Juho Kupiainen

Combining value and momentum in United Kingdom stock markets

Evidence from Piotroski F-Score

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Author: Juho Kupiainen
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ABSTRACT:
This thesis examines the relationship between value and momentum strategies in the United Kingdom stock markets. Using data on publicly traded firms, I investigate whether a traditional momentum (Jegadeesh & Titman, 1993) strategy can enhance the returns of Piotroski (2000) F-Score screened value investing strategy. Results indicate that the combination strategy yields minor alpha against standalone market, value and momentum strategies and the results are robust after controlling for Fama-French 6-factors and Sharpe ratio.

Similar to Bird and Casavecchia (2007), I find that the combination portfolio consists mostly of small market capitalization stocks. This is natural for high book-to-market stocks and poses significant barriers to entry for large investors looking to capitalize on this strategy. Although the alpha of the combination strategy is small, the Sharpe ratio of the strategy is larger than standalone value, momentum or market portfolios, indicating that high F-Score lowers the risk of the value-winner portfolio's monthly returns.

I propose several suggestions for future research. First, since I did not consider transaction costs or taxes, taking them into account would enhance the precision of the portfolio returns, although the impact of both is small due to the annual style of portfolio rebalancing. Furthermore, I constricted my strategy long-only so short-side impacts are not explored. One potential future research avenue would be to look into long-short strategies based on high book-to-market, F-Score and momentum. Lastly, this study was done using United States dollar returns. Calculating returns in Pound Sterling could yield minor improvements to the precision of portfolio return calculations.

KEYWORDS: value investing, piotroski f-score, momentum, portfolio management

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TIIVISTELMÄ:
Tässä tutkielmassa tutkitaan arvosijoitus- ja momentum-strategioiden välistä suhdetta Ison-Britannian osakemarkkinoilla. Tutkin, pystyykö perinteinen momentum-strategia (Jegadeesh & Titman, 1993) parantamaan Piotroski (2000) F-Scorella seulotun arvosijoitusstrategian tuottoja julkisesti listatuilla yrityksillä. Tulokset osoittavat, että yhdistelmästrategia tuottaa pienen alfan vertailtaessa tuottoja yksittäisiin markkina-, arvo- ja momentum strategioinin. Tulokset ovat tilastollisesti merkittäviä, kun tuottoja kontrolloidaan Fama-Frenchin 6-faktorin ja Sharpe-suhteen avulla.

Kuten Bird ja Casavecchia (2007), tutkimukseni yhdistelmäsalkku koostuu markkina-arvoltaan enimmäkseen pienistä osakkeista. Tämä on luonnollista arvo-osakkeille ja on merkittävä este institutionaalisille sijoittajille, jotka haluavat hyödyntää tätä strategiaa. Vaikka yhdistelmästrategian alfa on pieni, sen Sharpe-suhde on suurempi kuin yksittäisten arvo-, momentum- tai markkinasalkkujen Sharpe-suhde. Tämä osoittaa, että korkea F-Score alentaa yhdistelmästrategian kuukausituottojen riskiä.

Ehdotan useita aiheita tulevaisuuden tutkimusta varten. En ottanut huomioon transaktiokustannuksia tai veroja, joten niiden huomioon ottaminen parantaisi salkun tuottojen tarkkuutta, vaikka verojen ja transaktiokustannusten vaikutus on pieni salkun vuosittaisen tasapainottamisen vuoksi. Lisäksi strategiani koostuu vain ostopuolesta, eli lyhyeksi myynnin vaikutuksia ei tutkittu. Yksi mahdollinen tulevaisuuden tutkimusaihe olisi siis tutkia niin sanottuja long-short strategioita, jotka koostuvat arvo-osakkeista, F-Scoresta ja momentumista. Edelleen tämän tutkielman tuotot laskettiin Yhdysvaltain dollareissa. Laskemalla tuotot Englannin punnissa, salkun tuottolaskelmien tarkkuutta voisi parantaa.

KEYWORDS: arvosijoittaminen, piotroski f-score, momentum, salkunhoito

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1 Introduction

Academic research about combined value and momentum strategies is relatively new and limited. According to Asness (1997), value and momentum anomalies are linked to abnormal returns in stock markets yet both strategies show negative correlation with each other. A later study by Asness et al. (2013) shows that value and momentum strategies display negative correlation across and within different asset classes. Kok et al. (2017) and Israel et al. (2021) argue that momentum can be used to enhance value investing strategies due to negative or zero correlation with traditional value measures.

The purpose of this thesis is to study the profitability of value and momentum strategies in United Kingdom stock markets. Specifically, I test a combination of Piotroski F-Score screened high book-to-market high past price momentum (value-winner) strategy against standalone market, high book-to-market and momentum strategies. There has been a lack of recent research about the profitability of the value factor in the United Kingdom equities. This is surprising given the United Kingdom markets have great liquidity, stability and data availability. Moreover, United Kingdom's departure from the European Union, e.g., Brexit, between 2015 and 2020 and the global corona pandemic of 2020-2022 were unique events that negatively impacted the local equity markets. By analysing the effects of these events on value stocks, investors can gain a better understanding of the profitability of value and momentum investment strategies. This information can be used to develop more effective investment strategies for value investors in the United Kingdom.

This paper benefits both researchers and asset managers in evaluating the effectiveness of combined value and momentum investing strategies. I show that a combined value-winner strategy enhances the risk-adjusted returns of standalone value and momentum strategies, and the combination strategy has higher Sharpe ratio than standalone strategies. My work contributes to the timing issue of investing and the predictability of stock price reversals. Moreover, I provide new information about risk-managed returns for value and momentum portfolios in the United Kingdom stock markets.

1.1 Previous research

Fama and French (1992) show that firms with high book-to-market ratio outperform firms with low book-to-market ratio and argue that this is due to higher level of risk. They claim that these so-called value stocks are undervalued and unpopular with investors because high book-to-market value often signals about company's financial distress, meaning that these companies have either high levels of debt or weak cash flows. Subsequently, Fama and French (1993) present a 3-factor asset pricing model that explains value premium (HML), market risk (beta) and company size (SMB) effect on the stock returns.

Piotroski (2000) improves the quality of existing value investment strategies by introducing F-Score, a screening tool for evaluating the financial strength of companies. F-Score contains 9 binary signals that are assigned to three categories: profitability, liquidity, and operational efficiency. High F-Score significantly improves the returns of high book-to-market portfolios, and F-Score is able to distinguish financially strong companies amongst high book-to-market companies. On the other hand, low F-Score is specifically good at predicting the underperformance of high book-to-market firms. Piotroski (2000) hypothesizes that F-Score works because investors are slow to react to new information. Furthermore, Tikkanen and Äijö (2018) find that high F-Score screening improves traditional value investment strategies in European stock markets by 1.8-3.9% on average.

Jegadeesh and Titman (1993) show that past stock price movement predicts future price momentum and claim that the momentum anomaly is most likely caused by investors' over- and underreaction to new information. They show that the price momentum is persistent for up to 12 months after portfolio formation. Rouwenhorst (1998) finds similar evidence from European stock markets where the momentum is strongest in the small firms. Chan et al. (2000) show that momentum anomaly exists on international stock markets and that past trading volume is a strong predictor of stock price momentum.

Bird and Casavecchia (2007) suggest that analysts are reactive rather than predictive in their recommendations. They argue that many mispriced stocks follow a pricing cycle where price movements are somewhat consistent and end up having a turnaround. However, it is difficult to time the turnaround effect if it happens at all. They debate that even though value stocks have outperformed the markets many times in the past, the outperformance can be attributed to a few individual stocks while most of the value stocks underperform the markets. Many undervalued stocks are cheap because their financial situation or future growth prospects are poor. The authors refer to these types of companies as value traps.

To address the timing issue, combined value and momentum trading strategies have been studied by Bird and Casavecchia (2007), Leivo (2012) and Asness et al. (2013), for example. According to Asness (1997), Asness et al. (2013) and Kok et al. (2017), value and momentum long-short strategies have negative correlation with each other and that combination of the two strategies yields higher risk-adjusted returns than each strategy in isolation. Leivo (2012) shows that adding past price momentum strategy to traditional value strategies improves their risk-adjusted returns in Finnish stock markets while Pätäri et al. (2018) present that adding momentum factor to traditional value strategies improves the portfolio's risk-adjusted performance in the United States stock markets. Likewise, Pätäri et al. (2017) find similar evidence from German stock markets and show that combining Piotroski F-Score with traditional value measures improves the portfolios' raw and risk-adjusted returns compared to standalone value strategies. Lastly, Tikkanen and Äijö (2018) present that F-Score is able to increase the returns of a traditional Novy-Marx (2012) portfolio by average of 2,42 % per annum in European stock markets.

While combination strategies consisting of value, momentum and F-Score have been studied in the United States and European stock markets, there is a lack of recent research about the efficacy of combination strategies in individual stock markets in Europe. Recent studies by Ahmed and Safdar (2018), Walkshäusl (2019) and Zhu et al. (2023) show evidence that combination strategies consisting of Piotroski F-Score and

momentum yield better risk-adjusted returns than standalone value and momentum strategies. Ahmed and Safdar (2018) present that F-Score screened 6-month momentum strategy yields an abnormal annual return of 6,48 % while a standalone 6-month momentum strategy yields only 1,92 % per year in United States stock markets during 1973-2015. Zhu et al. (2023) present that F-Score is able to enhance the returns of a 50-day moving average strategy and a 52-week high momentum strategy in the United States stock markets. The combination strategy of 52-week high and F-Score yields a statistically significant risk-adjusted monthly return of 1,5 % per month while a standard 52-week high strategy yields only 0,8 % per month during 1985-2017. Likewise, Walkshäusl (2019) shows that a long-short momentum strategy screened by Piotroski F-Score yields a statistically significant monthly return of 1,78 % on European stock markets and that the returns of high F-score-winner portfolio are robust against return reversals for up to 3 years after portfolio formation.

This thesis focuses on United Kingdom stock markets because there is lack of recent research about the profitability of the value factor in the United Kingdom equities. Furthermore, the United Kingdom stock markets are liquid, stable and the data is widely available. Britain's exit from the European Union (Brexit) in 2015-2020 and the corona pandemic of 2020-2022 were also unique events that affected the local stock markets. Previous research by Kok et al. (2017) and Israel et al. (2021) suggest that the value factor has not worked in the United States markets during the recent times due to investor awareness of the factor anomaly and prices drifting away from their fundamental values. I aim to research whether the value premium has also suffered in the United Kingdom equities.

In order to study the impact of value, momentum and Piotroski F-Score on the United Kingdom stock markets, I construct a Piotroski F-Score screened high book-to-market portfolio combined with past price momentum (2-12) and compare the results against individual market-, value- and momentum portfolios. I also test the results against Fama-French (2018) 6-factor model to and evaluate each portfolios' Sharpe (1966) ratios to

see whether my strategy improves the portfolio's risk-adjusted returns. It is important to note that the negative correlation between value and momentum strategies, as reported by Asness (1997), by Asness et al. (2013), Kok et al. (2017) and Israel et al. (2021) only occurs for long-short strategies. Unlike Walkshäusl (2019) and Zhu et al. (2023), I limit my strategy to long-only because Israel and Moskowitz (2013) argue that shorting small stocks is costly and difficult due to limited liquidity and Tikkanen and Äijö (2018) explain that short selling is restricted to many institutional investors due to various rules and restrictions imposed to large investors. Return data is reported on United States dollars and transaction costs and taxes are left unexplored as Israel and Moskowitz (2013) show that transaction costs have little effect on value and momentum factors while Korajczyk and Sadka (2004) present that the momentum factor yields abnormal returns even after accounting for transaction costs. Finally, my data period covers the most recent times of 2000-2022 that prior academic research about the combined value and momentum strategies do not cover.

1.2 Hypothesis

While Piotroski F-Score (2000) has been able to enhance the returns of traditional value investing strategies in the past, there is lack of recent research about the combination of F-Score and momentum investing strategies in Europe and specifically United Kingdom. According to Ahmed and Safdar (2018), F-Score is nowadays included in many professional databases for investors, such as S&P's Capital IQ. Therefore, its use in improving traditional value investing strategies is useful.

I hypothesize that a high book-to-market investing strategy screened by high F-Score and combined with positive past price momentum can improve the portfolio's risk-adjusted returns. This is due to several reasons. First, high book-to-market multiple provides a universe of undervalued stocks relative to their book value. Most of these stocks are cheap for a reason but a few of them may outperform the stock markets. Fama and French (1993) show that value factor worked in the United States stock markets during

1963-1990 but later studies by Israel et al. (2021), Bevanda et al. (2021) and Spyrou (2020) show that the value factor has underperformed in the United States and European stock markets during the most recent times after the financial crisis of 2008. The puzzle is to find out whether value stocks have also suffered in the United Kingdom stock markets in modern times.

Piotroski (2000) shows that F-Score is able to distinguish financially strong and weak companies amongst all high book-to-market (value) stocks. As analysts and financial markets are slow to react to new information, F-Score may help to identify companies with the strongest future price momentum before the price reversal happens. Koutoupis et al. (2022) explain that F-Score is able to predict stock returns on European stock markets during 1989-2016 and that high F-Score is a good predictor of high stock returns for both large and small companies. Furthermore, Peng et al. (2023) present evidence that mutual funds containing stocks with high F-Score have statistically significant Carhart (1997) four factor alphas and higher Sharpe ratios than mutual funds containing stocks with low F-Scores.

Momentum based on historical price information is also a persistent phenomenon across stock markets through time as shown by Jegadeesh and Titman (1993), Chan et al. (2000) and Chui et al. (2010). Jones and Winters (1999) present that past winner momentum stocks consist of value and momentum characteristics that explain their abnormal returns while Bird and Casavecchia (2007) show that adding a momentum indicator to traditional value strategy helps timing the price turnaround effect in high value, e.g., low priced stocks. Finally, Bhootra (2018) shows that firms with high gross profitability have high past price momentum. Therefore, combining value, momentum and Piotroski F-Score in balanced manner can provide useful insights about the profitability of value and momentum stocks.

The hypothesis is as follows:

H1: Piotroski F-Score screened high book-to-market portfolio combined with high past price momentum yields higher risk-adjusted returns than standalone market, value or momentum strategies.

1.3 Assumptions and limitations

This study has several limitations. First, I do not consider trading costs. Taxes and trading costs and could be estimated but Israel and Moskowitz (2013) show that transaction costs have little effect on value and momentum factors. Furthermore, Korajczyk and Sadka (2004) present that momentum factor yields abnormal returns even after accounting for transaction costs. It is important to note, that United Kingdom stock markets have a government stamp duty of 0,5 % per transaction which could have a significant effect on portfolio returns depending on the rebalancing frequency. I use annual portfolio rebalancing due to the nature of annual publication cycle of financial statements. Therefore, the stamp duty has a minimal effect on my portfolio returns. Also, as the value premium is often strongest in the small companies, implementing a trading strategy consisting of only small companies could lead to liquidity constraints and high bid-ask spreads rendering the strategy unprofitable in real trading scenario. For this reason, I report the company sizes included in each value-winner portfolio per year.

Moreover, I limit this study to long-only leaving short side effects left unexplored. This is because, Israel and Moskowitz (2013) argue that shorting small stocks is costly and difficult due to limited liquidity. Furthermore, Tikkanen and Äijö (2018) explain that short selling is restricted to many institutional investors due to various rules and restrictions imposed to large investors. Likewise, Asness (1997) suggests that value strategy works best when holding momentum constant, meaning that past price momentum should not consist of long-short strategy. Therefore, testing long-short strategy would not be viable. Lastly, I report all the returns in United States dollars in order to test my results against the Fama-French factors. Therefore, local currency risks are left unexplored.

2 Theoretical framework

This chapter presents the theoretical background behind efficient market hypothesis, capital asset pricing model, Fama-French (1993) 3-factor model and Fama-French (2018) 6-factor model. First, I explain the theoretical framework of efficient market hypothesis, capital asset pricing model and Sharpe ratio. Then, I review the Fama-French 3-factor model that explains company size, market risk and value premium on stock returns. Finally, I present Fama-French (2015) 5-factor model that explains firm profitability and investment level on stock returns and the 6-factor model that that explains momentum factor on stock returns and is the latest model developed to explain factor anomalies.

2.1 Efficient market hypothesis

In order to measure whether stock markets are efficient and fully reflect all available information, Fama (1970) presents 3 different forms of market efficiency that can be used to test stock market efficiency: weak form, semi-weak form and strong form. Weak form tests market efficiency based on historical stock returns or price patterns. Fama (1970) explains that the weak form tests have been the most popular because of availability of data and continues that the results imply that the markets are mostly efficient. However, he notes that there is some evidence from daily stock price changes implying serial correlation between day-to-day stock prices leading to market movements not explained by the efficient markets. This thesis can be categorized as a weak form test, since I compare historical return data from United Kingdom stock markets.

Semi-weak form tests assume that every investor has access to all publicly available stock market data. According to Fama (1970), previous tests regarding stock splits and earnings announcements prove that investors are able to correctly price these events in specific stocks or companies leading to efficiently priced stock markets. Strong form assumes that investors have exclusive access to any information that might affect the stock markets. This includes private company specific information and private macro information,

for example, on interest rate changes. Fama (1970) explains further that strong form tests should be used as a benchmark for testing perfect market efficiency, which rarely holds. He also points out two potential scenarios that may lead to deviations from the perfect market efficiency. First, stock market dealers and brokers have access to buy and sell orders before they come to the market. This information can be used to front-run trades or generate trading strategies that take into account implied volatility from the orderbook. Second, insider trading based on private company information may lead to abnormal returns causing strong deviations from market efficiency as insiders often have information that has great impact on stock prices.

A later study by Fama (1991) shows that event studies seem to be the most suitable method of studying the speed of how fast stock prices react to company specific news. He explains that most event studies support the notion that the markets are efficient and that stock prices react quickly to firm specific events although there is some evidence of markets reacting slowly to firm specific events, namely post-earnings announcement drift (PEAD). The author points out that management buyouts, mergers and acquisitions on average generate large returns for the owners of target companies, but those returns may be zero or even negative for acquiring companies. Fama (1991) also points out that firm specific private information may lead to abnormal returns deviating from market efficiency, but this information is difficult to exploit due to transaction costs and because it is only available to company insiders. Furthermore, he notes that passive investing strategies have contributed to the efficiency of the stock markets and that most mutual fund managers lose to their indices in long-term after accounting for management fees.

Fama (1991) also explores the evidence about stock return predictability. He finds that there is some proof about short- and long-term return predictability in earnings-to-price ratios, default spreads between low- and high-grade bond yields and dividend yields. In dividend yields, the evidence indicates that stock prices change in the same direction as changes in dividends, e.g., if a company reduces or cuts dividends, their stock price falls.

Furthermore, he finds evidence that interest rate spreads between long- and short-term yields can predict stock returns in short-term and that firms issuing new stocks have lower returns in short- to medium-term.

In another study, Fama (1998) presents further evidence that the stock markets are efficient. He claims that most financial anomalies disappear once investors become aware of them and that over the long-term many anomalies turn into economically or statistically insignificant phenomena. Furthermore, many financial anomalies are strongest on small stocks and often limited to small capitalization firms. Fama (1998) explains that small firms often present problems in market efficiency tests and suggests that many anomaly studies may just have bad testing models. The only anomaly that survives various peer studies is the previously mentioned PEAD strategy that seems to hold even after the discovery of earnings drift and past price momentum, discovered by Jegadeesh and Titman (1993).

Shiller (2003) criticizes efficient market theorists for their assumption that the stock markets are efficient. He explains that there is no fundamental reason for why investors would consistently over- or underreact to firm specific news. He suggests that financial anomalies disappearing when investors get to know them is natural since new research replaces past academic research. Shiller (2003) explicitly explains that disappearing financial anomalies cannot be assumed as a proof that the markets are rational or efficient because the same phenomenon would be present in highly irrational markets. He adds that short- and medium-term stock price reversals should not be blindly assumed to be the product of efficient markets because each stock's intrinsic value is highly subjective.

Malkiel (2003) reviews the latest evidence about market efficiency and finds that the stock markets are mostly efficient although there may be extended periods, e.g., "bubbles", during which stock prices drift away from their rational values for some period of time. Additionally, he notes that momentum and short-term serial correlation between stock prices are anomalies that deviate from efficient markets but exploiting these

anomalies is troublesome because of transaction costs taking up huge part of the profits. Furthermore, he notes that momentum has been profitable in the 1990s but crashed during the 2000s. Similarly to Fama (1999), he also states that underreaction to firm specific news is as common as overreaction and that return reversals between company specific events is as common as before the event as after the event, implying that the stock markets are efficient.

Malkiel (2003) suggests that most financial anomalies are not economically profitable or large enough that they could be exploited for long periods of time. That is why factor anomalies may become less useful once investors get to know about them. Likewise, he sheds some light on why stock prices are mean reversing in short- and medium-term. Typically, behaviourists state that investors are over- or underreacting to company specific news because of overconfidence. However, according to Malkiel (2003), stocks together with bonds follow the pricing cycle from interest rates. Since central bank interest rates are mean reversing, stocks and bonds naturally follow the interest rate cycle. He also states that the tendency for stocks to rise in January and Mondays is not consistent, vulnerable to transaction costs and dependent on the sample period. That is, once investors know about January effect, for example, they shift their buying decisions earlier and earlier until the anomaly slowly disappears or become less significant.

According to Malkiel (2003), it is unwise to assume that the predictability of interest rate term structures or financial statistics would make a profitable investing strategy or aid in asset allocation. In fact, he notes similarly to Fama (1991), that most professional money managers underperform against their indices in the long-term and that historical fund performance calculations most likely suffer from survivorship bias when poorly performing funds are merged into larger ones, which is typical practise in the fund industry. Moreover, he suggests that the firm size anomaly may suffer from survivorship bias when only surviving small firms are left in portfolio return calculations and that small firms actually underperformed large firms during 1985-2000. The author also states that value anomaly may have been unique to the time period of 1960-1990 and suggests that it is

not relevant anymore. Lastly, Malkiel (2003) reminds that most anomalies will be arbitraged away by professional money managers as soon as the anomalies are published but that the stock markets can never be perfectly efficient because then there would be no incentive for smart money to find anomalies and abnormalities.

2.2 Capital asset pricing model

Capital asset pricing model (CAPM) is perhaps the most known asset pricing theory in modern finance, and it is still relevant to this day according to Paulo (2010). CAPM was first introduced by Sharpe (1964), who presents a theoretical model that explains expected returns of an investment based on its risk level. He presents that investors expect higher rate of returns for investments that have higher level of risk and uses stock market volatility (beta) as a measurement of that risk. The model is as follows:

$$E(R_i) = R_f + B_i(E(R_m) - R_f, \quad (1)$$

where: $E(R_i)$ = expected return of an investment

R_f= risk-free rate, that is typically a government bond representing a risk-free investment

$B_i(E(R_m)_i$ = sensitivity of an investment against stock market volatility. In detail, beta measures how much an individual investment's price moves relative to the overall stock market.

Sharpe (1964) explains that investors are able to reduce the risk of their investments with diversification. He continues, that a beta of 1 indicates that the investment moves perfectly together with the markets while beta below 1 indicates that the investment moves slower than the market returns. Subsequently, beta of over 1 indicates that the investment returns are more volatile than the market returns. Therefore, individual investors can reduce their portfolio's risk by investing in stocks that have a beta of lower

than 1 or they can diversify their investments to several smaller investments in order to reduce their overall portfolio volatility while maintaining their returns.

Capital asset pricing model is built on an assumption that all investors are rational, can lend at the risk-free rate and that all stock information is publicly available to every investor. Moreover, the model assumes that there is no transaction costs, taxes or other limits to arbitrage, e.g., the CAPM model assumes that the stock markets are efficient. Subsequently, the model rarely holds in practical portfolio management and firm investment calculations as shown by Paulo (2010). While CAPM is useful in defining stock market volatility as a risk measurement, it has problems when comparing the risk of different investments against each other. Therefore, Sharpe (1966) presents a ratio that explains portfolio's excess returns to its volatility, labelled as Sharpe ratio. The Sharpe (1966) ratio is calculated as follows:

$$S_p = \frac{R_p - R_f}{\sigma_p}, \tag{2}$$

where: S_p = Sharpe ratio

$\frac{R_p - R_f}{\sigma_p}$ = portfolio returns minus risk-free rate divided by standard deviation of the portfolio's excess returns.

Sharpe ratio measures the risk-adjusted returns of a portfolio and is useful in comparing portfolio performance of different portfolios against each other. Sharpe ratio is still used in modern portfolio management research because of its simplicity and ease of use as shown by Pätäri et al. (2018, 2017), Fama and French (2018) and Israel et al. (2021), for example.

It is worth noting that that both the CAPM and Sharpe ratio are based on historical stock and market returns and assume that the returns are normally distributed. Therefore, both models have limitations that need to be accounted for when used in practical

investment research. To address the normality assumption, I use Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) error terms in my study.

2.3 3-factor model

Fama and French (1993) are the first to introduce accounting ratios-based investing strategies and find that Sharpe's (1964) capital asset pricing model is unable to explain firm size and book value in United States stock markets during 1963-1990. They suggest that this is due higher level of risk. High book-to-market (value) stocks tend to have lower earnings related to their size and this effect seems to be persistent through time. To explore the value anomaly in detail, Fama and French (1993) present a 3-factor asset pricing model that explains value premium, market risk and company size effect on stock returns. The model is as follows:

$$R_{it} - F_t = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + e_{it}, \quad (3)$$

where: $R_{it} - F_t$ = monthly excess returns of each stock

a_i = intercept of the regression

$b_i Mkt_t$ = value-weighted monthly excess market returns

$s_i SMB_t$= average monthly excess returns between small capitalization stocks and large capitalization stocks

$h_i HML_t$ = average monthly excess returns between high book-to-market stocks and low book-to-market stocks

e_{it} = error term of the regression.

Fama and French (1993) suggest several reasons for why the 3-factor model is able to explain the stock returns in the United States. First, investors may from exhibit irrational behaviour when they overreact to new information during quarterly and annual statements. Therefore, high book-to-market firms might be temporarily undervalued until investors adjust their views for the firms' new growth prospects. Second, the size and value

factors may expose economic risks in business conditions, meaning that investors require a higher rate of return for small and poorly performing firms and that these companies are also more subject to adverse business conditions during economic downturns.

2.4 6-factor model

Fama and French (2015) introduce a 5-factor asset pricing model, where the Fama and French (1993) 3-factor asset pricing model is enhanced with two additional risk factors that explain firm profitability and investment level. The model is as follows:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}, \quad (4)$$

where: $r_i RMW_t$= difference between high and low profitable companies

$c_i CMA_t$ = difference between firms that invest a lot versus companies that invest little

These two factors are constructed similar to HML factor, and the rest of the factors are similar as introduced earlier in chapter 2.2.

Fama and French (2015) find that the model is robust on United States stock markets between 1963 to 2013 and that the results are not explained by the capital asset pricing model. Further research from Fama and French (2012) and Fama and French (2017) shows that both the 3-factor and 5-factor asset pricing models are robust on international stock markets as well. However, the 5-factor asset pricing model is unable to explain momentum anomaly.

Carhart (1997) introduces 4-factor asset pricing model, where the the Fama and French (1993) 3-factor asset pricing model is enhanced with the momentum factor. The model is able to explain mutual fund returns in the U.S. markets, but Fama and French (2012)

show that the model fails to explain stock returns on local stock markets, such as Europe and Asia Pasific. Majority of the 4-factor model's problems stem from extreme price momentum in winner decile and loser decile portfolios, which skew the results.

This study uses Fama and French (2018) 6-factor asset pricing model, where the 5-factor model is enhanced with a momentum factor. The 6-factor asset pricing model is robust on United States equity markets between 1936-2016 and the results cannot be explained by capital asset pricing model, 3-factor model or 5-factor model. The model is as follows:

$$R_{it} - F_t = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + m_i UMD_t + e_{it}, \quad (5)$$

where: $m_i UMD_t$= difference between high and low past price momentum companies

The momentum factor is constructed similar to HML factor, introduced earlier in chapter 2.2 with the exception that the momentum factor uses past price data from 1 year while skipping the past month's price data due to short-term reversal effect (2-12). The rest of the factors are similar to 5-factor model introduced earlier in this chapter.

3 Literature review

This chapter presents the most known and latest academic research done on value investing, Piotroski F-Score, momentum, and combined value and momentum strategies. First, I review evidence on why the value investing anomaly persists and what drives the value premium. In chapter 3.2 I introduce Piotroski F-Score and explain its ability to distinguish financially strong and weak companies amongst undervalued firms. Chapter 3.3 explains momentum anomaly and past price continuation in U.S. and EU stock markets while in chapter 3.4 I present the latest research done on combined value, momentumand F-Score strategies and justify the rationale of studying value and momentum strategies jointly. I also discuss about the improvement in risk-adjusted returns of the combined strategies across different markets and timing of the turnaround in past price momentum.

3.1 Value anomaly

Value investing is first introduced by Graham and Dodd (1934) who suggest that investors should identify intrinsic value of each stock and invest in those stocks that are the most undervalued compared to their market price. The authors present that intrinsic value should be determined by the stock's future earnings power but warned against using simple accounting ratios to determine if a stock is undervalued or not.

Value anomaly may persist because of investors' errors. Lakonishok et al. (1994) suggest that the value anomaly persists because investors are not diligent enough to analyse every undervalued stock. They suggest that investors under- and overreact to company specific news driving the value anomaly. However, Lakonishok et al. (1994) suggest that value stocks are not riskier than other stocks due to their high book-to-market value. In fact, they find that high book-to-market stocks outperform low book-to-market stocks by average of 10-11 % per year in the United States stock markets and that the value anomaly persists even on large capitalization stocks.

La Porta et al. (1997) presents that investors' errors play a significant role in high returns of value stocks and explains that returns after earnings announcements are higher for high book-to-market stocks than for low book-to-market stocks. Furthermore, the earnings announcement returns for large capitalization value stocks are lower than small firms, meaning that large companies are more likely to have multiple analysts to adjust the valuation of the firm even outside of earnings announcement dates. La Porta et al. (1997) continue that investors make errors in estimating future revenue and earnings growth rates and that they systematically underestimate the earnings growth of value stocks while overestimating the earnings growth of low book-to-value firms. The authors suggest that unsophisticated investors crowd towards low book-to-value, e.g., growth firms because they are typically large and well known, and thus viewed as low-risk investments. This causes value the opportunity to value firms to outperform the markets when they exhibit strong earnings growth during quarterly announcements.

There are several reasons for why stocks may become systematically undervalued related to their book values. According to Greenwald et al. (2004), value investing is not possible to every investor due to biases and constraints. For example, investors may have ethical investment guidelines that exclude certain industries. 'Sin stocks', like tobacco, gambling or defence companies may become systematically undervalued, because of investors' restrictions. Furthermore, ownership limitations and redemption rules restrict large investment funds from holding significant portions of small market capitalization stocks. Typically, large investors need to make an offer for the remainder of the company's shares if their ownership exceeds 10 percent, rendering investing to small firms less effective. Third, macroeconomic factors may explain the value anomaly. Vassalou (2003) shows that firm book value and size are linked to gross domestic product (GDP) growth in the United States stock markets. Essentially, HML and SMB factors predict low future GDP growth measured by macroeconomic news related to GDP growth. Greenwald et al. (2004) also present that companies with financial or legal difficulties are often neglected by analysts and therefore without analyst coverage leading to lower valuation than their peers. Kok et al. (2017) hint that this is the reason why the value anomaly has

not worked in recent years and suggest that sophisticated analysts have found out about financially distressed undervalued stocks and set the asset prices accordingly.

Investors' behavioural biases affect their investing. Greenwald et al. (2004) explain that many investors are afraid of taking risks and losing money, so a stock which price has fallen is an emotionally difficult decision for the investor. This is why firms with high book-to-market value are often neglected by investors. Furthermore, Lakonishok et al. (1994) propose that institutional investors and professional money managers tend to crowd towards stocks that have stable earnings and positive dividend growth. This is because investors remember recent events better than past events, causing them to crowd towards winning and well performing stocks. However, according Lakonishok et al. (1994), market winners become market losers within 2 to 3 years on average, meaning that stocks' future growth rates are mean reversing in the medium term. This is similar finding to Greenwald et al. (2004), who claim that typical value investing strategies may underperform the markets for up to 3 years but in the long-term some of them outperform the markets. For this reason, fund managers have difficulties in investing to undervalued stocks because their funds risk closure before the expected outperformance realizes. Lastly, Bird and Whitaker (2004) suggest that the value anomaly persists because value premium may simply be a compensation for holding risky stocks.

Value anomaly is linked to firm size. According to Penman and Reggiani (2018) high book-to-market value signals for risky growth, meaning that value stocks are more likely to suffer from extreme shocks related to their earnings growth than other stocks. Furthermore, the value anomaly is strongest in small market capitalization stocks which is natural since small companies tend to have riskier earnings growth than large and well-established firms. Malin and Veeraraghavan (2004) find similar evidence from European stock markets and show that small firms outperform large firms in France and Germany but not in the United Kingdom stock markets. They also present that low book-to-market firms outperform high book-to-market firms on all three markets and suggest that the value anomaly may not be effective in modern times in European markets. This is similar

finding to Bird and Whitaker (2003), who show that high book-to-market based value portfolios have underperformed the markets in Europe during 1990-2002 and suggest adding some kind of quality criteria for screening value stocks. Furthermore, Bird and Whitaker (2003) present that value premium is concentrated to small capitalization stocks, which makes it difficult for large investors to exploit.

A more recent study by Israel et al. (2021) show that traditional value strategies have suffered in the United States stock markets in most recent years. They suggest that this is due traditional value strategies consisting of stocks that have poor earnings growth or inflated accounting numbers. Furthermore, they present that investors have poor judgment in assessing the future long-term growth of their investments resulting in underperformance of value stocks once investors realize their investments are overvalued. Israel et al. (2021) also suggests that low interest rate environment of 2010s and increased knowledge of factor anomalies, especially value factor, have contributed to the underperformance of traditional value strategies in recent times. This is similar finding to Löeffler (2020), who shows that investors' interest in the value anomaly predicts value premium in short-term, meaning that increase in investor's interest leads to higher stock prices leading value premium non-existent and thus lower returns for value stocks in modern times. HML strategy yields 9,9 % per annum in the United States stock markets while investors' interest is low compared to 1,0 % per annum when investors' interest is high. However, the author reminds that the value premium still exists in the long-term and that investors' interest may only explain part of the decrease in the value premium.

Bevanda et al. (2021) show similar evidence from United States stock markets after the 2008 financial crisis. They show that growth firms outperform value stocks during 2008-2018 and that value premium has disappeared in large capitalization stocks in modern times. Similar to Israel et al. (2021) and Löeffler (2020), Bevanda et al. (2021) suggest that the low long-term interest rates have contributed to the outperformance of growth stocks in recent times since stock market valuation is largely based on discounting future cash flows. They also present that the growth of technology stocks has become an

increasing factor in the profitability of growth strategies. Particularly, the technology sector has outperformed typical value sectors which mostly consist of financial and industrial companies. However, they also point out that both value and growth stocks outperform their related index Dow Jones Industrial Average in modern times.

Spyrou (2020) shows that the value premium is not statistically significant in European stock markets during modern times 1997-2016. He also explains that that investor sentiment and behaviour drives the returns of value stocks especially during economic downturns, e.g., value stocks perform better when investors are optimistic about the stock markets during bear periods. Spyrou (2020) suggests that uncertainty during economic downturns causes investors to make bad investment decisions and that investors are biased towards recent negative news rather than looking at the long-term fundamentals of each company. This causes increased volatility during economic crises which leads to market crashes and value stocks with strong fundamentals to thrive. He also notes that value stocks exhibit countercyclical behaviour during economic crises, meaning that during boom years value stocks on average lose to the markets but during bear periods they beat the market returns.

3.2 Piotroski F-Score

According to Piotroski (2000), typical value investment strategies aim to find undervalued stocks, but do not pay enough attention to companies' financial strength and growth prospects. He presents that the returns from traditional investment strategies based on high book-to-market value are generated mostly by a few high-performing companies while most of the companies with high book-to-market value are unprofitable, referred later as 'value traps' by Penman and Reggiani (2018) and Kok et al. (2017), for example.

In order to identify financially strong firms amongst all high book-to-market firms, Piotroski (2000) proposes a financial score (F-Score) that measures companies' financial strength using nine binary signals. Each signal gets a value of one (zero), which is a good

(bad) signal about the company's financial situation and these signals can be divided into three categories: profitability, liquidity, and operational efficiency. Thus, an individual company's' F-Score can vary between 0 and 9, with zero being the worst and nine being the best. The total sum of the signals is added together each year, and the sum is called F-Score.

F-Score outperforms the United States markets during 1976-1996. Piotroski (2000) shows that a long-short portfolio based on F-Score yields 23,0 % per year on average. Furthermore, high F-Score portfolio yields a statistically significant excess return of 31,3 % per year while low F-Score portfolio yields only 7,8 % per year on average. He also shows that 57,0 % of companies yield negative excess returns for high book-to-market portfolio consisting of 14,043.00 companies. Therefore, high F-Score is able to identify and exclude underperforming firms out of all undervalued stocks and Piotroski (2000) asserts that the F-Score is the most effective for companies that have no analyst coverage and whose trading volume is low.

There may be several reasons for why the F-Score works. Piotroski (2000) explains that high book-to-market companies may have credibility issues in communicating their financial situation to investors and analysts. Because of weak profitability, the management's communication about the company's future profitability is not credible. He believes that the abnormal returns from the F-Score investment strategy are due to information asymmetry and investors reacting too slowly to positive news. Likewise, Turtle and Wang (2017) show that the Piotroski F-Score's positive impact on investment portfolio returns is due to investors underreacting to new financial information from financial statements. This underreaction is strongest in small and illiquid companies, without analyst coverage. Turtle and Wang (2017) argue that the improved returns are not only due to higher risk, but also because of market optimism and gradual stock price changes as investors react slowly to quarterly earnings announcements. Piotroski (2000) believes that analysts tend to neglect low-performing stocks and instead prefer stocks that have performed well in the past. Therefore, financial information about small companies is

not available or it's unreliable, causing investors to underreact when good news come to market and overreact when bad news come to market during quarterly and annual updates.

Subsequently, Piotroski and So (2012) show that the returns to standalone value and glamour strategies are explained by their financial strength measured by F-Score. In detail, strong returns of value stocks are concentrated to firms with high F-Score and weak returns of growth stocks are concentrated to firms with low F-Score. They show that high book-to-market firms screened with high F-Score outperform firms with weak fundamentals by 22 % per year. The authors continue that investors are not diligent enough to analyse the financial strength of companies, which causes errors in stock valuation and earnings forecasts. These errors are eventually corrected once the investors find out that financially strong companies release strong earnings reports. Furthermore, Piotroski and So (2012) present that the expectation errors investors make are stronger in times where there is a high investor sentiment measured by buying demand.

Walkshäusl (2017) find similar evidence from 15 European stock markets, where the strong returns of value firms are concentrated to firms with high F-Score and the low returns of growth firms are concentrated to firms with low F-Score. Additionally, the results are robust after controlling for Fama-French factors and persistent for up to 3 years after portfolio formation. Walkshäusl (2017) suggests that external financing activities of firms can explain the results and proposes a financing-based factor to capture these expectation errors. He explains that when a firm issues or repurchases shares, investors view them as under- or overvalued and thus the factor can capture the return behaviour of value and growth firms. Subsequently, Koutoupis et al. (2022) present that F-Score is able to predict stock returns on European stock markets during 1989-2016. They explain that high (low) F-Score is a good predictor of high (low) stock returns for both large and small companies. The authors suggest that F-Score's predictive ability is not because of risk but because of mispricing caused by investors when they gradually react to firm specific news, meaning that average investors are unable to spot financially strong firms

amongst all stocks. Similar to Walkshäusl (2017), Koutoupis et al. (2022) suggest using net financing indicator as a variable for predicting future stock profitability.

Navas et al. (2023) present strong evidence from French stock markets where F-Score is able to enhance the returns a Euronext Paris 100 index. A portfolio consisting of stocks with high F-Score yields risk-adjusted annual returns of 16,0 % during 2000-2020. Furthermore, a long-short strategy shorting low F-Score firms and buying high F-Score firms yields a statistically significant annual return of 25,0 %.

Choi and Sias (2012) show that Piotroski F-Score predicts stock returns on the United States stock markets during 1983-2006. They explain that sophisticated investors respond gradually to new firm specific fundamental information during quarterly and annual updates and eventually drive the stock prices up once they decide to invest in financially strong companies. In detail, high F-Score also predicts strong institutional demand for individual companies. The authors suggest that strong financial strength measured by high F-Score proxies for high expected profitability in the future and that large investors prefer to invest in these kinds of companies.

A more recent study by Peng et al. (2023) show that F-Score is useful in analysing the stock holdings of mutual funds in the United States during 1979-2015. They present that mutual funds containing stocks with high F-Score have statistically significant Carhart (1997) four factor alphas and higher Sharpe ratios than mutual funds containing stocks with low F-Scores. Furthermore, they note that while both mutual fund types containing high and low F-Score stocks have similar net returns, the returns of mutual funds that have stocks with high F-Score exhibit lower systematic and idiosyncratic risk, yielding better risk-adjusted returns to investors. These results are robust after controlling for transaction costs and fund fees. Peng et al. (2023) suggest that the since the net returns for both type of mutual funds are similar, the source for better risk-adjusted returns of high F-Score mutual funds is due to these funds containing low risk firms with strong financial fundamentals. Likewise, they note that actively managed mutual funds do not

chase for firms with high F-Score and suggest that the reason for this is because mutual fund flows do not follow changes in firm fundamentals during quarterly updates. This means that on average, investors do not care about company fundamentals when investing in mutual funds leading to potential problems in funds inflows causing actively managed mutual fund managers to invest in stocks that yield better fund inflows and management fees. They continue that investing on high F-Score firms may be difficult to mutual fund managers because the potential abnormal returns may realize only after one to two year holding periods which may cause investors to withdraw their funds early as they chase mutual funds with good recent past performance.

3.2.1 Profitability

Piotroski (2000) assigns four F-Score signals related to the company's profitability: return on assets (ROA), a change in return on assets compared to the previous financial year, operating cash flow (CFO) and accruals. The return on assets and operating cash flow indicators present how profit and cash flow have been generated by the capital available during the financial year. As high book-to-market companies underperform on average, profitability indicators such as operating cash flow and return-on-assets indicate the firm's ability to generate internal income through operations. The accruals can be used to evaluate whether the results come from operational activities or from accounting actions, e.g. paper profits. Return on assets is calculated as follows:

$$ROA = \frac{Net\ income\ before\ extraordinary\ items}{Total\ assets_{t-1}}, \tag{6}$$

where: ROA = return on assets for current year

$\frac{Net\ income\ before\ extraordinary\ items}{Total\ assets_{t-1}}$ = net income before extraordinary items for the current year divided by total assets at the beginning of the year.

F-Score gets a value 1 if positive and 0 if negative. Operating cash flow is calculated as follows:

$$CFO = \frac{Cash\ flow\ from\ operations}{Total\ assets_{t-1}}, \quad (7)$$

where: CFO = operating cash flow for current year

$\frac{Cash\ flow\ from\ operations}{Total\ assets_{t-1}}$ = net cash flow from operating activities for the current year divided by total assets at the beginning of the year.

F-Score gets a value 1 if positive and 0 if negative. Change in return on assets is calculated as follows:

$$\Delta ROA = ROA - ROA_{t-1}, \quad (8)$$

where: ΔROA = change in return on assets between current year and last year

$ROA - ROA_{t-1}$ = the current year's return on assets minus last year's return-on-assets.

F-Score gets a value 1 if positive and 0 if negative. Accruals are calculated as follows:

$$ACCRUAL = \frac{Net\ income\ before\ extraordinary\ items - Cash\ flow\ from\ operations}{Total\ assets_{t-1}}, \quad (9)$$

where: $ACCRUAL$ = income accruals for current year

$\frac{Net\ income\ before\ extraordinary\ items - Cash\ flow\ from\ operations}{Total\ assets_{t-1}}$ = the current year's net income before extraordinary items minus the current year's cash flow from operations divided by total assets at the beginning of the year.

F-Score gets a value 1 if negative and 0 if positive.

3.2.2 Liquidity

Piotroski (2000) includes three F-Score signals for liquidity. These are change in long-term debt, change in current ratio and whether the firm issued any equity during the year. He argues that if a company increases its debt, it is incapable of generating enough income through internal financing. The signal for a change in current ratio illustrates the company's ability to serve its future loan commitments. Furthermore, when a company issues shares, it demonstrates that it is incapable of gaining external financing and is financially distressed. Change in long-term debt is calculated as follows:

$$\Delta LEVER = \frac{Long\text{-}term\ debt_{t-1}}{Average\ total\ assets_{t-2,t-1}} - \frac{Long\text{-}term\ debt}{Average\ total\ assets_{t-1,t-0}}, \quad (10)$$

where: $\Delta LEVER$ = change in long-term during past two years

$\frac{Long\text{-}term\ debt_{t-1}}{Average\ total\ assets_{t-2,t-1}} - \frac{Long\text{-}term\ debt}{Average\ total\ assets_{t-1,t-0}}$ = long-term debt last year divided by average of total assets at t minus 2 year and total assets at t minus 1 year minus long-term debt current year divided by average of total assets at the beginning of the year and total assets at the end of the year.

F-Score gets a value of 1 if positive and 0 if negative. Change in current ratio is calculated as follows:

$$\Delta LIQUID = Current\ ratio - Current\ ratio_{t-1}, \quad (11)$$

where: $\Delta LIQUID$ = change in current ratio between current year and last year

$Current\ ratio - Current\ ratio_{t-1}$ = current ratio for the current year minus current ratio last year. Current ratio is calculated by dividing current assets with current liabilities.

F-Score gets a value 1 if positive and 0 if negative. Equity issued is calculated as follows:

$$EQ_{OFFER} = Equity\ issue - Equity\ issue_{t-1}, \quad (12)$$

where: EQ_{OFFER} = change in equity issued for current year compared to last year

$Equity\ issue - Equity\ issue_{t-1}$ = equity issued for the current year minus equity issued last year.

F-Score gets a value 0 if positive and 1 if negative.

3.2.3 Operational efficiency

Piotroski (2000) assigns 2 signals for operational efficiency, and these are change in gross margin ratio and change in asset turnover ratio. He asserts that operational efficiency indicators measure the company's ability to increase prices of its products or reduce inventory or manufacturing costs. Efficiency indicators can therefore be used to evaluate how efficiently the company operates. Change in gross margin ratio is calculated as follows:

$$\Delta MARGIN = Gross\ margin\ ratio - Gross\ margin\ ratio_{t-1}, \quad (13)$$

where: $\Delta MARGIN$ = change in gross margin ratio between current year and last year

$Gross\ margin\ ratio - Gross\ margin\ ratio_{t-1}$ = gross margin ratio for the current the year minus gross margin ratio last year. Gross margin ratio is calculated by dividing gross profit with sales.

F-Score gets a value 0 if positive and 1 if negative. Change in asset turnover ratio is calculated as follows:

$$\Delta TURN = Asset\ turnover\ ratio - Asset\ turnover\ ratio_{t-1}, \quad (14)$$

where: $\Delta TURN$ = change in asset turnover ratio between current year and last year

$Asset\ turnover\ ratio - Asset\ turnover\ ratio_{t-1}$ = asset turnover ratio for the current year minus asset turnover ratio last year. Asset turnover ratio is calculated by dividing sales with total assets at the beginning of the year.

F-Score gets a value 0 if positive and 1 if negative.

3.3 Momentum anomaly

Jegadeesh and Titman (1993) show that there is a strong past price momentum in United States stocks during 1965-1989. This momentum lasts for up to three to twelve months. They also note that last month's returns reverse the next month, and label it as short-term reversal effect. Jegadeesh and Titman (1993) introduce an investing strategy that selects stocks based on past J month returns and holds them for K months. The strategy is as follows:

1. Stocks are sorted in ascending order based on their past J month returns at the start of each month.
2. Ten equally weighted portfolios are formed based on these rankings and the top decile portfolio is named as 'losers' decile while the bottom decile is named as 'winners' decile.
3. The strategy buys the winner portfolio each month and finances that by selling the loser portfolio, e.g., a long-short or zero-cost strategy and holds this position for K months.
4. The portfolio weights are rebalanced each month.

A long-short portfolio constructed by 6-month past price momentum yields a compounded annual excess return of 12,01 % on average. The last month's return data is skipped due to short-term reversal effect. Jegadeesh and Titman (1993) suggest that the past price momentum may be due to investors overreacting to new information causing

stock prices to deviate from their rational values. Specifically, investors display delayed price reactions to firm-specific information, such as earnings or guidance announcements. They also suggest that past price momentum may be caused by return persistence, meaning that winner stocks keep winning in the stock markets for up to 12 months after portfolio formation. Subsequently, Jegadeesh and Titman (2001) present further evidence that the momentum profits are positively significant for up to 12 months after forming the portfolio and that momentum anomaly is strongest on small companies. Likewise, Bird and Whitaker (2004) suggest that the momentum anomaly is caused by investors' over- and underreaction to firm specific news.

Chan et al. (1996) and Novy-Marx (2012) find similar evidence from intermediate past returns. When the portfolios are formed based on the past 12 to 7 months or past 6 month returns, long-short momentum strategy yields higher risk-adjusted returns than recent past performance introduced by Jegadeesh and Titman (1993) and these returns are not explained by the Fama-French 3-factor model. Similar to Jegadeesh and Titman (1993), Chan et al. (1996) find that investors are slow to react to company specific news leading to strong past price momentum once investors gradually adjust their views of companies' future growth prospects. Essentially, analysts are slow to update company prospects especially when a firm announces negative news. This is because analyst covering a particular stock are often paid by the same company, leading to reluctancy when updating investing recommendations to their clients. Likewise, Gutierrez and Kelley (2008) find similar evidence from weekly momentum strategies, where a long-short strategy based on weekly momentum earns positive abnormal profits for up to one year after portfolio formation. They propose that company specific news, like earnings or guidance updates, drives this price momentum.

Novy-Marx (2012) also finds that the momentum effect is present on international equity indices, commodities and currencies but is especially strong in large capitalization stocks. Likewise, Chui et al. (2010) find that momentum is strong in international equity markets and suggest that investor overconfidence may be behind the momentum

anomaly. Rouwenhorst (1998) finds further evidence that the momentum anomaly is present on European stock markets. He also suggests that investors underreact to company specific news driving the momentum anomaly. Rouwenhorst (1998) further states that price momentum in the United States markets also drive price momentum in European stock markets and that past price momentum is stronger in small firms than large firms. Furthermore, Chan et al. (2000) show that the momentum effect exists in international equity indices and that past trading volume predicts momentum's strength. They suggest that investors exhibit herding behaviour when trading stocks and essentially crowd towards past winners while exiting from past loser stocks causing the momentum anomaly.

Bird and Whitaker (2003) show further evidence from European stock markets where 6- and 12-month momentum strategies beat their indices during 1990-2002. Looking closer, the top 20 % quantile portfolio based on past positive price momentum yields 1,0 % per month risk-adjusted returns in the United Kingdom stock markets with 1 year holding period. The authors state that European momentum portfolios exhibit bias for small stocks, which hinders investors' ability to invest in them due to liquidity constraints.

Economic states affect momentum returns. Barroso and Santa-Clara (2015) show that momentum crashes during economic bear periods and Cooper et al. (2004) present evidence that momentum anomaly is driven by economic upturns and downturns. In detail, short-term momentum is driven by economic upturns, but the returns reverse in long-term. Therefore, macroeconomic factors play a significant role behind momentum profits across stock markets. Similar to Chui et al. (2010), Cooper et al. (2004) suggest that investors' overconfidence is the main driver behind momentum anomaly. First, investors tend to take too much credit for their wins attributing them to their investing skills. Second, investors blame their losses on external factors seeing investment losses as bad luck. This overconfidence gets a boost when positive firm specific news confirms investors' choices and fuels the initial price surge creating momentum. Eventually, as new information emerges, investors recognize their mistakes, and the market corrects itself.

A recent study from Reinhold and Lepori (2022) shows further evidence that macroeconomic news affect stock returns in the United Kingdom stock markets. In detail, higher than expected economic news increase stock prices. Positive surprises on gross domestic product (GDP), retail sales and Bank of England's policy rate yield to statistically significant returns on FTSE 100 index. This is because investors believe stronger economy leads to increased cash flows for equities and strong consumer demand as measured by retail sales and strong economic growth as measured by GDP proxy for this growth.

Investment analysts tend to recommend high momentum stocks for investors. Azzi et al. (2006) present evidence that stock analysts have a strong bias for high past price momentum stocks in European stock markets. This causes the momentum effect to increase for stocks with high past price momentum since many institutional investors follow analyst recommendations for their investment strategies. Azzi et al. (2006) also show that analysts in United Kingdom stock markets prefer small firms but their recommendations have a negative effect for future stock performance while analysts in Germany and Italy provide better insights for stocks that outperform the stock markets. Furthermore, some analysts tend to change their recommendations to value stocks during economic downturns but the bias changes to high momentum stocks once the economy recovers.

La Porta (1996) finds similar evidence from analysts forecasts and presents that firms with low analyst expectations about future earnings growth outperform firms with high expected growth rates by 20 % per annum. Subsequently, analyst revise their recommendations about future earnings growth after the companies update their financial forecasts during quarterly announcements and these revies are larger for firms with high expected future earnings growth. Furthermore, La Porta (1996) suggests that firms with low future expected earnings growth are not riskier than firms with high expected growth rates and that these firms also perform better than their counterparts during economic downturns.

Jones and Winters (1999) show evidence that past winner momentum stocks consist of value and momentum characteristics that explain their abnormal returns on United States stock exchanges. These abnormal returns exist for up to two years after portfolio formation. The authors state that market inefficiency is the reason for why past winner stocks continue winning and that both positive feedback trading and increased institutional interest contribute to this phenomenon. Increased institutional interest is particularly associated with underreaction when large investors herd towards stocks that post positive earnings surprises. Jones and Winters (1999) explain that it is easier to invest in past winner stocks than loser stocks for large institutions because if the winning stock loses value in the future, the cost of the investing mistake can be viewed as a small misfortune when everyone else makes the same mistake. Furthermore, they suggest that rapid price increases in stocks may be due to buying spree coming of unsophisticated investors and other large investors once institutional investors make a purchase decision. Lastly, Jones and Winters (1999) suggest that momentum strategies may be most profitable with firms that have low or non-existent analyst coverage.

Firm profitability affects momentum returns. Bhootra (2018) shows that firms with high gross profitability have high past price momentum returns in the United States stock markets during 1962-2015. He also presents that a combination long-short strategy consisting of 52-week high past price momentum stocks and high gross profitability stocks yields a value-weighted monthly return of 1,24 % per month while standalone 52-week momentum strategy only yields 0,48 % per month. Furthermore, the Sharpe ratio of the combination strategy is about double than the market portfolio and high gross profitability also enhances the returns of a standard 2-12 momentum strategy introduced by Jegadeesh and Titman (1993). Bhootra (2018) suggests that investors' underreaction may be behind the strong results of his study and that risk-based explanations cannot fully explain the results due to his strategy containing highly profitable firms with assumedly lower risk.

3.4 Combined value, momentum and F-Score

Academic research related to combined value, momentum and F-Score strategies is relatively new but promising. Kok et al. (2017) find evidence that the value (HML) factor has not worked during the modern time periods from 2002 to 2015 in the U.S. stock markets. They argue that this is due to increased investor awareness of the factor anomaly and reduced arbitrage costs. The authors state that while HML factor is unable to deliver abnormal returns it can still be useful in identifying companies with inflated accounting numbers. Kok et al. (2017) suggest that book-to-market, price-to-earnings (P/E) and forward-earnings-to-price (E/P) strategies could be improved by including other strategies, such as momentum, in the strategy due to their negative correlation between each other. Israel et al. (2021) add further that momentum can enhance value investing strategies due to negative or zero correlation with traditional value measures. Thus, momentum strategy can be a powerful diversification tool for value investors when the two strategies are studied jointly.

Asness (1997) presents that value and momentum strategies are negatively correlated, yet both anomalies are associated with abnormal returns in the United States stock markets during 1963-1994. Momentum is strong for expensive, e.g., low value stocks and weak for cheap, e.g., high value stocks. He suggests that book-to-market value signals for companies' financial distress and that firms with strong past price continuation are not financially distressed. Furthermore, past winner stocks are generally not financially distressed regardless of their book-to-market value. Asness (1997) states that investors' aversion to holding cheap stocks may explain the value premium and why the premium eventually dissipates with momentum winner stocks.

Studying value and momentum jointly improves the mean-variance frontier of the investment portfolio. Asness et al. (2013) show that value and momentum strategies are negatively correlated both across and within different asset classes. Their study includes stock markets in United States, United Kingdom and Japan, equity index futures, government bonds, currencies, and commodity futures. A combination of value and

momentum strategies yields positive abnormal returns, and the returns are not explained by the current asset pricing models. The authors also note that different value strategies are positively correlated between different countries and that momentum strategies share the same effect.

Asness et al. (2013) present two reasons for this negative correlation. First, funding risk may explain why value stocks keep losing during economic downturns and momentum stocks keep winning during economic upturns. As business funding dries up, high book-to-market firms experience difficulties in gaining external financing. On the other hand, high past price momentum firms are able to secure external financing during economic booms. Second, liquidity risk may explain why value and momentum stocks experience higher amounts of volatility during changing economic periods. This volatility is high for undervalued (value) and winner (high past price momentum) stocks because when a firm issues negative financial updates, investor selling pressure for most popular and crowded stocks becomes high, leading to high volatilities when investors exits their positions at the same time.

Bird and Casavecchia (2007) find similar evidence from European stock markets, where the combination of value and price momentum strategies improves portfolio risk-adjusted returns compared to standalone value and momentum strategies. They explain that adding momentum indicator to traditional value strategy helps timing the price turnaround effect in low priced, e.g., high value, stocks. Moreover, the authors assert that stock prices drift from their intrinsic values in somewhat predictable way and suggest that stock analysts are weak in predicting when the turnaround effect happens updating their investment recommendations mainly after positive or negative news hit the markets.

Bird and Whitaker (2004) show that traditional value strategies based on high book-to-market ratio can be enhanced with simple price momentum on European stock markets. A value strategy combined with 6-month past price momentum yields 1,6 % per month

during 1990-2002. Furthermore, both standalone value and standalone momentum strategies are negatively correlated with each other, but positively correlated with the markets. Bird and Whitaker (2004) present that high book-to-market based value strategies consists of companies that are generally small and whose liquidity is low, which presents a challenge for investors looking to capitalize on these strategies. They suggest that on average, stocks go through a pricing cycle where they first trend in one direction going above or below their intrinsic value and then the trend reverses overshooting through the intrinsic value in another direction. The reason why a combined value-momentum strategy can yield better results than standalone strategies is because it can detect the mispricing before the pricing cycle completes. Lastly, Bird and Whitaker (2004) comment that transaction costs only affect a small portion of the annual returns of the value-winner strategy.

Leivo (2012) shows that adding past price momentum strategy to traditional value strategies improves their risk-adjusted returns in Finnish stock markets. The best performing portfolio is a combination of composite value and 6-month momentum strategies, e.g., a value-winner strategy. Composite value strategy consists of dividend-to-price (D/P), book-to-price (B/P) and earnings-before-income-taxes-depreciation-and-amortization-to-enterprise-value (EBITDA/EV) strategies. The value-winner strategy yields 19,5 % per year on average between 1993-2009. Leivo (2000) also notes that individual value-winner strategies in general outperform Finnish stock markets during bull-periods but yield losses during economic downturns. He explains that value-winner strategies display higher volatility during bear-periods and that momentum enhances value strategies only during economic uptrends. The author explains that this is not an issue for long-term investors because historically stock markets have been more bullish than bearish. Pätäri et al. (2012) find similar results in the Finnish stock markets and present that value-winner strategies outperform market portfolio on risk-adjusted basis. They also note that adding momentum to the strategy slightly improves the results.

Pätäri et al. (2018) show that adding momentum factor to traditional value strategies improves the overall portfolio's risk-adjusted performance in the United States stock markets. They note that dividend-to-price strategy together with 6-month momentum strategy yields the best risk-adjusted returns out of all traditional value strategies. Furthermore, the improvement in risk-adjusted returns is not limited to low market capitalization stocks but also improves portfolios consisting of large companies. Pätäri et al. (2017) find similar evidence from German stock markets and show that combining Piotroski F-Score with traditional value measures improves the strategies' raw and risk-adjusted returns compared to standalone value strategies during 2000–2015. They also find that firms with high F-Score have high correlation with high past price momentum stocks and that these firms on average yield lower losses during economic downturns than standalone strategies.

F-Score improves traditional value investing strategies across European stock markets. Tikkanen and Äijö (2018) show that a high book-to-market portfolio screened with high F-Score yields a compounded annual growth rate (CAGR) of 18,51 % while a standalone high book-to-market portfolio yields only 14,72 %. High F-Score screening has the highest impact on earnings-before-income-taxes-depreciation-and-amortization-to-enterprise-value (EBITDA/EV) strategy, where the combination yields a compounded annual growth rate of 19,62 % while the standalone EBITDA/EV strategy yields 17,40 % CAGR. Furthermore, Tikkanen and Äijö (2018) present that F-Score is able to increase the returns of a traditional Novy-Marx (2012) portfolio by 2,42 % per annum measured by their compounded annual growth rates.

Piotroski F-Score improves 6-month momentum returns. Ahmed and Safdar (2018) show that a combined value-winner strategy yields an abnormal return of 6,48 % per year during 1973-2015 while a standard 6-month momentum strategy yields only 1,92 % per year in United States stock markets. The results are robust after controlling for Fama-French 5-factors and the value-winner's risk-adjusted returns measured by Sharpe ratio are better than the standalone momentum strategy. The authors suggest two reasons for why

the F-Score is useful in enhancing the performance of traditional momentum strategies. First, the price momentum might be driven by irrational noise trading that drives stock prices away from their intrinsic values. Once investors realize there is no economic fundamentals backing up the stock price, e.g., low F-Score, the price eventually returns to its fundamental level. Second, high F-Score is able to identify stocks that have persistent outperformance backed by their strong financials.

Likewise, Ahmed and Safdar (2018) present that firms with high F-Score have lower downside risk than standalone momentum stocks during economic bear periods. They also show that analyst forecasts are reactive rather than predictive and that analyst recommendation updates are stronger for firms with high past price momentum and high F-Score than for firms that have weak fundamentals, e.g., low Piotroski F-Score.

Walkshäusl (2019) shows that a standard momentum portfolio enhanced by Piotroski F-Score delivers higher risk-adjusted returns than standalone momentum portfolio in European stock markets during 1990-2017. A long-short strategy that is long on high F-Score-winner portfolio and short on low F-Score-loser portfolio yields a statistically significant monthly return of 1,78 % and the results are robust after controlling for Fama-French 5-factors. He explains that the future returns of momentum winners and losers are largely based on their financial strength as measured by F-Score and that the returns of high F-score-winner portfolio are robust against return reversals for up to 3 years after portfolio formation. Furthermore, momentum stocks with low F-Score are prone to return reversals in intermediate term. Walkshäusl (2019) proposes mispricing as a reason for why the value-winner portfolio outperforms standard momentum strategies and suggests that that with F-Score investors are able to identify the future outperforming high momentum stocks. Likewise, he explains that average investors do not analyse the fundamental financial strength of firms before investing in them.

Zhu et al. (2023) show evidence that high F-Score is able to enhance the returns of a standard 52-week high momentum strategy in the United States stock markets during

1985-2017. The combination strategy yields a statistically significant risk-adjusted monthly return of 1,5 % per month while a standard 52-week high strategy yields only 0,8 % per month. They also present that institutional investors do not underreact to 52-week highs of stock prices, but small unsophisticated investors do, and that F-Score is also able to enhance the returns of a 50-day moving average strategy. Zhu et al. (2023) propose that Piotroski F-Score is a good indicator of potential future over- and underreaction to firm specific financial news and argue that the combination strategy together with 52-week past price momentum can enhance the returns of the strategy due to F-Score's ability to spot financially strong firms amongst all high past price momentum stocks.

4 Data and methodology

This chapter presents the data and methods used in this study. First, I justify the rationale for focusing the research on United Kingdom equities. I also introduce the data gathering and time period used. Then, I explain the portfolio formation and holding period. The last chapter discusses the risk-adjustment methods used in this study.

4.1 Data

This thesis focuses on United Kingdom stock markets because there is lack of recent research about the profitability of the value factor in the United Kingdom equities. Furthermore, the United Kingdom stock markets are liquid, stable and the data is widely available. Britain's exit from the European Union (Brexit) in 2015-2020 and the corona pandemic were also unique events and by analysing the effects of these events on stocks, investors can gain a better understanding of the profitability of value and momentum investment strategies. Previous research by Kok et al. (2017) and Israel et al. (2021) suggest that the value factor has not worked in the United States markets during the recent times due to investor awareness of the factor anomaly and prices drifting away from their fundamental values. Therefore, it is interesting to study whether the same effect is present on the United Kingdom equities. This information can be used to develop more effective investment strategies for value investors in the United Kingdom.

The data is collected from Thomson Reuters Datastream. My benchmark index is FTSE 350, which consists of FTSE 100 (100 biggest companies in the United Kingdom by market capitalization) and FTSE 250 (categorized as small capitalization stocks) indices. My reason for including both small and large companies is because I want to know whether the value anomaly is stronger in small market capitalization stocks as suggested by earlier literature by Fama and French (1993) and whether company size has any effect on price momentum. I categorize firms as small companies with market value below $1.0 billion, firms as medium companies with market value over $1.0 billion but below $2.5

billion and firms as large companies with market value over $2.5 billion. Fama-French factors are collected from Kenneth R. French's website[1] for European data. This includes risk-free rate that is based on one-month United States Treasury bill rate.

Previous studies on value and momentum have used data periods between 15-39 years. My goal is to capture modern financial and price data because the stock markets, investment strategies and investors have largely changed during the past 22 years. I also aim to capture the dotcom bubble in late 2000s and the financial crisis in 2008. Therefore, my data period is 01/2000-12/2022[2].

I will use similar methods as employed by Bird and Asness et al. (2013) Casavecchia (2007), Leivo (2012) and Piotroski (2000). To reduce look ahead bias, I will use accounting data from the end of May each year to make sure the accounting data is available at the time of portfolio formation and rebalancing. I exclude companies on the financial sector, real estate investment trusts (REIT), depositary receipts (DR), companies with a negative book value, companies whose fiscal year has not ended in December and stocks with share prices less than £1 at the beginning of each month. If an issuer has had two or more stock series listed, only the one with a higher liquidity is included in the sample and if a firm delists, I assume the delisting return is zero. Monthly pricing data is adjusted for dividends and stock splits and is then converted to United States dollars with the month end currency exchange rate between Pound Sterling and United States dollars.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] The actual data period begins from 1998 because momentum data is looking past 12-month price data and F-Score data is based on past annual statements.

The final price and accounting data is as follows:

Table 1. Descriptive statistics for price and accounting data.

Descriptive statistics (price data)	
Mean	625.890
Standard Error	92.008
Median	301.693
Standard Deviation	1723.770
Sample Variance	2971382
Kurtosis	250.557
Skewness	14.701
Range	30240.680
Minimum	4.571
Maximum	30245.260
Sum	219687.200
# of companies	350
# of months	276

Descriptive statistics (accounting data)	
# of observations	66263
# of companies	8044700
# of years	22

4.2 Portfolio formation

In order to measure portfolio returns, I calculate the returns to standalone market portfolio, high book-to-market portfolio, high momentum portfolio and high F-Score screened high book-to-market high momentum (value-winner) portfolio. First, I calculate book-to-market value for each stock at the end of May each year. In order to reduce the skewness of extreme momentum portfolios, as shown by Fama and French (2012), I use terciles portfolios instead of deciles or quantiles in my study. Thus, FTSE 350 stocks are sorted by their book-to-market ratio into terciles. I keep the highest tercile book-to-market ratio firms (undervalued stocks) and calculate Piotroski F-Score for them. Then, I keep the firms with F-Scores of 7 to 9 (high F-Score). Next, I calculate the average monthly

return for each stock during the past 12 months excluding the most recent month (2-12 momentum). I then place the remaining stocks into terciles based on their past price momentum and invest in the highest tercile stocks (value winner) for 1 year until portfolio rebalancing.

I measure monthly buy-and-hold returns for long-only portfolios starting from the beginning of January each year and report returns from January 2000 to December 2022. The holding period will be one year, and the portfolio will be rebalanced once a year in June. I limit my strategy to long-only as Israel and Moskowitz (2013) show evidence that long positions produce majority of momentum and value profits. They also state that long-only value and momentum strategies yield consistent alphas across different asset classes and markets over time. Piotroski (2000) used a long-short zero cost investment strategy in his research, but due to practicality of my research, I cannot expect to hold yearlong short positions without incurring any margin costs or collateral requirements.

4.3 Risk-adjustment measures

To investigate whether the results are statistically significant, I use ordinary least squared (OLS) modelling with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) error terms in my regressions. Standard returns are calculated as natural logarithmic returns for all portfolios and Fama-French factors. I report returns to market portfolio, standalone value- and momentum portfolios, and F-Score enhanced joint value and momentum portfolio (value-winner). I also calculate compounded annual growth rate (CAGR), high-water mark and maximum drawdown for each portfolio with a hypothetical $10,000.00 starting cash. I adjust for risk by comparing the results against Sharpe (1966) ratio that adjusts for return volatility and analyse each portfolios' excess return distribution in order to explore how close the returns follow normal distribution. Finally, I regress the value-winner returns against the Fama-French (2018) 6-factor model and standalone market-, value- and momentum portfolios because one of the tenets of this thesis is to improve the risk-adjusted returns of my strategy.

Testing value-winner versus standalone market, value and momentum jointly is not viable due to correlation and multicollinearity between the factors since all portfolios are constructed long-only[3]. The major weakness of the joint model stems from correlation between value-winner and market portfolio, where the variance inflation factor is the highest. Therefore, portfolios are only tested separately. The regressions for the hypothesis are as follows. Value-winner versus market portfolio:

$$R_{VW} - RF_t = a_{VW} + b_{VW}FTSE_t + e_{VWt}, \quad (15)$$

where: $R_{VW} - RF_t$ = monthly excess returns of value-winner portfolio VW

a_{VW} = intercept of the regression

$b_{VW}FTSE_t$ = value-weighted monthly excess market returns of FTSE 350 stock index portfolio

e_{VWt} = error term of the regression.

Value-winner versus high book-to-market portfolio:

$$R_{VW} - RF_t = a_{VW} + c_{VW}BM_t + e_{VWt}, \quad (16)$$

where: $c_{VW}BM_t$ = monthly excess returns of high book-to-market portfolio.

The rest of the factor are constructed similar as above in equation 15. The regression for value-winner versus momentum portfolio is as follows:

$$R_{VW} - RF_t = a_{VW} + d_{VW}MOM_t + e_{VWt}, \quad (17)$$

where: $d_{VW}MOM_t$ = monthly excess return of high momentum portfolio.

[3] See Appendix 2 table 11 for variance inflation factors for value-winner versus FTSE 350, value and momentum OLS regression.

The rest of the factor are constructed similar as above in equation 15.

The regression against the Fama-French 6-factor model is as follows:

$$R_{VW} - RF_t = a_{VW} + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + m_i UMD_t + e_{it} \quad , \tag{18}$$

The factors are constructed similar to 3-factor, 5-factor and 6-factor models introduced earlier in chapters 2.2 and 2.3, respectively. Risk-free value-winner returns are calculated similar to the hypothesis regression introduced earlier in this chapter. It is important to note that the Fama-French factors are based on European data from 15 European countries. Therefore, they are not United Kingdom specific factors but best estimates of factor returns for European stock markets.

5 Results

This chapter presents the results and risk-adjusted performance of this study. First, I present portfolio returns for both standalone value and momentum strategies and then for value-winner strategy. Then, I compare the results using risk-adjustment methods like Fama-French factors, volatility and Sharpe ratio. Lastly, I compare the results of the value-winner portfolio against standalone market-, value- and momentum portfolios. In the last chapter I discuss about the results and limitations of this study.

5.1 Portfolio returns

How did the standalone high book-to-market and 2-12 momentum strategies perform against the FTSE 350 index during the past 22 years? What about the value-winner strategy? In order to measure practical portfolio returns, I form a $10,000.00 starting portfolio and calculate buy-and-hold returns for each of the 3 strategies and market portfolio.

The FTSE 350 index itself had an abysmal performance during the past 22 years as seen from below:

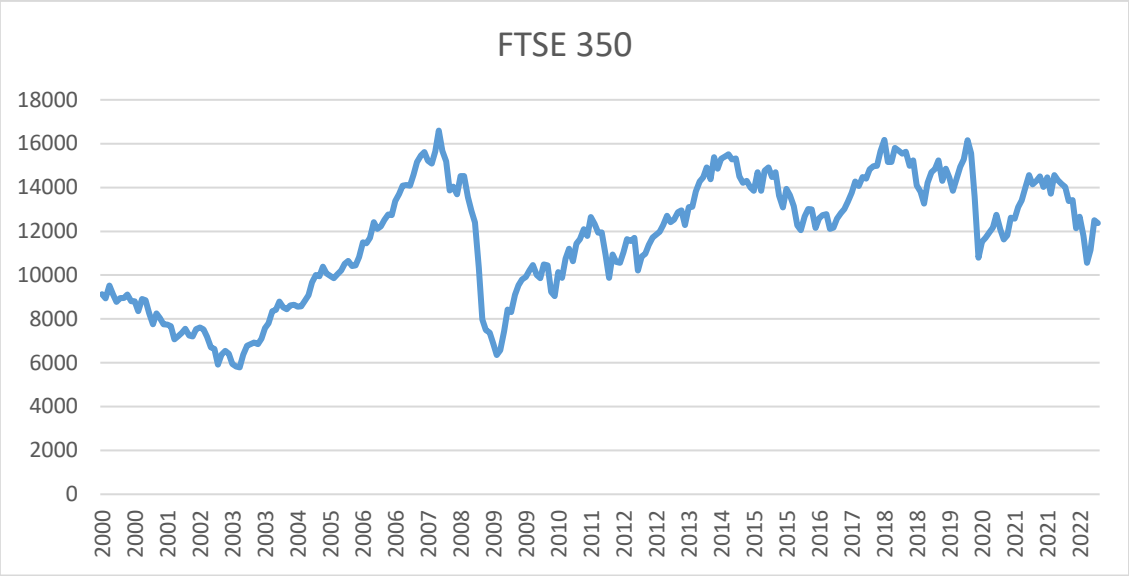

Figure 1. FTSE 350 return index 2000-2022.

With a compounded annual growth rate of only 1,46 %[4], the United Kingdom stock index suffered not only from the dotcom bubble of 2000s and financial crisis of 2008, but also from the Brexit referendum of 2015 and corona pandemic of 2020. High-water mark for the market portfolio was $16,596.52 in October 2007 while maximum drawdown was -61,7 % in February 2009 with a portfolio value of $6,357.42.

The results for the high book-to-market (value) are mixed. The value portfolio wins the markets prior to 2008-2009 financial crisis but loses to the market index after the crisis, as shown from the graph below:

[4] See Appendix 1 table 7 for closer breakdown of CAGR, high-water mark and maximum drawdown for each portfolio.

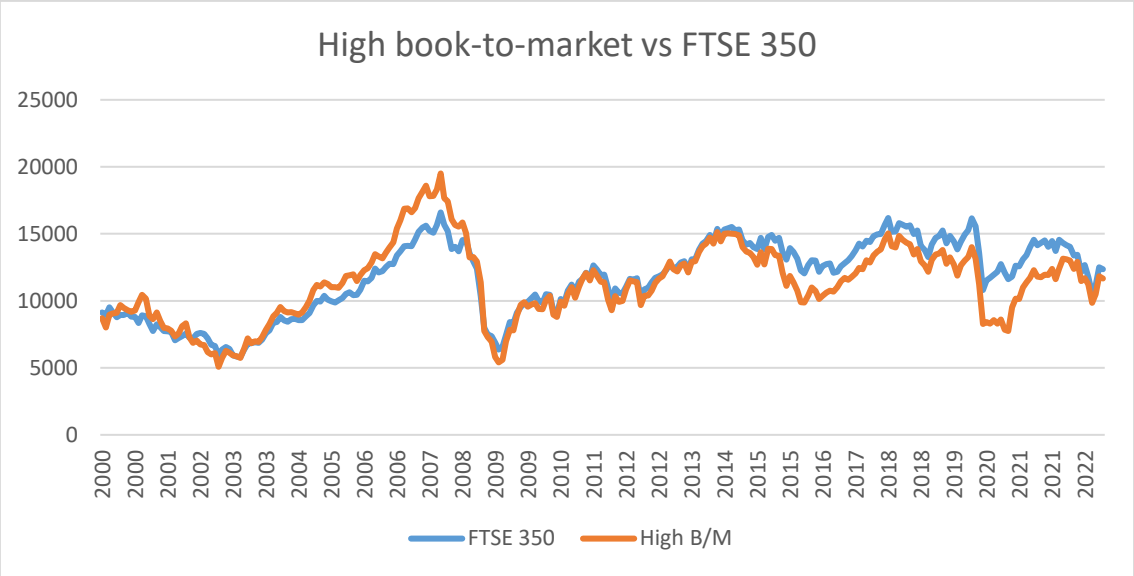

Figure 2. FTSE 350 return index versus high book-to-market portfolio 2000-2022.

In the financial crisis, the value portfolio crashes a massively -72,3 % as measured by maximum drawdown from the high-water mark of $19,505.88 in October 2007 to $5,411.48 in February 2009. After the financial crisis, the value portfolio's returns keep lagging behind the market portfolio. This is similar finding to Kok et al. (2017), who show that the value factor (HML) did not work in the United States markets during 2002-2015. Albeit my value portfolio differs from the high book-to-market minus low book-to-market value factor (HML), we can decipher that value strategies based on high book-to-market ratio may not be effective in the United Kingdom stock markets in modern times.

The momentum portfolio performs a lot better than the index. The standalone momentum portfolio has a compounded annual growth rate of 3,0 % during the investment period and outperforms the market index by average of 1,48 % per annum:

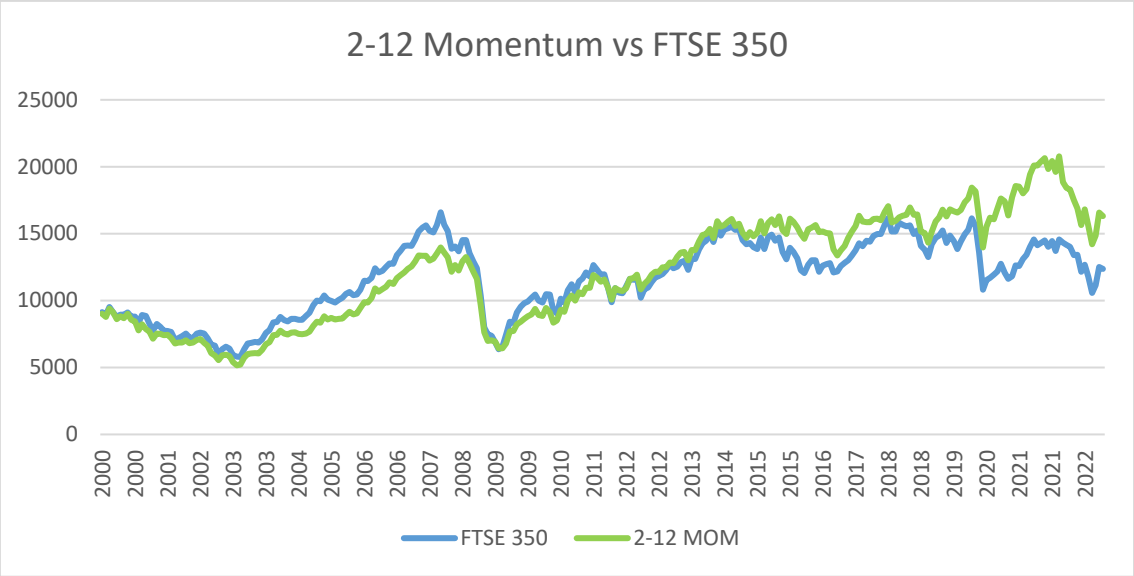

Figure 3. FTSE 350 return index versus high past price momentum portfolio 2000-2022.

It is interesting to note that the momentum portfolio loses to the market index prior to 2011. This may be due to two major stock market shocks, namely the dotcom bubble and the financial crisis, during which momentum portfolio crashes. The maximum draw-down for the momentum portfolio is -51,5 % from high-water mark of $13,258.68 in May 2008 to $6,428.55 in March 2009. Afterwards, the momentum portfolio outperforms the market index from September 2011 onwards. The highest value for the momentum portfolio is $20,777.25 in December 2021.

Value-winner portfolio also outperforms the market index but worse than the standalone momentum portfolio:

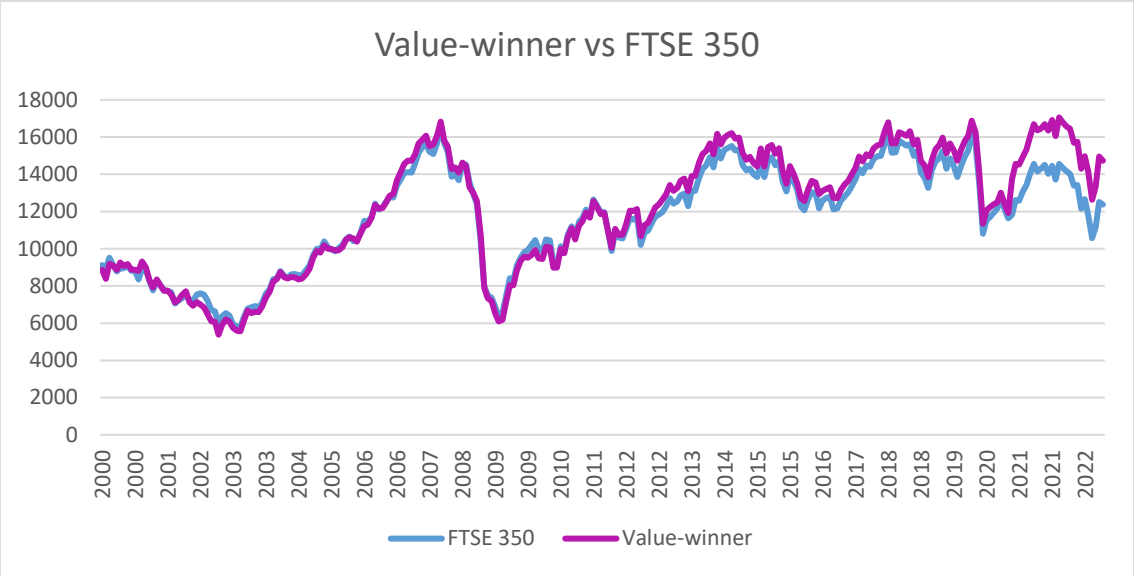

Figure 4. FTSE 350 return index versus value-winner portfolio 2000-2022.

The high F-Score screened value-winner portfolio outperforms the market index by average of 1,04 % per annum. Maximum drawdown for the value-winner portfolio is -63,8 % from the high-water mark of $16,829.13 in October 2007 to $6,086.97 in February 2009. We can see that momentum enhanced high F-Score high book-to-market portfolio outperforms the markets especially in the late 2010s and presumably continues to do so. Prior to 2010s, the included momentum factor draws the value-winner portfolio's returns below market returns in several years but especially in 2002 and 2009. This is a sharp contrast to the standalone high book-to-market portfolio that failed to outperform the markets in the recent years. I can tentatively conclude that including high F-Score and momentum in the value strategy enhances the portfolio's returns.

5.2 Risk-adjusted performance

In order to measure risk-adjusted performance, I first calculate annual excess returns for FTSE 350 index, high book-to-market portfolio, 2-12 momentum portfolio and value-winner portfolio. Volatility is the standard deviation of annual returns 2000-2022.

Table 2. Annual excess returns 2000-2022.

Portfolio/ method	*FTSE 350*	*High B/M*	*2-12 MOM*	*Value-winner*
Average return	0,019	0,028	0,028	0,028
Volatility	0,216	0,256	0,271	0,221
Sharpe ratio	0,088	0,109	0,102	0,128

Value-winner portfolio has the highest average excess returns of 2,82 %, but it is important to note that all the portfolios have rather low Sharpe ratios. This is because their volatilities tend to be high compared to their average annual returns. Still, value-winner portfolio's Sharpe ratio is better than the index portfolio, high book-to-market portfolio and momentum portfolio.

The main drawback of using Sharpe ratio to compare returns is its assumption that returns are normally distributed. This is not always the case, so let us examine closer the return distributions for each portfolio.

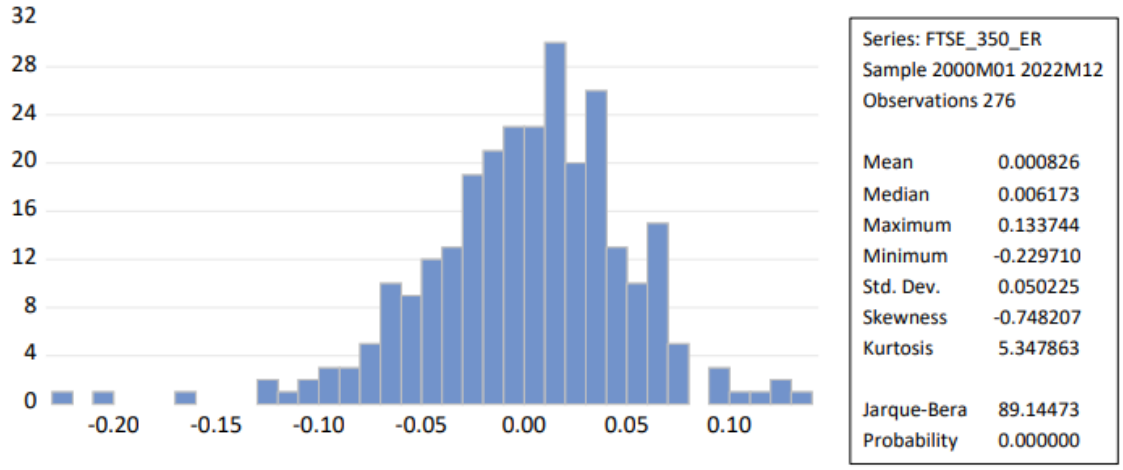

Figure 5. FTSE 350 index monthly excess return distribution.

Skewness for normal distribution should be zero, so we can see that the market index's monthly excess returns are negatively skewed during the observation period of 2000-2022. The FTSE 350 index also has positive kurtosis of 5.35 when normal distribution has a kurtosis of 3. Maximum excess monthly return for the market portfolio was 13,4 % in

May 2009, which was the beginning of recovery from the financial crisis of 2008. On the other hand, the largest excess monthly losses were -23,0 % that happened during October 2008, one month after Lehman Brothers collapsed.

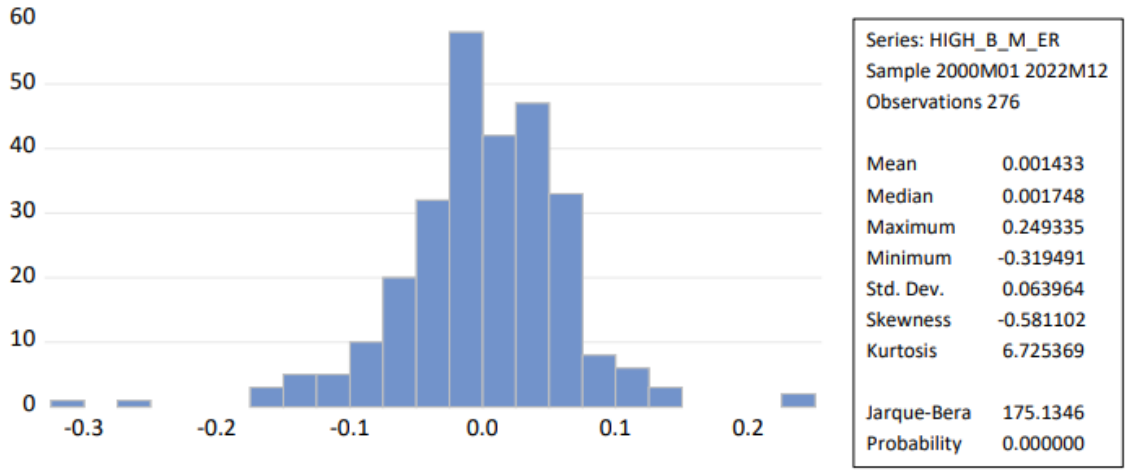

Figure 6. High book-to-market portfolio monthly excess return distribution.

The high book-to-market (value) portfolio also suffers from negative skewness and even higher positive kurtosis, meaning that the return distribution skews to the left and has thin tails. The maximum excess monthly return for the value portfolio was 24,9 % in April 2009 and the largest excess monthly losses were -32,0 % in October 2008.

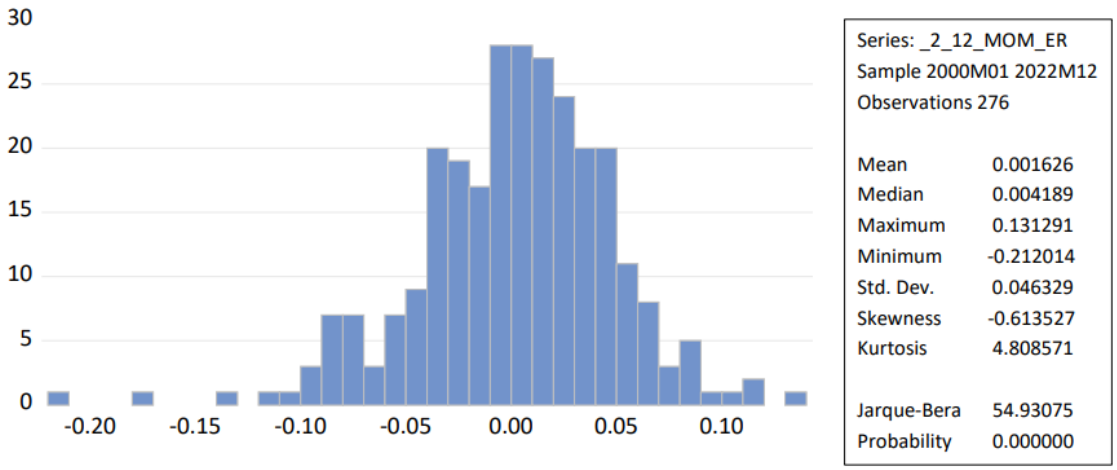

Figure 7. 2-12 momentum portfolio monthly excess return distribution.

The momentum portfolio has a negative skewness of -0.61 and excess kurtosis of 4.8. The maximum monthly excess return was 13,1 % in May 2009 and the largest excess monthly losses were -21,2 % in October 2008. It is interesting to note that Jarque-Bera test, that measures whether the series is normally distributed, is the lowest on momentum portfolio, meaning that it is the most normally distributed return series compared to the market index, value portfolio and value-winner portfolio.

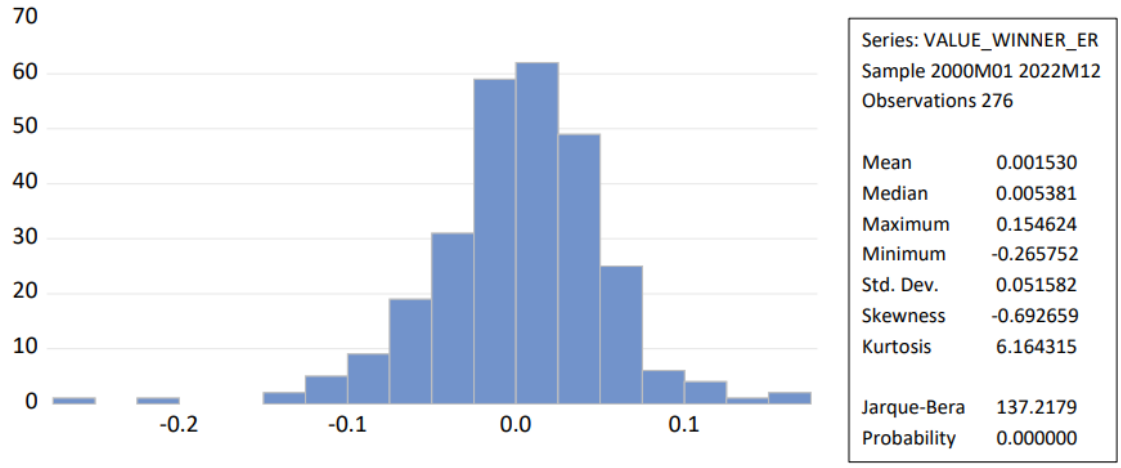

Figure 8. Value-winner portfolio monthly excess return distribution.

The value-winner portfolio has higher negative skewness than both value and momentum portfolios. Kurtosis is higher than the momentum portfolio but lower than the high book-to-market portfolio. The highest returns for the value-winner portfolio were 15,5 % in November 2020 while the largest losses were -26,6 % in October 2008.

In total, the high F-Score screened value-winner portfolio did outperform the market index, standalone value and standalone momentum portfolios. Furthermore, its Sharpe ratio is higher than the standalone strategies, meaning that my strategy improved the returns of a standard high book-to-market portfolio and adding momentum to the strategy decreased its volatility leading to higher Sharpe ratio than standalone momentum strategy[5].

Can the value-winner portfolio's excess returns be explained by Fama-French factors? In order to examine the relationship between the Fama-French 6 factors, I regress the excess returns against the Fama-French 6 factors.

Table 3. Value-winner versus Fama-French factors OLS regression.

Variable	*Coefficient*	*Standard error*	*T-statistic*	*Probability*
a	0,001	0,001	0,772	0,441
Mkt	0,431***	0,034	24,359	0,0000
SMB	0,078	0,082	0,949	0,343
HML	0,099	0,079	1,255	0,210
RMW	0,092	0,086	1,079	0,282
CMA	0,086	0,166	0,519	0,604
UMD	0,119***	0,038	3,132	0,002
	R-squared		0,879160	
	F-statistic		326,179	

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Ordinary least squares (OLS) regression with Newey-west standard errors shows that the value-winner strategy's excess returns cannot be explained by Fama-French 6 factors. However, excess market returns, and momentum factor are statistically significant,

[5] See monthly excess returns for each portfolio on Appendix 1 figures 9, 10, 11 and 12.

meaning that adding these two factors improves the portfolio's mean-variance frontier[6]. R-squared coefficient for the regression is high, showing that these the Fama-French risk factors can explain the variation in value-winner portfolio's returns. Based on this evidence, the market returns explain some of the value-winner portfolio's returns with a coefficient of 0,43. Positive momentum factor coefficient also means that we are invested in positive past price momentum stocks. It is interesting to note that company size (SMB), value (HML) and profitability (RMW) factors have no statistical significance. This may be due to Fama-French European factors incorporating data from 16 European indices, meaning that these factors cannot explain United Kingdom only data. On top of that, my value portfolio consists of only high book-to-market stocks whereas Fama-French HML factor consists of the average of high and low book-to-market stocks. The same average return methods are used for other Fama-French factors. HML not being able to explain the returns of my value-winner strategy is similar finding to Asness (1997), where he explains that value strategy mostly fails with firms that have strong past price momentum and Malin and Veeraraghavan (2004) who show that the value factor has not outperformed the United Kingdom stock markets in recent times.

Finally, since Fama-French 6-factors are based on European data from 15 countries, I regress the value-winner portfolio's returns against standalone market, value and momentum strategies separately in order to see if these strategies can explain the value-winner portfolio's excess returns.

Table 4. Value-winner versus FTSE 350 OLS regression.

Variable	*Coefficient*	*Standard error*	*T-statistic*	*Probability*
a	0,009***	0,001	8,098	0,000
FTSE	1,080***	0,018	58,750	0,000
	R-squared		0,913	
	F-statistic		2863,024	

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

[6] See Wald-test and variance inflation factors on Appendix 2 tables 9 and 10.

The regression shows that value-winner portfolio's excess returns are explained by the FTSE 350 factor with high statistical significance. However, the intercept (a) is also statistically significant but with low coefficient, meaning that the high F-Score among other unknown variables explain the rest of the value-winner portfolio's excess returns. With high R-squared coefficient and high factor probabilities, it seems that high F-Score only improves the portfolio's excess returns by a coefficient of 0,009.

Table 5. Value-winner versus value OLS regression.

Variable	*Coefficient*	*Standard error*	*T-statistic*	*Probability*
a	0,008***	0,001	6,300	0,000
BM	0,816***	0,023	34,978	0,000
	R-squared		0,844	
	F-statistic		1482,775	

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Value-winner versus high book-to-market factor is a similar story. Value factor (BM) explains most of the strategy's returns, but the strategy also produces a small alpha of 0,008. Both factors are highly statistically significant with 1% significance level and high R-squared tells that the model has high explanatory power.

Table 6. Value-winner versus momentum OLS regression.

Variable	*Coefficient*	*Standard error*	*T-statistic*	*Probability*
a	0,008***	0,002	4,357	0,000
MOM	1,097***	0,038	28,808	0,000
	R-squared		0,802	
	F-statistic		1109,004	

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Again, similar results show that the value-winner portfolio has a small but statistically significant alpha of 0,008 and momentum factor explains most of the strategy's results. Both factors are highly statistically significant, and the model produces high R-squared statistic. In conclusion, the value-winner portfolio does produce a small alpha against all standalone portfolios.

It is interesting to note that value-winner portfolio's returns are concentrated to relatively small companies[7] as predicted in earlier research by Bird and Casavecchia (2007). This is due to the strategy's focus on high book-to-market companies, which tend to be neglected by the analysts and investors compared to the large established companies. On a risk-adjusted basis, I can conclude that the value-winner strategy is a viable option to enhance standalone value investing strategy based on high book-to-market ratio. However, high F-Score seems to have little effect on the excess returns of this strategy where most of the profits come from the market, high book-to-market and high past price momentum companies.

5.3 Discussion

Combining high Piotroski F-Score and high past price momentum with a high book-to-market strategy can significantly improve the returns of a standalone value strategy. The standalone high book-to-market strategy, focused solely on the high book-to-market ratio, delivers a compounded annual growth rate (CAGR) of only 1,47%. In contrast, incorporating high F-Score and high past price momentum increases the CAGR to a statistically significant 2,57%. Although, the coefficient for Piotroski F-Score is only 0,8-0,9 % per month, the results indicate that F-Score and momentum are useful in enhancing the returns of book-to-market based investing strategies.

I suggest that the reason for value-winner strategy's outperformance is due to the following reasons. First, since high book-to-market (value) companies are typically financially distressed and have overstated book values, high F-Score may help in identifying the financially strongest firms out of all value stocks. Second, by including past price momentum, the strategy can somewhat predict the upcoming turnaround of stock price reversals. As value stocks are often small companies without analyst coverage, their price volatilities tend to be high after earnings or financial updates. By having high past price

[7] See Appendix 1 table 8 for complete breakdown of company sizes for value-winner portfolio.

momentum and financially strong firm, the investors buying those firms drive the price momentum even further and due to the small firm size, the subsequent stock returns can be substantive.

According to my results, there are minor inefficiencies in the United Kingdom stock markets that Piotroski F-Score screened value-winner strategy can exploit. However, I do not know if these results can be replicated overfea other time periods or other local European stock markets. Similar to Malkiel (2003), I suggest that the stock markets can never be fully efficient, evidenced by value-winner's small alpha, otherwise there would be no incentive for professional money managers to actively manage funds.

There are several limitations to the results of this study. First, annual portfolio sizes tend to be small compared to the FTSE 350 index. This is natural, since there are only a handful of companies that are undervalued, have high past price momentum and high F-Score each year. Therefore, the results of this study must be taken with caution. Second, because value-winner portfolio's companies are small, there are limits on how much institutional or large investors could benefit from this strategy due to liquidity and other constraints related to small companies. Third, since the stock price data is converted from Pound Sterling to United States dollars each month, there are inherit risks associated with currency conversions and timing of this study. If investors are to implement this strategy, they should carefully assess the impact of currency related risks, such as interest rates and economic environment. Since momentum tends to crash during economic downturns, as shown by Barroso and Santa-Clara (2015), investors implementing this strategy should hedge their exposure against the possible drawdowns of this strategy.

Furthermore, since transaction costs and taxes are not explored, the value-winner strategy suffers from a small inaccuracy related to realized portfolio returns. This inaccuracy is not large because, the portfolio is only rebalanced once a year. Therefore, the United Kingdom government stamp-duty of 0,5 % per transaction and other possible transaction costs related to implementing this strategy are minimal. I would also like to point

out that using one-month United States Treasury bill rate as a risk-free rate affects the excess return calculations. Although, the deviation from Bank of England risk-free rate is not large, there is natural difference between United States and United Kingdom in the timing of interest rate changes. Typically, the United Kingdom and the rest of the Europe follow the changes of United States interest rates with a lag of few months. I estimate that the effect of using United States -based risk-free rate is not large due to the T-bill's low rate throughout the entire observation period.

In conclusion, the evidence presented in this study shows that investment strategies based on simple accounting ratios can be enhanced by incorporating Piotroski F-Score and past price momentum in the strategy. These findings suggest that sophisticated investors can enhance their value investing strategies beyond the typical book-to-market based strategies.

6 Conclusions

High F-Score and high past price momentum enhanced high book-to-market portfolio outperforms the United Kingdom stock markets 2000-2022 while a standalone high book-to-market portfolio fails to do so. In fact, a standalone value strategy loses to the FTSE 350 market index by -0,062% on average per year during the observation period measure by compounded annual growth rate. This may be due to the value strategy's inability to find not only undervalued companies but also companies that have temporarily inflated accounting numbers that are eventually noticed by investors, as suggested by Kok et al. (2017). I propose that that High F-Score is able to find financially strong companies out of all undervalued firms and that their past price momentum is somewhat strong during times of economic growth. Although the coefficient for this effect is somewhat low, high F-Score is still useful in sorting out financially strong companies out of all undervalued stocks.

While past empirical evidence from Fama and French (1993) and Bird and Casavecchia (2007) suggest that small capitalization stocks outperform their indices, these stocks face several limitations that hinder investors' ability to exploit them. These stocks tend to be less liquid, meaning it can be difficult for large investors to buy them in large quantities. Furthermore, their volatilities tend to be high, meaning that large investors may have trouble when buying or selling these companies due to their bid-ask spreads.

My study did not consider taxes or transaction costs. This is mainly because of annual portfolio rebalancing cycle. For further research, it would be interesting to know whether taxes or transaction costs have effects on the strategy if the portfolio would be rebalanced one a quarter or once a month. I also left short-side effects unexplored due to wanting to study the strategy's practical effects in the United Kingdom stock markets. For that reason, I could not expect to hold one year long short positions. However, it would be interesting to see how a long-short strategy would perform in the United Kingdom stock markets during the same time period of 2000-2022. This is important because the negative correlation between value and momentum, as mentioned by Asness (1997),

Asness et al. (2013), Kok et al. (2017) and Israel et al. (2021) is observed only in long-short strategies. Therefore, my results may also be explained by positive correlation. Lastly, my strategy used United States dollar based natural logarithmic returns. This is due to the Fama-French factors being United States dollar based, so one further research topic would be to exploring the effects of my strategy in Pound Sterling. This would also require calculating each Fama-French factor separately for United Kingdom stock markets.

Piotroski F-Score has a few limitations that are not explored in this research. Namely, issued equity as liquidity measurement can be misleading. As many firms issue equity to compensate employees, a negative score in this signal would be unrelated to the financial health of the company. Therefore, sophisticated investors should look at the net equity issued during each year, that accounts for share purchases as well.

It would also be interesting to see which momentum strategy yields the best combination of Piotroski F-Score screened high book-to-market combination strategy. This study focused on using a standard 2-12 momentum but 52-week high past price, 6-month high and Novy-Marx (7-12) momentum could be interesting strategies to compare to.

My study expands the existing research done on value and momentum strategies but also provides new information about the value premium and information asymmetry in the United Kingdom stock markets. While accounting fundamentals do influence stock returns, there may be periods when stock prices deviate significantly from fundamental information, leading to underperformance for value strategies. I suggest that high Piotroski F-Score is able to identify financially strong companies amongst all stocks. Therefore, combining value and momentum in a balanced manner can provide investors significant edge in somewhat efficient stock markets.

I conclude that the awareness of value strategies may have contributed to the underperformance of value investing strategies in the United Kingdom stock markets. However,

the traditional momentum strategy is still relevant and combining the two strategies can enhance the portfolio's overall performance given that the portfolio is screened with high Piotroski F-Score.

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Appendices

Appendix 1. Return statistics

Table 7. Monthly return statistics for $10,000.00 portfolios 2000-2022.

Portfolio/ Statistic	*FTSE 350*	*High B/M*	*2-12 MOM*	*Value-winner*
CAGR	0,015	0,014	0,029	0,024
High-water mark ($)	16,596.52	19,505.88	13,258.68	16,829.13
Peak-through value ($)	6,357.42	5,411.48	6,428.55	6,086.97
Maximum draw-down (%)	-61,7 %	-72,3 %	-51,5 %	-63,8 %

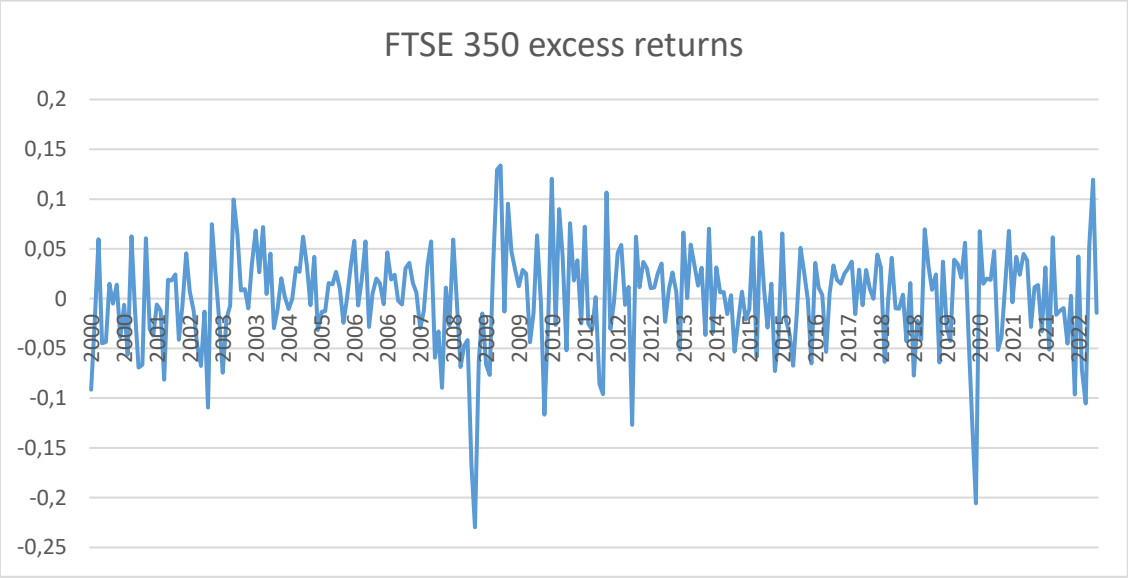

Figure 9. FTSE 350 index monthly excess returns.

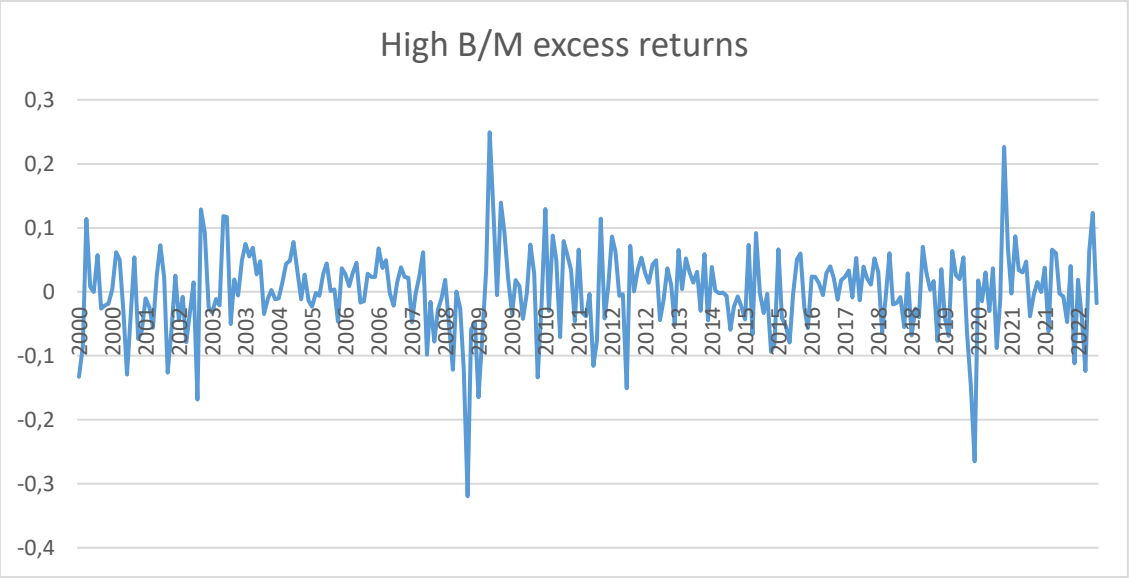

Figure 10. High book-to-market portfolio monthly excess returns.

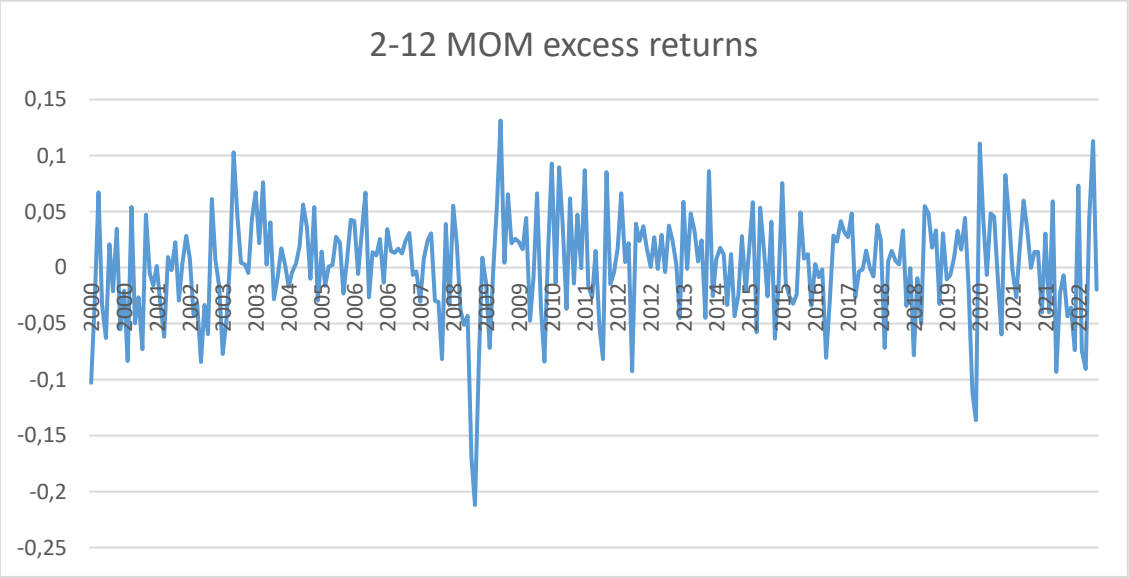

Figure 11. 2-12 momentum portfolio monthly excess returns.

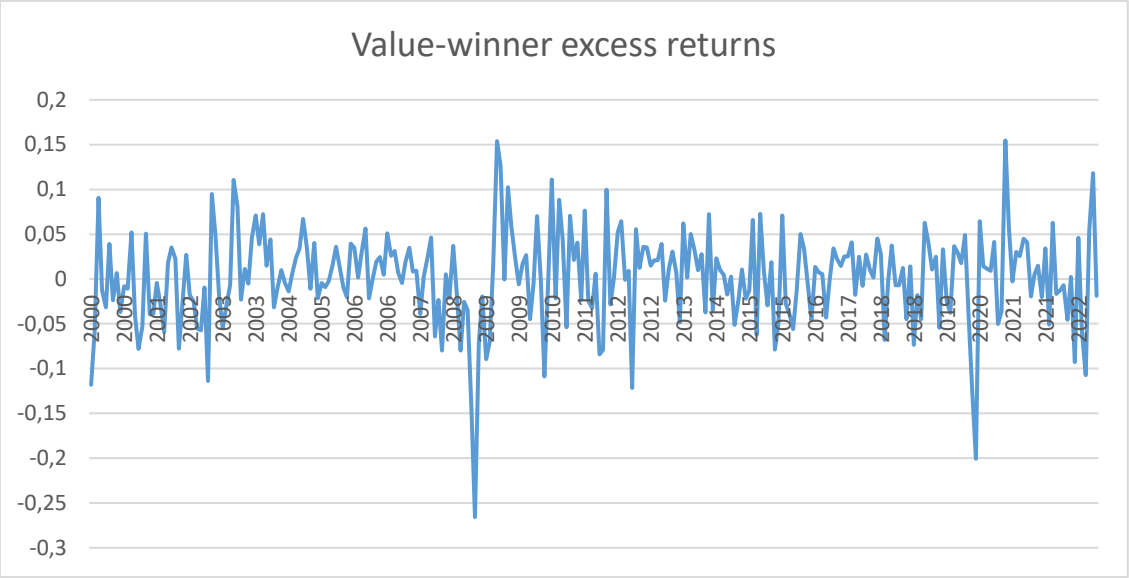

Figure 12. Value-winner portfolio monthly excess returns.

Table 8. Average annual company sizes for value-winner portfolio 2000-2022.

Market capitalization/ year	*> $1,000.00 M*	*$1,000.00-2,500.00 M*	*< $2,500.00 M*
2000	7	3	1
2001	8	2	0
2002	7	2	0
2003	9	4	0
2004	11	3	1
2005	8	1	1
2006	12	3	2
2007	11	2	1
2008	19	6	3
2009	7	2	2
2010	13	4	3
2011	14	3	0
2012	8	6	1
2013	4	4	2
2014	6	2	1
2015	11	3	0
2016	7	3	0
2017	9	2	2
2018	3	5	1
2019	6	3	0
2020	13	7	4
2021	5	3	0
2022	7	2	1

Appendix 2. Regression statistics

Table 9. Wald-test for testing Mkt-Rf and UMD factors jointly.

Test statistic	*Value*	*Degrees of freedom*	*Probability*
F-statistic	304,646	(2, 269)	0,0000
Chi-square	609,291	2	0,0000

Under the null hypothesis, the critical value for chi-squared distribution with 5% significance level and 2 degrees of freedom is 5.99. Adding these 2 factors to the value-winner strategy increases its mean-variance frontier and maximum squared Sharpe ratio.

Table 10. Variance inflation factors for value-winner versus Fama-French 6-factor OLS regression.

Variable	*Coefficient variance*	*Uncentered VIF*	*Centered VIF*
C	0,000	1,800	NA
Mkt-Rf	0,001	2,761	2,618
SMB	0,007	1,495	1,369
HML	0,006	3,729	2,553
RMW	0,007	2,219	2,178
CMA	0,027	4,503	4,449
UMD	0,001	2,449	2,293

Variance inflation factors are below 5 for each of the factors meaning that there is no multicollinearity between the regressors in the model.

Table 11. Variance inflation factors for value-winner versus FTSE 350, value and momentum OLS regression.

Variable	*Coefficient variance*	*Uncentered VIF*	*Centered VIF*
C	0,000	1,163	NA
FTSE	0,005	29.690	27.654
BM	0,001	12,273	11,466
MOM	0,002	11,482	10,257

Variance inflation factors above 10 for each of the factors mean that there is severe multicollinearity between the regressors in the model.