversal returns are mainly driven by positive performance of past loser stocks. When the risk-adjusted performance is measured with Fama and French (1996) three-factor model, low and middle priced loser stocks have significantly positive abnormal performance. In buy-losers and sell-winners zero-cost strategy, only the middle-priced stocks maintain significant positive returns. In addition to three-factor model, the returns are also measured with liquidity-augmented CAPM. Abnormal returns disappear for low-

priced loser stocks when adjusted for liquidity and market risk, whereas abnormal returns for middle-priced loser stocks endure. These findings go against the hypothesis that long-term reversal returns are driven only by low-priced stocks. Also, the findings generally support overreaction hypothesis.

Chou, Wei and Chung (2007) use different ranking and holding period lengths from one month to three years and find that long-term return reversals are profitable in Japanese markets throughout all the time periods. The most prominent reversals occur in the one-month and in the two-year and longer periods. The results are robust even when the companies with the most extreme past returns are excluded, or when there is a one-month skip between portfolio formation and holding period. Chou et al. (2007) also separate the study's horizon to bull and bear markets based on the market's aggregate performance. The analyzed strategies perform better when either formation or holding period is in the bull market but are robust during both bull and bear market environments. Opposite to overreaction hypothesis, reversal returns are linked mainly to lead-lag effect, which means that there are positive autocorrelations between the stocks. Chou et al. (2007) use Fama and French (1996) three-factor model to explain reversal returns and argue that the returns are not due to pricing errors of the model, but rather attributed to cross-autocorrelations in company-specific error components.

Galariotis (2012) analyzes the profitability of long-term return reversals in French stock markets and finds that portfolios are profitable on average, but the performance of hedge portfolios is not consistent from one period to another. The most profitable strategy is to take long-only positions in losers during stable market conditions, as the results indicate that the winners do not systematically revert to losers. The returns are not explained by risk factors of Fama and French (1996) three-factor model. Rather the reversal returns in French stock markets are linked to overreaction hypothesis in the case of loser stocks, as for example the returns of the strategy increase with more extreme portfolio formations, meaning that less companies are included in the portfolio.

Differing from previously reviewed studies, Gropp (2004) analyzes the reversals in U.S stock markets from 1926 to 1998 using industry sorted portfolios. Alongside a standard long-term return reversal strategy based on the method of De Bondt and Thaler (1985), a parametric reversal strategy is used in the study. The purpose of parametric reversal strategy is to benefit from the mean reverting component in asset prices, and in fact the parametric reversal strategy outperforms the standard reversal strategy and an equal-weighted market index. Bornholt, Gharaibeh and Malin (2015) also form industry port-folios and find strong evidence of long-term industry reversals in U.S stock markets. In addition to a standard reversal strategy, the specialty of the study is to use longer for-mation periods up to 11 years. Moreover, a late-stage return reversal strategy is used, which exploits double-sort method with long-term past performance and recent short-term performance with an aim to pick stocks which are more likely to have reversals. The late stage return reversal strategy performs better than a standard reversal strategy. In-terestingly, the industry reversals are documented in longer time periods up to 108, 120 and 130 months, whereas reversals are not observed in conventional reversal strategies using formation and holding periods from three to five years.

Similar industry reversals are also observed in international markets, as Wu and Mazouz (2016) analyze UK stock markets and find reversals in loser and winners industries, with the losers significantly outperforming the winners in subsequent five-year holding pe-riod. The returns of industry reversal portfolios are robust to seasonal effects and the ability of traditional risk factors from the three- and five-factor models by Fama and French (1996; 2015) to explain the reversal returns is limited. Although, statistically sig-nificant abnormal returns are weak in the five-factor model regressions. Moreover, the reversals are robust after controlling to stock- and industry-level momentum effect. The long-term industry reversals are linked to mispricing instead of risk-based explanation, as the returns increase for relatively lower analyst coverage and higher accrual industries. On the other hand, risk-adjusted abnormal stock-level reversals disappear entirely and are linked to tax loss selling hypothesis as they happen only during January and April, with April being tax year-end in UK. In addition, they study the relation of industry and

individual stock reversals and find that individual stock returns are heavily influenced by the past returns of industries, and therefore suggest that the stock reversals are due to industry components.

3.2 Fundamental strength

Financial statement information and fundamental analysis has been used to enhance various investment strategies, and for instance profitability related fundamental metrics have challenged asset pricing models such as Fama and French's (1996) three-factor model. One of the popular metrics to sort firms to financially strong and weak is Piotroski's (2000) FSCORE. FSCORE is used as an accounting-based analysis tool, and it is created by aggregating nine signals which measure firm's historical profitability, financial leverage and operational efficiency, with a high FSCORE value indicating strong fundamentals and a low FSCORE value indicating weak fundamentals. In the original study, Piotroski (2000) combines the FSCORE with book-to-market ratio with a goal to differentiate the fundamental strength of often neglected and thinly followed value stocks, as the valuation of these stocks with poor recent performance can rely on various accounting fundamentals such as profitability and leverage. Also, Piotroski (2000, p. 2) notes that the good performance of the value strategy of buying high book-to-market stocks relies on the good performance of a few stocks, whereas the majority of value stocks earn negative market-adjusted returns in the subsequent years. Therefore, it seems intuitive to try to enhance the returns of contrarian strategies by separating the firms with high fundamental strength from firms with deteriorating fundamentals.

Piotroski (2000) finds predictable future return patterns when high book-to-market companies are sorted to financially strong and weak companies with FSCORE. In addition, FSCORE works as a leading indicator of firms' future profitability and earnings performance. The results show that value investors can increase their average annual returns by at least 7.5% by choosing financially strong companies. By creating an arbitrage strategy which buys expected winners and sells expected losers, annual returns are

substantially high at 23%. The strategy is robust throughout the whole time period from 1976 to 1996. The findings are linked to investors' underreaction to historical information, with investors' underweighting new financial information which contradicts with old information. The benefit of fundamental analysis by using FSCORE with high book-to-market firms focuses on small and medium sized firms with relatively lower analyst following, which is linked to be driven by lower information dissemination amongst these groups. In large firms and stocks with relatively high analyst following, strong market adjusted returns disappear which goes in line with gradual information diffusion model by Hong and Stein (1999). Therefore, the study also works as a supportive test of behavioral models in value investing environment.

Regarding fundamental analysis with a simple profitability measure of gross profits-to-assets, Novy-Marx (2013) finds that profitability significantly increases the performance of value strategy, with the effect being significantly strong among large-cap firms. Therefore, firm profitability-related metrics have shown power in explaining returns in different size groups, also in large caps. These findings are very puzzling from the perspective of original risk-based explanation for value effect, as the financial distress has been considered as the main driver for the value premium. Moreover, higher profitability leads to higher average returns on itself without controlling for value.

In a follow-up study to Piotroski (2000), Piotroski and So (2012) form portfolios with FSCORE and book-to-market ratios, and they continue to enhance the returns of conventional value/glamour strategy by including fundamental strength-based sorting in portfolio formation. In their study, book-to-market ratio and FSCORE are used as proxies to measure investors' market-based and fundamental-based expectations about the firm's future earnings performance. For instance, low book-to-market ratio indicates high future performance expectations and high book-to-market ratios indicates low future performance expectations. They find that the value/glamour effect on the returns is statistically and economically significant with firms where the expectations are incongruent with firm's current fundamental strength. In other words, their hypothesis means there

are expectations errors which can be observed with released financial information. On the other hand, firms with congruent expectations implied by book-to-market ratios and current fundamental strength do not have statistically and economically significant value/glamour effect on the returns. In their study, E[E[BM] denotes the expectations implied by book-to-market ratios, and E[E[FSCORE] denotes the expectations implied by current fundamental strength. The expectations framework can be depicted by using the matrix presented in Table 2:

Table 2. Value/Glamour portfolios (Piotroski & So, 2012, p. 2847).

	Low BM Firms "Glamour" (Strong expectations)	Middle BM Firms	High BM Firms "Value" (Weak expectations)
Low FSCORE (Weak fundamentals)	E[E|BM]> E[E|FSCORE] Overvalued firms	Potential for overvalued firms	E[E|BM]≈E[E|FSCORE]
Middle FSCORE	Potential for overvalued firms	E[E|BM]≈E[E|FSCORE]	Potential for undervalued firms
High FSCORE (Strong fundamentals)	E[E|BM]≈E[E|FSCORE]	Potential for undervalued firms	E[E|BM]<E[E|FSCORE] Undervalued firms

In their expectation errors hypothesis, the incongruent portfolios with the strongest value/glamour effect are in upper-left and bottom-right corners of the matrix. Specifically, their strategy buys firms with high FSCORE and high-book-to-market in the bottom-right corner and short sells firms with low FSCORE and low book-to-market in the upper-left corner. Moreover, Piotroski and So (2012) find that investor sentiment's variation has a significant effect on portfolios with stocks that have incongruent fundamental- and market-based expectations. They suggest, that when investor sentiment is high (low), the returns to the portfolios with incongruent market expectations and fundamental strength are relatively higher (lower). On the other hand, congruent value/glamour portfolios do not have significant relation with the sentiment.

Choi and Sias (2012) find that financial strength, measured by FSCORE, has ability to predict future returns and in addition the future demand of institutional investors. The study suggests that future stock returns are predicted by fundamental strength partly because fundamentals predict the institutional demand, which drives the prices and generates higher returns for companies with high FSCORE. Institutional investor demand comes in two stages, with more sophisticated high-turnover institutions responding to the signals about fundamental strength before less sophisticated institutions with lower turnover. These findings support a behavioral framework of gradual incorporation of public information, where investors either react slowly to new information which opposes the current view, or where investors are prevented from reacting to new information due to market frictions.

With similar methodology to Piotroski and So (2012), Ng and Shen (2016) test the performance of FSCORE portfolios in seven Pacific-Basin stock markets. The mean returns of portfolios with strong fundamental stocks are higher when compared to portfolios with weak fundamentals at the significance level of 1% in all the seven markets included. Similarly, FSCORE sorting can enhance the returns of traditional book-to-market and size strategies, with the effect being more significant for the latter. Long-only strategy which buys value or small-cap stocks with high FSCORE outperforms the hedged zero-cost strategy in most of the markets, with the long-only value strategy gaining statistically significant positive returns in five of the seven markets included, whereas long-only size strategy gains statistically significant returns in all of the markets. Moreover, the long-only and zero-cost strategies are robust after controlling for common risk factors.

Similar to Ng and Shen (2016), Hyde (2018) analyzes portfolios sorted solely with FSCORE. With Australian stock sample, he finds that a zero-cost strategy which buys high FSCORE stocks and sells low FSCORE stocks is profitable, with high FSCORE firms having significantly higher returns than low FSCORE firms. The returns are explained with the four-factor model, which augments the three-factor model with 12-month momentum factor.

Abnormal returns are gained only with equal-weighted strategy that includes micro-cap stocks, whereas the abnormal returns disappear when using value-weighted returns.

Walkshäusl (2017) tests expectation error hypothesis in European stock markets and finds similar results to Piotroski and So (2012), as the returns of value-growth strategies are concentrated on firms with expectation errors. Interestingly, the returns of the strategy sustain up to three years after the portfolio formations and exist amongst large companies. The obtained results are not explained by common risk factors, by using CAPM and the four-factor model to explain the returns. In addition, Walkshäusl (2017) studies the effect of prior external financing activities in the strategies. The study links prior stock issuances and repurchases as the explaining factor for value/glamour strategy returns in cases of portfolios with incongruent market expectations and fundamental strength. In other words, the return difference of repurchasing and issuing firms shows ability at explaining the returns of incongruent strategies. The thesis behind using prior financing activities as a factor for mispricing is that firms can exploit these activities in cases of under- or overvaluation, for instance by issuing capital when the firm's stock is assumed to be overvalued.

Tikkanen and Äijö (2018) combine FSCORE and several value strategies in various European stock markets, by using various financial ratios such as earnings-to-market and EBITDA-to-enterprise value to form the value portfolios. With the study focusing only on long-only portfolios, FSCORE enhances the performance of all value strategies analyzed in the study, with the best performance gained with EBITDA-to-enterprise value-sorted high fundamental strength portfolios. Compared to traditional value strategies, one of the highest improvements is gained by combining high FSCORE stocks and traditional book-to-market sorting. In addition to other risk measures, the study uses Fama and French (2015) five-factor model for explaining the returns and for analyzing the factor loadings of the strategies. Tikkanen and Äijö (2018) find that the returns are not fully explained by the model. Moreover, the study suggests that high FSCORE indicates

positive future profitability, as the profitability factor loading is positive and statistically significant in the five-factor model regression.

By focusing on German stock market, Pätäri, Leivo, Hulkkonen and Honkapuro (2018) have similar findings as Tikkanen and Äijö (2018), as FSCORE-based screening can enhance the performance of a wide section of value strategies, and also low-accrual stocks. In addition, they find that outperformance of FSCORE-sorted strategies is concentrated on bearish market periods, when stock markets are in downtrend. FSCORE-based fundamental strength sorting enhances the average performance of the strategies also on bull market periods, but the effect is not as substantial. Moreover, the study finds a strong positive relationship between high FSCORE stocks and price momentum.

In addition to value firms, quantitative fundamental analysis based on historical information is reported to be able to separate future winners and losers amongst growth firms with low book-to-market ratios. Mohanram (2005) forms an aggregate index named GSCORE, which is created by using eight signal values from financial statement information that are assumed to be more suitable for growth stock analysis, such as stability of growth and capital expenditures. The study finds that high GSCORE firms with strong fundamentals have significantly higher returns than low GSCORE firms with weak fundamentals. In similar fashion as FSCORE, GSCORE also predicts the future performance of earnings, as firms with high GSCORE are more likely to gain abnormal returns around subsequent earnings announcements. The good performance of the zero-cost long-short strategy is focused on the low returns of low GSCORE growth firms, and therefore the ability of shorting stocks is needed for the strategy to be profitable. The strategy is robust in highly followed large cap firms with high liquidity, which facilitates the implementation of short strategies. The results are also robust to common risk factors, and the returns of the strategy are linked to mispricing and misinterpretation of financial information instead of risk-based explanations.

By employing both FSCORE and GSCORE, Duong, Pescetto and Santamaria (2014) study the effect of fundamental analysis on value and growth context in UK stock markets. The study implies that value investors should focus on the financially strong high FSCORE value stocks, while avoid shorting growth stocks with poor fundamentals as the short side is not profitable. Similarly to previous study by Mohanram (2005), growth investors should focus on shorting low GSCORE growth stocks as it covers the most of profits. Duong et al. (2014) link glamour and value effects to a one of the suggested investor behavior biases, known as confirmation bias, in which investors search and support information which is in line with their current views, and misinterpret opposing information. From value investing perspective, confirmation bias can be interpreted as investors either reacting fairly or overreacting to bad financial information and underreacting to good information, which differs from their current view. On the other hand, growth investors react to good information quite efficiently or overconfidently and underreact to bad information, which once again differs from their own view of the stock's prospects. Overall, the results of the study are not restricted to small sized and thinly traded stocks.

Turtle and Wang (2017) analyze performance of portfolios by combining FSCORE and momentum, where the portfolios are long on past winners and short on past losers based on past returns. Especially the portfolios with high fundamental strength and high momentum have strong ex-post returns, which are not merely explained by compensation for higher risk. By using size, illiquidity and idiosyncratic risk as measures of information uncertainty, they find that the performance of portfolios increases when information uncertainty is higher. In other words, the observed mis pricings are mainly linked to gradual price adjustments to underreactions in environments of high information uncertainty or investor sentiment, which is consistent with the behavioral framework from Daniel et al. (1998). Similarly, Chen et al. (2016) analyze momentum returns and combine FSCORE and GSCORE in the analysis. By incorporating these two fundamental metrics to momentum strategy, they obtain higher returns than with a standalone momentum strategy. Chen et al. (2016) argue, that the both fundamental scores incorporate

information that is not priced in the market in a timely manner, which generates higher returns.

Similarly, Ahmed and Safdar (2018) manage to enhance the returns of momentum strategy with financial statement analysis by using FSCORE. They hypothesize, that firms with incongruent fundamental strength and past performance should experience return reversals in the future, as their past performance is driven by non-fundamental drivers such as noise trading. On the other hand, firms with congruent fundamentals and past performance are more likely to continue to perform as in the past as their fundamentals are in line with the past performance. In accordance with their hypothesis, Ahmed and Safdar (2018) find that firms with congruent fundamental strength and past performance have substantially more persistent returns than firms with incongruent fundamentals and past performance, which indicates that fundamental strength plays a critical role in momentum returns. A zero-cost strategy which buys strong winners and sells weak losers gains significantly higher average annual returns than a standard momentum strategy, with the average returns of the strategies being 11.59% and 4.35%, respectively. In addition, financial statement analysis can decrease the downside risk of momentum strategies. Consistent with the findings from U.S stock markets by Ahmed and Safdar (2018), Walkshäusl (2019) finds that momentum returns in European stock markets are also depended on the firms' fundamental strength, and non-existent with firms that have incongruent fundamental strength and past performance. Interestingly from the perspective of this study, past losers with strong fundamentals and past winners with weak fundamentals exhibit significant return reversals in holding periods that are longer than one year.

Regarding reversal strategies, Zhu et al. (2019) find results which are consistent with behavioral models of slow diffusion of information and investors' underreaction from Hong and Stein (1999) and Hong et al. (2000). Zhu et al. (2019) suggest that FSCORE has a significant link on the performance of short-term reversal-based strategies. The study shows that high FSCORE firms with poor past performance during the past one month

have significantly high monthly returns, whereas companies with low FSCORE and good performance during the past month have systematic negative reversals. Compared to the standard zero-cost short-term reversal strategy without fundamental-based sorting, the returns of the fundamental strength-based reversal strategy are almost four times higher. This arbitrage strategy, called fundamental-anchored reversal (FAR) strategy is created by buying past losers with high fundamental strength and selling past winners with low fundamental strength. On the other hand, fundamental-unanchored reversal (FUR) strategy, which is created by buying past losers with low financial strength and selling past winners with high financial strength, performs significantly worse than the FAR-strategy. Importantly, the FAR-strategy's reversals withstand in non-January months and gain abnormal returns when controlled with the risk factors of the three- and five-factor models. The results suggest that profitability of the strategy is strongly linked to investor sentiment and therefore to mis pricing.

4   Data and methodology

This chapter presents the data and methodology which are used to form and analyze the fundamental long-term reversal strategies. Chapter 4.1 presents formation of FSCORE and the portfolios. In Chapter 4.2, the risk-adjusted performance measures used in the study are presented.

In this study, the stocks are double sorted to portfolios with past performance and FSCORE-values. Stock and market index performance data is collected from Thomson Reuters Datastream, and financial statement information for the calculation of FSCORE is collected from Worldscope. Stock market data includes the stocks included in S&P 1500 index at the time of data collection at the end of May 2019. S&P 1500 consists of all the stocks included in the S&P 500, S&P 400, and S&P 600 indices.

4.1   FSCORE and portfolio formation

To measure the fundamental strength of firms, stocks are sorted to portfolios based on the FSCORE-value calculated with the most recent year-end financial statement information before the portfolio formation. Originally presented by Piotroski (2000), FSCORE is used here similarly and separated to nine signals based on firm profitability, change in financial leverage/liquidity and change in operational efficiency. Every signal gives a binary value of one or zero, and by aggregating the signal values FSCORE gives a total value between zero and nine for every stock. The signal points consist of the following nine attributes (Piotroski & So, 2012, pp. 2870-2871):

- positive return on assets (*ROA*)
- positive cash flow from operations (*CFO*)
- positive change in return of assets (*ΔROA*)
- positive difference on current year's net income before extraordinary items minus cash flow from operations (*ACCRUAL*)

- positive change in long term debt (*ΔLEVER*)
- positive change in current ratio (*ΔLIQUID*)
- no issuance of new equity (*ISSUANCE*)
- positive change in gross margin (*ΔMARGIN*)
- positive change in asset turnover ratio (*ΔTURN*)

FSCORE-value of nine signals the highest level of financial strength and value of zero signals the lowest. The more detailed definitions of the financial performance signals are reported in the Appendix 1. The aggregate FSCORE can be expressed with the following equation (Piotroski & So, 2012, p. 2871):

$$FSCORE = F_{ROA} + F_{CFO} + F_{\Delta ROA} + F_{ACCRUAL} + \qquad (7)$$
$$F_{\Delta LEVER} + F_{\Delta LIQUID} + ISSUANCE + F_{\Delta MARGIN} + F_{\Delta TURN}$$

In the portfolio formation, the reversal portfolios are first created by ranking the stocks to quartiles based on the past 36 months returns, with both ranking and holding periods set to be three years. The returns are measured using compound returns. The stocks with the compound return at the 1st quartile and below are sorted to loser portfolio, and the stocks with the return at the 3rd quartile and above are sorted to winner portfolio. This process is repeated for every non-overlapping period of 36 months.

The portfolios are sorted to subgroups between high and low fundamental strength, with FSCORE equal to seven and above indicating high fundamental strength and FSCORE equal to three and below indicating low strength. In total four double sorted portfolios are formed for every non-overlapping time period on the last trading day of June based on the past 36-months returns and previous year-end accounting variables. In addition, simple loser and winner portfolios without FSCORE-sorting are formed and reported in the study. The last trading day of June is chosen as the portfolio formation date as in the previous literature by Turtle and Wang (2017), Walkshäusl (2017), and Tikkanen and Äijö (2018), to make sure that the accounting information was available for investors at the

formation of portfolios. In addition, financial firms with Datastream industry codes 4300-4395 are excluded from the sample. This is similar to previous studies using FSCORE, as the calculation methodology of financial statements for financial firms differs from the other firms (Piotroski & So, 2012; Walkshäusl, 2017; Tikkanen & Äijö, 2018).

Table 3 presents the number of stocks in each portfolio for each three-year holding period. Simple loser and simple winner portfolios are the strategies without FSCORE double sorting. Low fundamental loser (LF-L) and high fundamental loser (HF-L) portfolios include past loser stocks with low and high fundamental strength, respectively. Low fundamental winner (LF-W) and high fundamental winner (HF-W) portfolios include past winner stocks with low and high fundamental strength, respectively. As it can be seen from Table 3, number of stocks is increasing for the more recent portfolios. This is explained by the data collection method, as the data includes only the stocks included in S&P 1500 at the time of data collection at the end of May 2019. This leads to a survivorship bias, which can positively skew the returns of the portfolios. Analyzing unconditional long-term returns, Loughran and Ritter (1996, p. 1964) show, that the effect of survivorship bias is stronger with past losers than past winners in three-year holding periods. They report that on average 20 percent of simple losers and ten percent of the winners do not survive the whole holding period. Therefore, especially the loser portfolios' returns can be upwardly biased in this study. Moreover, the returns of low fundamental strength portfolios can be relatively more positively skewed due to survivorship bias, as Piotroski and So (2012, p. 2845) suggest that low FSCORE firms tend to have more de-listings due to reasons related to performance than firms with high FSCORE.

Table 3. Number of stocks in portfolios.

	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W
7/1/1991-6/30/1994	117	117	14	14	3	35
7/1/1994-6/30/1997	129	129	18	25	3	52
7/1/1997-6/30/2000	162	160	22	33	8	68
7/1/2000-6/30/2003	187	187	25	45	14	66
7/1/2003-6/30/2006	210	210	43	30	7	109
7/1/2006-6/30/2009	224	224	18	60	9	118
7/1/2009-6/30/2012	241	240	44	40	9	103
7/1/2012-6/30/2015	255	254	21	68	10	129
7/1/2015-6/30/2018	270	269	23	71	14	121

Table 3 shows that the number of stocks in the low fundamental winner strategy is low throughout the analysis period, which limits the reliable use of it in the analysis. Therefore zero-cost strategy formed by buying high fundamental losers and selling low fundamental winners is not formed in this study, as it is done in the value/growth framework by Piotroski and So (2012) with so-called incongruent value/glamour strategy. Low number of past winners with low fundamental strength and significantly higher number of past winners with high fundamental strength is economically explainable, as it can be expected that stocks that have performed the best also tend to have stronger fundamental strength.

Panel A in Table 4 presents the distribution of FSCORE values at the year-end before portfolio formations. In total, the sample includes 7,380 firm-year observations. The sample includes significantly more high (7-9) FSCORE values than low (0-3) FSCORE values, the amounts being 2,612 and 541, respectively. For instance, the sample has only three FSCORE values of zero.

Table 4. Distribution of FSCORE values and descriptive statistics of variables.

Panel A: Distribution of FSCORE values.

FSCORE	N
0	3
1	27
2	125
3	386
4	919
5	1 474
6	1 834
7	1 506
8	878
9	228
Total	7 380

Panel B: Descriptive statistics of FSCORE and market value

	Mean	25th	Median	75th	Std. Dev.
FSCORE	5.84	5.00	6.00	7.00	1.57
Market value	8417.03	453.97	1413.52	4974.55	28611.74

Panel B in Table 4 reports descriptive statistics of two variables, FSCORE and market value, with the latter depicted as the market value of equity in millions at the end of June in the year of portfolio formation. Mean FSCORE value of the sample is skewed towards higher FSCORE values, being 5.84. As a comparison, the mean FSCORE reported by Walkshäusl (2017, p. 849) is slightly lower at 5.56 in European stock markets. Mean market value of the sample is markedly higher than median market value, which indicates that the sample has substantial skewness towards large capitalization stocks. Mean market value of $8,417 million is significantly higher than in the study by Ahmed and Safdar (2018, p. 14) which has a mean market value of $3,185 million.

The returns for each three-year fundamental reversal strategies are calculated as value-weighted compound returns, presented in annual and monthly terms to compare the returns of winner and loser portfolios with high and low fundamental strength levels. Traditionally many studies use equal-weighted returns in portfolio formation, but value-weighted returns are used here to give more reliable results, as equal-weighted returns would overestimate the role of microcaps (Hou, Xue, & Zhang, 2018). Also, investor's

total wealth effect is better captured by using value-weight (Fama, 1998). Table 5 presents the descriptive statistics of raw monthly returns of each portfolio.

Table 5. Descriptive statistics of raw monthly returns.

	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W	Market[1]
Mean	0.013	0.010	0.013	0.014	0.012	0.011	0.009
Median	0.016	0.010	0.016	0.015	0.011	0.009	0.013
Maximum	0.177	0.160	0.182	0.198	0.523	0.176	0.114
Minimum	-0.156	-0.229	-0.172	-0.149	-0.270	-0.242	-0.175
Std. Dev.	0.046	0.052	0.061	0.054	0.079	0.059	0.041
Skewness	-0.256	-0.540	-0.255	0.003	0.589	-0.483	-0.680
Kurtosis	4.599	4.746	3.377	4.183	8.675	4.847	4.679
Observations	324	324	324	324	324	324	324

[1] Russell 1000 total return index is used as the benchmark market index

Table 5 shows, that the low fundamental winner strategy is highly leptokurtic, which means that it is more unreliable as it has a higher probability to have extreme values. It also has the highest standard deviation. The key strategy of interest, the high fundamental losers, has the highest mean raw monthly return of the seven portfolios, being 1.4%. It also has the least negative minimum monthly raw return at -14.9%.

4.2 Risk-adjusted performance measures

Risk-adjusted return performance of the strategies is analyzed using Sharpe and Sortino ratios. In addition, the strategies are regressed with the common risk factors of Fama and French (2018) three-, five-, and six-factor models. Sharpe (1966) ratio is commonly used in portfolio and mutual fund analysis. In Sharpe ratio, risk-return relationship is interpreted in a way that higher variability of returns (risk) typically means higher returns. The ratio uses portfolio's returns' standard deviation as the risk measure. A higher Sharpe ratio means better risk-adjusted performance. Sharpe ratio can be expressed with the following equation:

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

where R_p = return of the portfolio p

R_f = risk-free return

σ_p = standard deviation of the portfolio p's excess return

The numerator of the ratio depicts the reward that the investor gets on top of risk-free return. Therefore, Sharpe ratio illustrates the reward that investor receives for a unit of risk. (Sharpe, 1966) In contrast to Sharpe ratio, Sortino (1994) ratio replaces standard deviation with downside deviation in the denominator. Downside deviation measures only the standard deviation of the returns below a discretionary minimum acceptable return (MAR), in other words, the root-mean-square deviation of portfolio returns below a specified minimum acceptable return. In this study, the risk-free rate is used as the minimum acceptable return in a similar fashion as by Tikkanen and Äijö (2018). By using Sortino ratio, extreme positive and negative returns are not treated equally, and therefore the portfolio's ratio is not negatively affected when gaining extreme positive returns. Sortino ratio can be expressed with the following equation:

$$SoR_p = \frac{R_p - MAR}{DD} \tag{9}$$

where R_p = return of the portfolio p

MAR = minimum acceptable return

DD = downside deviation

In a more meticulous risk analysis, Fama and French (2018) three-, five-, and six-factor models are used to analyze whether the performance of the strategies is explained by the common risk factors. Also, the risk characteristics of the strategies can be analyzed by comparing individual factor loadings. The six-factor model can be expressed with the following equation:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + \quad (10)$$

$$r_i RMW_t + c_i CMA_t + m_i UMD_t + e_{it}$$

where R_{it} = return of the portfolio i for time t

R_{Ft} = risk-free return

R_{Mt} = return on the value-weighted market portfolio

SMB_t = risk factor related to size

HML_t = risk factor related to book-to-market equity

RMW_t = risk factor related to profitability

CMA_t = risk factor related to investment

UMD_t = risk factor related to momentum

e_{it} = zero-mean residual

The five-factor model is identical to the equation (10), except that the factor for momentum (UMD) is omitted from the model. Moreover, the three-factor model omits the factors for profitability (RMW) and investment (CMA) from the regression, leaving only the market, size (SMB) and book-to-market (HML) factors. In all the three models, intercept α_i measures abnormal returns for the portfolio *i*. In a case that α_i is positive and statistically significant, the returns of the strategies are not explained with the model, and thus the strategy gains abnormal returns. The factors, excess returns of the market, and one-month T-bill return which is used as the risk-free rate for the factor models and Sharpe and Sortino ratios, are gathered from Kenneth R. French's online data library.[1] The factor regressions conducted in this study are corrected for heteroskedasticity and autocorrelation by using Newey and West's (1987) standard errors.

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[1] The factors are publicly available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

5 Results

This chapter presents the empirical results, and the hypotheses *H1* and *H2* are tested. By using portfolio analysis, hypothesis *H1* tests whether firms with incongruent past long-term returns and fundamental strength have stronger long-term reversals than firms with congruent past returns and fundamental strength. This hypothesis is motivated by the results of previous literature such as Piotroski and So (2012), Walkshäusl (2017), Ahmed and Safdar (2018), and Zhu et al. (2019). By using regression analysis, hypothesis *H2* tests whether the returns of the fundamental long-term reversal strategies are explained by common risk factors. If the hypothesis *H2* holds, the strategies do not gain abnormal returns and they are explained by common risk factors.

Chapter 5.1 presents the results regarding strategies' raw and risk adjusted returns. In Chapter 5.2, the returns are analyzed in a year-to-year basis, to see whether the reversals persist throughout the three-year holding periods. The discussion around hypothesis *H1* is at the focus in the first two subchapters. Chapter 5.3 presents the results of Fama and French (2018) three-, five-, and six-factor model regressions, and hypothesis *H2* is tested.

5.1 Raw and risk-adjusted returns

Panel A in Table 6 reports the monthly and annual compound raw returns of the strategies for the sample period 7/1/1991-6/30/2018. Simple loser and simple winner portfolios include stocks that are sorted only by past returns. Low fundamental loser (LF-L) and high fundamental loser (HF-L) portfolios include past loser stocks with low and high fundamental strength, respectively. Low fundamental winner (LF-W) and high fundamental winner (HF-W) portfolios include past winner stocks with low and high fundamental strength, respectively.

Panel A of Table 6 shows, that the high fundamental loser strategy yields the highest monthly raw return of 1.25%, followed by the simple loser strategy (1.18%) and the low

fundamental loser strategy (1.13%). In this comparison, the loser strategy with incongruent fundamental strength leads to higher raw returns than the congruent low fundamental loser strategy, and the returns are also higher than with the strategy of buying losers without fundamental sorting. Similar effect cannot be found amongst the winners, as the low and high fundamental winner strategies have almost equal raw returns.

Table 6. Monthly and annual compound raw returns, Sharpe, and Sortino ratios.

Panel A: Compound raw returns (%)							
	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W	Market
One month	1.18	0.89	1.13	1.25	0.91	0.91	0.80
Annual	15.15	11.28	14.49	16.03	11.46	11.51	10.08

Panel B: Compound raw returns without January (%)							
	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W	Market
One month	1.17	0.96	1.02	1.26	1.12	0.97	0.85
Annual	14.98	12.20	12.96	16.20	14.32	12.25	10.71

Panel C: Annual Sharpe and Sortino ratios							
	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W	Market
Sharpe	0.78	0.47	0.56	0.71	0.32	0.43	0.52
Sortino	1.13	0.64	0.84	1.11	0.48	0.59	0.69

Panel B in Table 6 shows how excluding January returns from the holding period affect raw returns of the strategies. Raw returns of the simple loser and the high fundamental loser strategies stay almost unchanged, with the latter slightly increasing to monthly return of 1.26%. On the other hand, monthly raw returns of the low fundamental losers decrease from 1.13% to 1.02%. Results from the low fundamental losers are similar to Yaqiong (2012, p. 2762), as he reports that the subsequent value-weighted returns of the lowest decile of past long-term losers drop from 1.63% to 1.04% when Januaries are excluded. The results from the loser side are also similar to Zhu et al. (2019, p. 29), who find that the short-term monthly fundamental-anchored reversals sustain without January, whereas the returns of fundamental-unanchored reversals become negative. In addition, Panel B in Table 6 shows that excluding January returns affects the returns of the

winner strategies. In fact, all the three winner strategies have higher raw returns when Januaries are excluded, with the monthly raw returns of the low fundamental winners increasing the most from 0.91% to 1.12%. These results are consistent with Grinblatt and Moskowitz (2004, p. 557), who report that the returns of the winners reverse during Januaries and thus January has a negative effect on winner returns, whereas outside Januaries there are only little reversals.

Panel C of Table 6 reports the risk-adjusted returns of the strategies. When measuring the risk-adjusted returns with Sharpe ratio, the simple loser has the highest ratio of 0.78 followed by the high fundamental loser with a ratio of 0.71. The high fundamental losers have a higher Sharpe ratio than the low-fundamental losers (0.56) or the market (0.52). Similarly, the high fundamental winners have higher Sharpe ratio than the low funda-mental winners, but both strategies lose to the simple winners which do not have FSCORE-based fundamental strength sorting.

When measuring the risk only by downside deviation by using Sortino ratio in Panel C of Table 6, the simple loser still has the highest risk-adjusted return with a ratio of 1.13, closely followed by the high fundamental loser (1.11). Both strategies have substantially higher Sortino ratio than the market which has a ratio of 0.52. With both winners and losers, the high fundamental strategies have higher risk-adjusted returns than the low fundamental strategies.

5.2   Year-to-year returns

This sub-chapter analyzes the persistence of the returns throughout the three-year hold-ing periods in year-to-year basis, in a similar fashion as by Walkshäusl (2017) in the value/glamour context. Compounded raw returns of the strategies are reported in the analysis. Statistical significance of the year-to-year returns is measured with one tail paired two-sample t-test, where the average return difference between the fundamental reversal strategies and the market portfolio Russell 1000 is measured. Figure 1 shows

raw returns of the high- and low fundamental loser portfolios during the first holding years. For instance, the returns for year 1991 depicts compounded raw returns from beginning of July 1991 to end of June 1992.
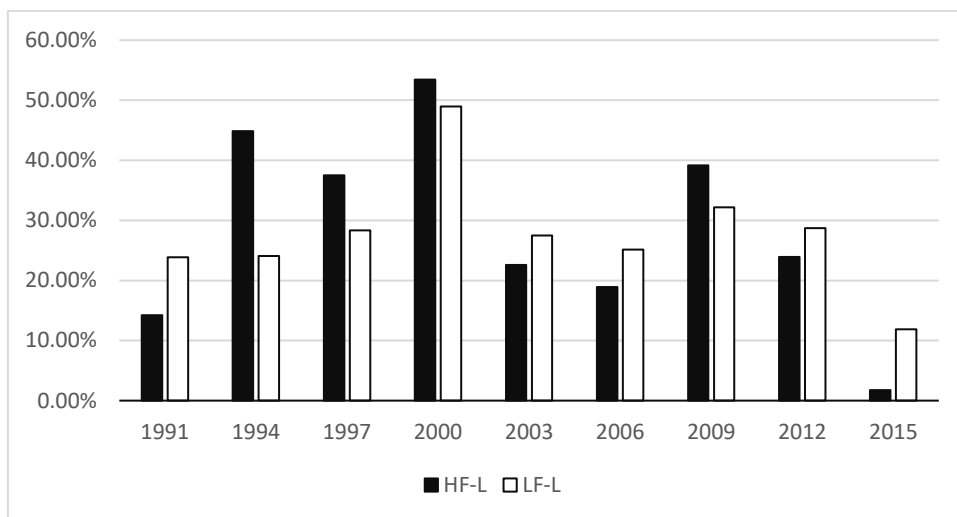

Figure 1. Returns of the fundamental loser portfolios for the first holding years.

Figure 1 shows, that all the portfolios for the high and low fundamental losers have positive raw returns for the first holding years. The first-year average returns are highly statistically significant at 1% level for the both strategies, with the average returns being 28.48% (t-statistic = 2.59) for the high fundamental losers, and 27.85% (t-statistic = 2.49) for the low fundamental losers. Figure 2 shows the raw returns for the second holding years for the high-and low fundamental loser portfolios.
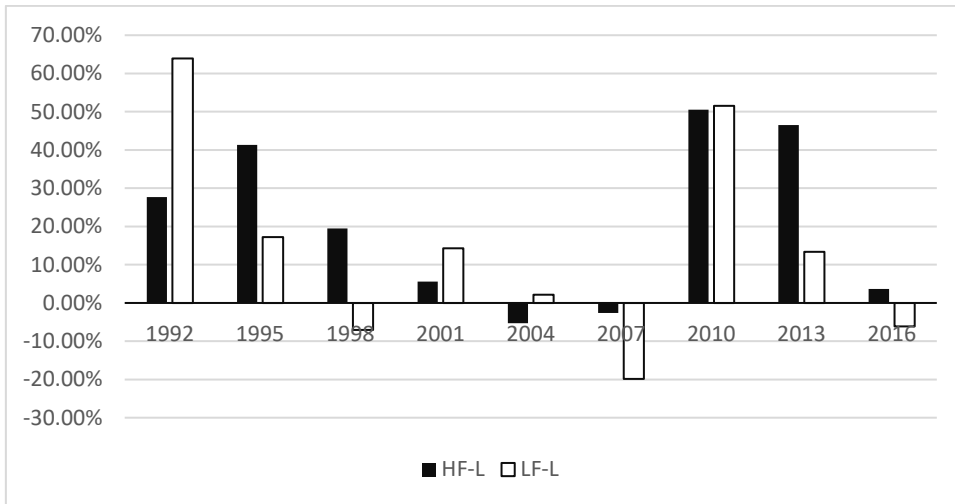
Figure 2. Returns of the fundamental loser portfolios for the second holding years.

Figure 2 shows, that the second holding years' average returns for the high and low fundamental losers decrease from the first holding years, being on average 20.77% (t-statistic = 1.93) for the high fundamental losers, and 14.40% (t-statistic = 0.25) for the low fundamental losers. The average raw returns for the high fundamental losers are statistically significant at level of 5%, whereas the returns of the low fundamental losers become insignificant. Seven out of nine of the high fundamental loser portfolios have positive returns for the second holding years, whereas six out of nine are positive for the low fundamental losers. Finally, the third years' raw returns are shown in the Figure 3.
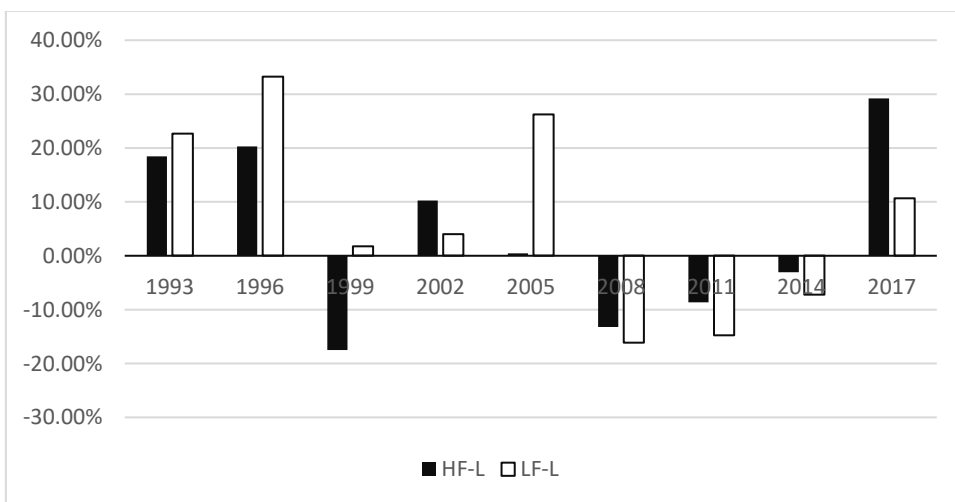

Figure 3. Returns of the fundamental loser portfolios for the third holding years.

Figure 3 shows, that the returns continue to decrease for the high and low fundamental loser portfolios in the third holding years. The average annual returns for the high and low fundamental losers are 4.02% (t-statistic = -0.15) and 6.72% (t-statistic = 0.41), respectively, with the both average returns being statistically insignificant. In the third holding years, five of nine high fundamental loser portfolios have positive returns, whereas six of nine low fundamental loser portfolios have positive returns. These results indicate that the reversal returns are stronger and more robust for the high fundamental losers than for the low fundamental losers, and the reversals for the high fundamental losers occur approximately in two years after the portfolio formation. These results indicate, that for instance an asymmetric strategy with a three-year formation and only a one-year holding period could be more optimal strategy.

The year-to-year raw returns for the high and low fundamental winner portfolios are reported in the Appendix 2. Similar return reversals do not occur for the winners as for the losers, as six out of nine of the low fundamental winner portfolios have positive returns in the first year, eight in the second year and seven in the third year. Similarly, seven portfolios of the high fundamental winners have positive returns in the first and second year, and eight of the third-year portfolios have positive raw returns. The first and second year average raw returns of the high fundamental winner portfolios are statistically insignificant, whereas the third-year returns become significant at level of 10% (t-statistic = 1.58). The first and third year average raw returns of the low fundamental winners are statistically insignificant, whereas the second-year average raw returns are significant at level of 10% (t-statistic = 1.30). These results are consistent with Galariotis (2012), who studies simple unconditional long-term return reversals and finds that systematical reversals occur only within the past losers. The results are also consistent with Duong et al. (2014), who suggest in a value context that investors should rely on long-only strategy with high FSCORE value stocks, as the short side with low fundamental growth stocks is not profitable.

Reviewing the Chapters 5.1 and 5.2 from the perspective of hypothesis *H1,* the results show that the reversals are stronger for the loser strategy with incongruent current fundamentals and past returns (HF-L) than for the loser strategy with congruent current fundamentals and past returns (LF-L). On the other hand, the past winners with incongruent fundamentals and past returns (LF-W) do not have systematical reversals. Therefore, the hypothesis *H1* is supported when considering only the past loser reversals.

5.3   Factor model regressions

Next, it is tested whether the returns of the strategies are explained by the common risk factors of Fama and French (2018) three, five-, and six-factor models. Table 7 reports the loadings of the three-factor model, where market, size (SMB) and value (HML) are the explaining factors. After controlling for the three factors, the simple loser and the high fundamental loser strategies gain monthly abnormal returns of 0.32% and 0.42%, respectively. Both strategies' abnormal returns are statistically significant at 5% level. Therefore, the three-factor model cannot fully explain the returns of the loser strategies, except in case of the low fundamental losers. As a comparison, the abnormal returns gained by FSCORE-sorted incongruent value/glamour strategy are higher, as Piotroski and So (2012, p. 2866) report monthly abnormal returns of 0.98% when regressed with the four-factor model which adds momentum factor to the regression. With the winner strategies, the returns are explained by the risk factors of the three-factor model.

Table 7. Three-factor model loadings.

	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W
alpha	0.315**	0.185	0.170	0.423**	0.219	0.222
	(2.068)	(1.289)	(0.785)	(1.976)	(0.674)	(1.133)
Market	0.932***	1.107***	1.071***	0.962***	1.192***	1.171***
	(16.182)	(22.816)	(14.482)	(12.049)	(11.724)	(19.441)
SMB	0.122**	-0.167***	0.460***	-0.010	0.223**	-0.245***
	(2.483)	(-4.155)	(6.489)	(-0.102)	(2.123)	(-3.568)
HML	0.431***	-0.394***	0.524***	0.421***	-0.313*	-0.442***
	(4.677)	(-8.129)	(5.358)	(3.278)	(-1.819)	(-6.891)
Adj. R-Sqr.	0.749	0.847	0.634	0.549	0.459	0.743

T-statistics are reported in the parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Regarding different risk characteristics, Table 7 shows that all the three loser portfolios have positive and highly significant value factor loadings, with the low fundamental losers having the highest loading at 0.524. Therefore similar value-effect can be captured by using long-term past returns, as for instance Piotroski and So (2012) and Walkshäusl (2017) has captured by using pricing multiples. The simple loser and the low fundamental loser strategies also have positive and significant size factor coefficients, with the latter having substantially higher loading at 0.460. On the other hand, the high fundamental losers do not have a significant size factor loading.

The winner strategies have different risk characteristics when compared to loser strategies. In Table 7, all the winner strategies have a negative and significant value factor coefficient on 10% significance level or higher, with the high fundamental winners having the most negative loading at -0.442. This is consistent with Fama and French (1996), who find that the long-term winners tend to have a negative value factor loading, whereas the long-term losers have a positive value factor exposure. Also, the simple winners and the high fundamental winners have a negative and statistically significant coefficient on size factor, indicating that the winners tend to be larger firms, with an exception of the low fundamental winners. In both the low fundamental losers and the low fundamental winners, the size factor coefficient is positive and statistically significant which indicates

that the low fundamental firms tend to be smaller firms, which is consistent with previ-
ous research by Walkshäusl (2017).

Table 8 reports the loadings of the five-factor model, where profitability (RMW) and in-
vestment (CMA) factors are added to the model. After controlling for the five factors, the
alphas become insignificant for all the strategies and therefore abnormal returns are not
gained. This is opposite to the study by Tikkanen and Äijö (2018) who implement equal-
weight FSCORE-sorted value portfolios in various European markets, and gain statistically
significant abnormal returns when regressing with the five-factor model. Similarly, Zhu
et al. (2019) find statistically significant five-factor model abnormal returns with equal-
weight portfolios with fundamental-anchored short-term reversal strategy. However, the
abnormal returns decrease and become insignificant when using value-weighted port-
folios. In this study value-weighted portfolios are used instead of equal-weight, which
can substantially decrease the abnormal returns of the strategies, as also shown by Hou,
Xue, and Zhang (2018) who show that most of the anomalies disappear when value-
weight returns are used instead of equal-weight.

Table 8. Five-factor model loadings.

	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W
alpha	0.080	0.160	0.061	0.123	0.230	0.222
	(0.610)	(1.164)	(0.255)	(0.637)	(0.642)	(1.160)
Market	1.055***	1.106***	1.141***	1.113***	1.172***	1.155***
	(18.940)	(21.100)	(15.607)	(15.250)	(10.988)	(16.988)
SMB	0.190***	-0.086*	0.438***	0.108	0.304***	-0.163**
	(3.166)	(-1.872)	(5.935)	(1.159)	(2.927)	(-2.136)
HML	0.130*	-0.278***	0.224*	0.107	-0.263	-0.274***
	(1.686)	(-4.156)	(1.776)	(0.848)	(-1.594)	(-2.870)
RMW	0.269***	0.176***	0.024	0.394***	0.076	0.155
	(3.049)	(2.661)	(0.227)	(3.139)	(0.485)	(1.426)
CMA	0.497***	-0.299***	0.493***	0.511**	-0.244	-0.377**
	(4.086)	(-2.604)	(2.664)	(2.311)	(-0.784)	(-2.145)
Adj. R-Sqr.	0.783	0.858	0.644	0.583	0.461	0.752

T-statistics are reported in the parentheses. *, ** and *** indicate statistical significance at the 10%, 5%
and 1% levels, respectively.

Also, the risk characteristics of the strategies change when adding profitability and investment factors to the model. Table 8 reports that the magnitude of the loser strategies' value factor loadings decrease and become less significant. In case of the high fundamental losers, value factor becomes insignificant. This is consistent with Fama and French (2015), who find that value factor becomes redundant when profitability and investment factors are included in the model. Especially the investment factor (CMA) is substantially positive and statistically significant for all the three loser strategies, which is consistent with Titman et al. (2004). The investment factor loading is highest for the high fundamental loser strategy and it varies between 0.493 and 0.511 between the loser strategies. This indicates that the past losers tend to make conservative investments in both high and low fundamental strength levels.

The simple loser and the high fundamental loser strategies also have a positive and highly significant profitability factor loadings, being 0.394 for the latter, whereas the low fundamental losers have statistically insignificant profitability factor loading. Positive and statistically significant profitability exposure of the high fundamental loser strategy is consistent with previous research, as FSCORE works as a leading indicator of future profitability (Piotroski, 2000; Piotroski & So, 2012). The loser strategies' size factor exposures stay similar with the five-factor model, as the simple losers and the low fundamental losers have positive and highly significant loadings.

From the winner strategies' perspective, Table 8 shows that the low fundamental winners still have positive and highly significant size factor exposure of 0.304, whereas for the high fundamental winners it is negative and statistically significant at level of 5%. Also, the simple winners and the high fundamental winners still have negative and statistically significant value factor loadings. The simple winner strategy also has a positive and highly statistically significant profitability exposure. Opposite to loser strategies, the simple winner and the high fundamental winner strategies have negative and statistically

significant investment factor loadings, therefore being more aggressive on the use of capital expenditures, which is also consistent with Titman et al. (2004).

Adjusted R-squared in Table 8 shows, that the five-factor model explains the returns of the portfolios reasonably well. With an exception of the low fundamental winner strategy, which has an adjusted R-squared of 46.1%, all the portfolios have an adjusted R-squared above 50%, with the simple winner portfolio having the highest at 85.8%. The low fundamental winner strategy has the highest market exposure with the market beta of 1.172, whereas the simple loser strategy has the lowest with 1.055.

Table 9 presents the results for the regressions with the six-factor model, which augments the five-factor model with momentum (UMD) factor. Adding momentum factor does not make significant changes to the big picture as there is only a slight increase in the adjusted R-squared for all but one strategies, as the simple loser's adjusted R-squared stays the same as with the five factor model. Similarly, the factor loadings do not have a significant change.

Table 9. Six-factor model loadings.

	Simple loser	Simple winner	LF-L	HF-L	LF-W	HF-W
alpha	0.074	0.195	0.105	0.068	0.131	0.295
	(0.551)	(1.392)	(0.416)	(0.338)	(0.376)	(1.553)
Market	1.057***	1.093***	1.124***	1.133***	1.209***	1.128***
	(19.133)	(21.004)	(14.764)	(16.305)	(10.631)	(17.212)
SMB	0.189***	-0.078*	0.448***	0.095	0.282***	-0.147**
	(3.063)	(-1.766)	(5.743)	(1.006)	(2.708)	(-2.085)
HML	0.136*	-0.310***	0.184	0.156	-0.174	-0.339***
	(1.743)	(-4.848)	(1.647)	(1.171)	(-1.090)	(-3.791)
RMW	0.267***	0.188***	0.040	0.375***	0.042	0.181*
	(2.969)	(3.037)	(0.381)	(2.978)	(0.252)	(1.875)
CMA	0.494***	-0.280***	0.517***	0.482**	-0.297	-0.338**
	(4.030)	(-2.625)	(3.167)	(2.245)	(-0.949)	(-2.197)
UMD	0.009	-0.055	-0.069	0.085*	0.154	-0.113**
	(0.223)	(-1.497)	(-0.752)	(1.661)	(1.495)	(-2.430)
Adj. R-Sqr.	0.783	0.860	0.646	0.586	0.467	0.759

T-statistics are reported in the parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

As Table 9 shows, momentum is statistically significant for two strategies, the high fundamental losers and the high fundamental winners. The high fundamental losers have a slightly positive momentum exposure with a low magnitude and statistical significance of 10%. Interestingly, the high fundamental winners have a negative exposure of -0.113 to momentum factor, being statistically significant at level of 5%. Although both momentum and long-term reversals are past return-based phenomena, they occur in different time horizons and have opposing characteristics, which could explain the low momentum exposure in the strategies presented in this study.

Reviewing the chapter from the perspective of hypothesis *H2,* the results show that the returns of the fundamental reversal strategies are explained by the common risk factors. When using only the three-factor model to explain the returns, the high-fundamental losers have statistically significant monthly abnormal returns of 0.42%, which disappear when profitability and investment factors are added to the model. Therefore, the hypothesis *H2* is supported by the empirical results.

6 Conclusions

This paper examines the relation between long-term return reversals and fundamental strength. Fundamental strength is measured using Piotroski's (2000) FSCORE, which measures firms' profitability, change in financial leverage/liquidity and change in operational efficiency. This study is motivated by the findings of Piotroski and So (2012), who find that value/growth-strategy's returns are focused in portfolios with incongruent expectations implied by FSCORE and book-to-market multiples. In this study, long-term return reversals are expected to be stronger on high (low) fundamental strength portfolios with lowest (highest) past return performance, in which the future performance expectations implied by past long-term returns are incongruent with current fundamentals.

As hypothesized, long-term past losers with high fundamental strength have stronger reversals than losers with low fundamental strength. On the other hand, similar return reversals are not observed with past winners. The raw returns of the high fundamental losers are robust to excluding Januaries from the sample. Contrarily, annual raw returns of past losers with low fundamental strength decrease by approximately 1.50% when Januaries are excluded. On the other hand, the returns of all winner strategies increase when Januaries are excluded. Simple fundamental analysis with FSCORE can also help to enhance risk-adjusted performance measured with Sharpe (1966) and Sortino (1994) ratios, as the high fundamental winners and losers have higher risk-adjusted returns than the low fundamental counterparts. The risk-adjusted returns of the high fundamental losers are also higher than the market but ultimately lose to the simple reversal strategy without FSCORE sorting.

The returns of the fundamental reversal strategies are explained by common risk factors. When using only Fama and French (1996) three-factor model to explain the returns, the simple loser strategy without FSCORE sorting and the high fundamental loser strategy gain statistically significant and positive abnormal returns. However, statistically significant abnormal returns of all the strategies disappear when investment and profitability factors are added to the model. In factor loading level, the loser strategies are

characterized as having conservative capital expenditures, whereas the winner strategies are characterized as being aggressive with capital expenditures, consistent with previous research by Titman et al. (2004). More specifically, the high fundamental loser strategy is characterized as containing profitable firms with conservative capital expenditures. Including momentum factor in the analysis with Fama and French (2018) six-factor model does not change the conclusions, as it does not have a significant exposure in the fundamental reversal strategies.

Consistent with the findings in various frameworks, such as value/glamour (Piotroski & So, 2012; Walkshäusl, 2017), short-term return reversals (Zhu, Sun, & Chen, 2019), price momentum (Ahmed & Safdar, 2018; Walkshäusl, 2019), and unconditional high/low FSCORE-sorting (Ng & Shen, 2016; Turtle & Wang, 2017; Hyde, 2018), high FSCORE firms have better performance than low FSCORE firms within both past winners and losers, when considering the risk-adjusted performance. As the low fundamental strength winners do not have systematical reversals, the reversal effect relies on the past losers with incongruent fundamentals. However, it is important to keep in mind, that making inferences about the low fundamental strength winners is unreliable, as only a few firms with such a combination were found.

Following the criticism by Fama (1998) and Hou et al. (2018) about using equal-weight returns in empirical studies, this study uses value-weight returns which can be manifested as the lack of abnormal returns and more reliable results. On the other hand, one must be critical in interpreting the results of this study due to survivorship bias caused by the data collection methodology. Especially the returns of loser portfolios can be upwardly biased, as delisted companies are not included in the analysis. Additional research could be done with larger data set without survivorship bias, which would also allow to have more extreme portfolio formations to see whether the returns are sensitive to portfolio size in a similar fashion as with unconditional long-term reversals in the study by Galariotis (2012). Also, additional research could be done of the role of fundamental strength in the January effect, as past long-term losers with high fundamental

strength seem to have more robust returns than low fundamental counterparts when January returns are excluded, in a similar fashion as with the short-term monthly return reversals reported by Zhu et al. (2019).

References

Ahmed, A. S., & Safdar, I. (2018). Dissecting stock price momentum using financial statement analysis. *Accounting & Finance, 58*, 3-43. https://doi.org/10.1111/acfi.12358

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *Journal of Finance, 68*(3), 929-985. https://doi.org/10.1111/jofi.12021

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307-343. https://doi.org/10.1016/S0304-405X(98)00027-0

Baytas, A., & Cakici, N. (1999). Do markets overreact: International evidence. *Journal of Banking and Finance, 23*(7), 1121-1144. https://doi.org/10.1016/S0378-4266(98)00133-2

Black, F., Jensen, M. C., & Scholes, M. C. (1972). The Capital Asset Pricing Model: Some Empirical Tests. In M. C. Jensen (Ed.), *Studies in the Theory of Capital Markets* (pp. 79-121). Praeger Publishers.

Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments* (9th ed.). McGraw-Hill/Irwin.

Bornholt, G., Gharaibeh, O., & Malin, M. (2015). Industry long-term return reversal. *Journal of International Financial Markets, Institutions & Money, 38*, 65-78. https://doi.org/10.1016/j.intfin.2015.05.013

Chen, H. Y., Lee, C. F., & Shih, W. K. (2016). Technical, fundamental, and combined information for separating winners from losers. *Pacific-Basin Finance Journal, 39*, 224-242. https://doi.org/10.1016/j.pacfin.2016.06.008

Choi, N. Y., & Sias, R. W. (2012). Why Does Financial Strength Forecast Stock Returns? Evidence from Subsequent Demand by Institutional Investors. *The Review of Financial Studies, 25*(5), 1550-1587. https://doi.org/10.1093/rfs/hhs001

Chou, P. H., Wei, J. K., & Chung, H. (2007). Sources of contrarian profits in the Japanese stock market. *Journal of Empirical Finance, 14*(3), 261-286. https://doi.org/10.1016/j.jempfin.2006.07.003

Conrad, J. S., & Kaul, G. (1998). An anatomy of trading strategies. *The Review of Financial Studies, 11*(3), 489-519. https://doi.org/10.1093/rfs/11.3.489

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance, 53*(6), 1839-1885. https://doi.org/10.1111/0022-1082.00077

De Bondt, W. F., & Thaler, R. H. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F., & Thaler, R. H. (1987). Further Evidence On Investor Overreaction and Stock Market Seasonality. *Journal of Finance, 42*(3), 557-581. https://doi.org/10.1111/j.1540-6261.1987.tb04569.x

Duong, C., Pescetto, G., & Santamaria, D. (2014). How value-glamour investors use financial information: UK evidence of investors' confirmation bias. *The European Journal of Finance, 20*(6), 524-549. https://doi.org/10.1080/1351847X.2012.722117

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance, 25*(2), 383-417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F. (1991). Efficient Capital Markets: II. *Journal of Finance, 46*(5), 1575-1617. https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fama, E. F. (1998). Market Efficiency, Long-term Returns, and Behavioral Finance. *Journal of Financial Economics, 49*(3), 283-306. https://doi.org/10.1016/S0304-405X(98)00026-9

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance, 47*(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance, 51*(1), 55-84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics, 105*(3), 457-472. https://doi.org/10.1016/j.jfineco.2012.05.011

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics, 116*, 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & French, K. R. (2016). Dissecting Anomalies with a Five-Factor Model. *The Review of Financial Studies, 29*(1), 69-103. https://doi.org/10.1093/rfs/hhv043

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics, 128*(2), 234-252. https://doi.org/10.1016/j.jfineco.2018.02.012

Galariotis, E. (2012). Recent evidence on the performance and riskiness of contrarian portfolios. *The European Journal of Finance, 18*(7), 603-617. https://doi.org/10.1080/1351847X.2011.628795

Garcia-Feijoo, L., & Jensen, G. R. (2014). The monetary environment and long-run reversals in stock returns. *Journal of Financial Research, 37*(1), 3-26. https://doi.org/10.1111/jfir.12026

George, T. J., & Hwang, C. Y. (2007). Long-term return reversals: Overreaction or taxes? *Journal of Finance, 62*(6), 2865-2896. https://doi.org/10.1111/j.1540-6261.2007.01295.x

Gordon, M., & Shapiro, E. (1956). Capital Equipment Analysis: The Required Rate of Profit. *Management Science, 3*(1), 102-110.

Grinblatt, M., & Moskowitz, T. J. (2004). Predicting stock price movements from past returns: the role of consistency and tax-loss selling. *Journal of Financial Economics, 71*(3), 541-579. https://doi.org/10.1016/S0304-405X(03)00176-4

Gropp, J. (2004). Mean reversion of industry stock returns in the U.S., 1926–1998. *Journal of Empirical Finance, 11*(4), 537-551. https://doi.org/10.1016/j.jempfin.2004.04.002

Hong, H., & Stein, J. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *The Journal of Finance, 54*(6), 2143-2184. https://doi.org/10.1111/0022-1082.00184

Hong, H., Lim, T., & Stein, J. C. (2000). Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. *Journal of Finance, 55*(1), 265-295. https://doi.org/10.1111/0022-1082.00206

Hou, K., Xue, C., & Zhang, L. (2018). Replicating Anomalies. *The Review of Financial Studies*. https://doi.org/10.1093/rfs/hhy131

Hyde, C. E. (2018). The Piotroski F-score: evidence from Australia. *Accounting & Finance, 58*(2), 423-444. https://doi.org/10.1111/acfi.12216

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *The Journal of Finance, 45*(3), 881-898. https://doi.org/10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance, 48*(1), 65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of Financial Economics, 6*(2), 95-101. https://doi.org/10.1016/0304-405X(78)90025-9

Kothari, S. P., & Warner, J. B. (1997). Measuring long-horizon security price performance. *Journal of Financial Economics, 43*(3), 301-339. https://doi.org/10.1016/S0304-405X(96)00899-9

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance, 49*(5), 1541-1578. https://doi.org/10.1111/j.1540-6261.1994.tb04772.x

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics, 47*(1), 13-37. https://doi.org/10.2307/1924119

Loughran, T., & Ritter, J. R. (1996). Long-Term Market Overreaction: The Effect of Low-Priced Stocks. *The Journal of Finance, 51*(5), 1959-1970. https://doi.org/10.2307/2329546

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance, 7*(1), 77-91.

Miller, M. H., & Modigliani, F. (1961). Dividend Policy, Growth, and the Valuation of Shares. *The Journal of Business, 34*(4), 411-433. https://doi.org/10.1086/294442

Mohanram, P. S. (2005). Separating winners from losers among low book-to-market stocks using financial statement analysis. *Review of Accounting Studies, 10*(2-3), 133-170. https://doi.org/10.1007/s11142-005-1526-4

Newey, W., & West, K. (1987). A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 703-708. https://doi.org/0012-9682

Ng, C. C., & Shen, J. (2016). Screen winners from losers using simple fundamental analysis in the Pacific-Basin stock markets. *Pacific-Basin Finance Journal, 39*, 159-177. https://doi.org/10.1016/j.pacfin.2016.06.003

Novy-Marx, R. (2013). The other side of value the gross profitability premium. *Journal of Financial Economics, 108*(1), 1-28. https://doi.org/10.1016/j.jfineco.2013.01.003

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal Of Political Economy, 111*(3), 642-685. https://doi.org/0022-3808

Pätäri, E., Leivo, T., Hulkkonen, J., & Honkapuro, J. (2018). Enhancement of value investing strategies based on financial statement variables: the German evidence. *Review of Quantitative Finance and Accounting, 51*(3), 813-845. https://doi.org/10.1007/s11156-017-0689-y

Piotroski, J. D. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal Of Accounting Research, 38*, 1-41. https://doi.org/0021-8456

Piotroski, J. D., & So, E. C. (2012). Identifying expectation errors in value/glamour strategies : a fundamental analysis approach. *The Review of Financial Studies, 25*(9), 2841-2875. https://doi.org/10.1093/rfs/hhs061

Roll, R. (1977). A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics, 4*(2), 129-176. https://doi.org/10.1016/0304-405X(77)90009-5

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance, 19*(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sharpe, W. F. (1966). Mutual Fund Performance. *The Journal of Business, 39*(1), 119–138. https://doi.org/10.1086/294846

Sortino, F. A., & Price, L. N. (1994). Performance Measurement in a Downside Risk Framework. *The Journal of Investing, 3*(3), 59-64. https://doi.org/10.3905/joi.3.3.59

Tikkanen, J., & Äijö, J. (2018). Does the F-score improve the performance of different value investment strategies in Europe? *Journal of Asset Management, 19*(7), 495-506. https://doi.org/10.1057/s41260-018-0098-3

Titman, S., Wei, K. C., & Xie, F. (2004). Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis, 39*(4), 677-700. https://doi.org/10.1017/S0022109000003173

Turtle, H. J., & Wang, K. (2017). The value in fundamental accounting information. *Journal of Financial Research, 40*(1), 113-140. https://doi.org/10.1111/jfir.12119

Walkshäusl, C. (2017). Expectation errors in European value-growth strategies. *Review of Finance, 21*(2), 845-870. https://doi.org/10.1093/rof/rfw012

Walkshäusl, C. (2019). The fundamentals of momentum investing: European evidence on understanding momentum through fundamentals. *Accounting & Finance, 59*, 831-857. https://doi.org/10.1111/acfi.12462

Williams, J. B. (1938). *The Theory of Investment Value.* Harvard University Press.

Wu, Y., & Mazouz, K. (2016). Long-term industry reversals. *Journal of Banking and Finance, 68*, 236-250. https://doi.org/10.1016/j.jbankfin.2016.03.017

Wu, Y., Li, Y., & Hamill, P. (2012). Do Low-Priced Stocks Drive Long-Term Contrarian Performance on the London Stock Exchange? *The Financial Review, 47*(3), 501-530. https://doi.org/10.1111/j.1540-6288.2012.00338.x

Yaqiong, Y. (2012). Momentum, contrarian, and the January seasonality. *Journal of Banking and Finance, 36*(10), 2757-2769. https://doi.org/10.1016/j.jbankfin.2011.12.004

Zarowin, P. (1990). Size, Seasonality, and Stock Market Overreaction. *Journal of Financial and Quantitative Analysis, 25*(1), 113-125. https://doi.org/10.2307/2330891

Zhu, Z., Sun, L., & Chen, M. (2019). Fundamental strength and short-term return reversal. *Journal of Empirical Finance, 52*, 22-39. https://doi.org/10.1016/j.jempfin.2019.02.006

Appendices

Appendix 1. Definitions of the financial performance signals of FSCORE

Financial performance signal	Definition	Indicator variable
Profitability		
ROA	Net income before extraordinary items $_t$ / Total assets $_{t-1}$	If ROA > 0, then *F_ROA* equals 1, otherwise 0
CFO	Cash flow from operations $_t$ / Total assets $_{t-1}$	If CFO > 0, *F_CFO* equals 1, otherwise 0
ΔROA	Return on assets $_t$ - Return on assets $_{t-1}$	If ΔROA > 0, *F_ΔROA* equals 1, otherwise 0
ACCRUAL	(Net income before extraordinary items $_t$ - Cash flow from operations $_t$) / Total assets $_{t-1}$	If ACCRUAL < 0, *F_ACCRUAL* equals 1, otherwise 0
Changes in financial leverage/liquidity		
ΔLEVER	Total debt $_t$ / (Total assets $_t$ + Total assets $_{t-1}$)/2 – Total debt $_{t-1}$ / (Total assets $_{t-1}$ + Total assets $_{t-2}$)/2	If ΔLEVER < 0, *F_ΔLEVER* equals 1, otherwise 0
ΔLIQUID	Current assets $_t$ / Current liabilities $_t$ – Current assets $_{t-1}$ / Current liabilities $_{t-1}$	If ΔLIQUID > 0, *F_ΔLIQUID* equals 1, otherwise 0
ISSUANCE	Proceeds from sale/issuance of common equity in year *t*	If ISSUANCE > 0, *ISSUANCE* equals 0, otherwise 1
Operating efficiency		
ΔMARGIN	(Net sales $_t$ – Cost of goods sold $_t$)/Net sales $_t$ - (Net sales $_{t-1}$ – Cost of goods sold $_{t-1}$)/Net sales $_{t-1}$	If ΔMARGIN > 0, *F_ΔMARGIN* equals 1, otherwise 0
ΔTURN	Net sales $_t$ / (Total assets $_t$ + Total assets $_{t-1}$)/2 – Net sales $_{t-1}$ / (Total assets $_{t-1}$ + Total assets $_{t-2}$)/2	If ΔTURN > 0, *F_ΔTURN* equals 1, otherwise 0

Appendix 2. Year-to-year returns of the fundamental winner strategies

Year 1

Year 2

Year 3