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MASTER'S THESIS

AN ANALYSIS OF MOMENTUM AND VALUE EFFECT ON THE FTSE 100 STOCK INDEX

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INTRODUCTION

One of the hottest topics in financial markets and portfolio management nowadays are different investment strategies with which investors try to “beat the market”. To “beat the market” investors make use of information by exploiting market anomalies, tracking repetitive patterns in prices or by exploiting irrational behaviour of other market participants. Among the most prominent and used techniques to outperform the market are momentum and value investment strategies. Value and momentum are recognized as market anomalies because they are not in line with the traditional asset pricing theory, contradicting the efficient market hypothesis (Schwert, 2003).

The efficient market hypothesis, developed by Eugene Fama (1970), argues that security prices “fully-reflect” all available information and that markets are efficient. Proponents of efficient markets believe that it is not possible to outperform the market on a risk-adjusted basis because all information is already incorporated in the price, and consequently prices only react to new information. Moreover, the efficient market hypothesis states that on the market, there is no security mispricing. If the theory holds, it is impossible to “beat the market”, meaning that active investment strategies such as momentum and value, based on active stock selections, can outperform the profitability of the market only by increased risk or by chance.

The first analysis of the two market anomalies goes back to the early nineties when Fama and French (1992) discovered that portfolios constructed of value stocks can earn a positive risk premium. A year later, a positive excess return of momentum portfolios was found by Jagadeesh and Titman (1993). Since then, momentum and value have been massively used and are considered to be persistent market phenomena, observed in many markets and in various time periods.

Momentum investing is based on the assumption that recent price trends will continue in the short run (usually up to 12 months). This short-term price persistence is known as momentum effect. Strategies that follow momentum effect take a long position in securities with the highest short-term past returns, while simultaneously, short position is taken in securities with the lowest short-term past returns. The strategy is attractive because the only information needed is past security price, which is nowadays available to all market participants. Positive momentum premiums have been observed by many researches. Soon after the pioneering article of Jagadeesh and Titman (1993), many authors for example Rouwenhorst (1998), Chan, Jagadeesh and Lakonishok (1996), Moskowitz and Grinblatt (1996), Chui, Titman and Wei (2000) confirmed the existence of momentum premiums on the United States (hereinafter: US) market and beyond. The first goal of this thesis is to empirically asses the profitability of portfolios created based on momentum effect on the Financial Times Stock Exchange (hereinafter: FTSE 100) in the period from January 1996 to February 2018, following the pioneering work of Jagadeesh and Titman (1993).

The main idea of **value investing**, however, is to buy (sell) stocks that have significantly lower (higher) prices than their intrinsic values. Meaning that stocks are under (over) priced by the market and consequently their price is expected to rise (fall) in the future. Investors use different indicators to assess whether a security is identified as overvalued or undervalued. Empirical studies have shown that stocks with high ratios, e.g. book-to-market, earnings-to-price, etc., achieve higher returns on average. In literature, such stocks are known as **value stocks**. In comparison, **growth stocks** are supposed to be overpriced by the market and tend to increase in capital value rather than yield high return. In existing literature, the most commonly used criteria to evaluate if stock is under/overvalued are the following price ratios: book-to-market (B/M), earnings yield (E/P) and dividend yield (D/P). Researchers, for example Basu (1977), Rosenberg, Reid and Lanstein (1985), Fama and French (1993, 1998, 2012), Dimson, Nagel and Quigley (2002), have found that value stocks achieve better results than growth stocks and can outperform the overall market. In this thesis, we used the 3 most common ratios – B/M, E/P and D/P to create different zero-investment value strategies on the FTSE 100 in the time period 1996–2018 to evaluate profitability of value strategies and to asses if positive value premium has been historically present in the United Kingdom (hereinafter: UK) market.

To date, vast empirical research has been carried out, where value and momentum have been examined separately, but only few research papers consider the value and momentum combined strategy. This thesis is motivated by one of the most known authors in the field, Cliff S. Asness. Asness (1997) performed a momentum and value combined analysis and emphasized that combining momentum and value investment strategies can lead to increased profits and decreased risk. By combining both strategies into one strategy, we are able to invest in undervalued stocks that show momentum at the same time. In a recent study titled "Value and momentum everywhere" Asness, Moskowitz and Pedersen (2013) provide evidence that the combined strategy is also applicable and profitable across different asset classes (e.g. stocks, currencies, commodities, indices, bonds, etc.).

It has been shown that the combined strategy is superior to pure value or momentum in many ways. For example, Asness, Moskowitz and Pedersen (2013) found abnormally large positive returns for both individual strategies and also that strategies are negatively correlated. The authors argue that the combined momentum and value portfolio is closer to the efficient frontier than pure value or pure momentum portfolio because the combined portfolio exhibits less volatility and results in improved Sharpe ratios. This theory was tested by Cooper, Mitrache and Priestley (2016), Fisher, Shah and Titman (2016) and Babameto and Harris (2008), Franz and Regele (2016) and others. Following these papers, we analysed if this would also hold for the UK market. We conducted an empirical analysis of a 50/50 weighted long-short momentum and value combined strategy in the period 1996–2018.

Previous research has shown that value and momentum strategies have many different characteristics and that many doubt their synergies. For example, one of the differences between them is that value investing is usually more long-term oriented and looks for undervalued (overvalued) securities, while momentum investing only looks for highly promising (worst performing) and probably riskier securities in the short-run. Secondly, to be efficient, momentum portfolios need to be rebalanced relatively frequently (monthly or quarterly at least), while value portfolios are more long-term oriented and rebalancing can be done only once or twice a year. The third difference is that momentum returns are inclined to be pro-cyclical while returns of value strategies are more prone to counter-cyclicality (Bird & Whitaker, 2004).

Researchers argue that because of the **negative correlation** in momentum and value price movements, the combined strategy can smooth long-term performance and control volatility risk. Negative correlation between strategies has been reported by Asness (1997), Asness, Moskowitz and Pedersen (2013), and lately by Cooper, Mitrache and Priestley (2016) and Franz and Regele (2016). In relation to these discoveries, investors should consider the concept of mixing both strategies. The intuition is that momentum and value often perform well at different points in time and by combining, investors can achieve better results in terms of return and risk.

The **main objective** of this master thesis is to apply and test the pure momentum, pure value and combined investment strategy on FTSE 100 over a 22-year time period. All 3 investment strategies are tested in order to evaluate how efficient is the UK market and to assess how these strategies performed in the observed time period (1996–2018). Firstly, momentum and value strategies are analysed individually. Secondly, a simple combined active investment strategy is proposed. The **main interest** is to build a momentum, value and combined strategy with zero initial investment cost, known as long-short strategy. Moreover, calculations ignore taxes and transaction costs by assuming they have a negligible effect on momentum and value returns. Also, the empirical analysis is not concentrated on testing asset pricing models but rather to examine and evaluate performance of different portfolio strategies. We examined if value and/or momentum premium has been historically present on the UK market. We analysed the significance of returns and compared them to the benchmark performance in the same period. We compared excess returns of strategies and evaluated their performance with various risk and performance metrics.

To summarize, the **basic research questions** are the following:

- Is the FTSE 100 market semi-strongly efficient?
- Is momentum strategy profitable on the FTSE 100 stocks index in the period January 1996–February 2018?
- Is value strategy profitable on the FTSE 100 stocks index in the period January 1996–February 2018?

- Is there a negative correlation between momentum and value strategies?
- Are strategies that have less/more stocks in the portfolio more/less risky?
- Is it better to invest in stocks by investing in the best-performing stocks according to momentum or value characteristics or is it better to create a long-short position?
- Is a combined value-momentum strategy superior in performance relative to pure momentum or pure value performance?

Research methodology used in the thesis is based on existing literature and empirical analysis of the momentum and value effect on the FTSE 100 index in the period 1996–2018. The following methodology is applied:

- Research on existing literature on value, momentum, their explanations, evidence, existence and methodologies. The theoretical part includes insight in both anomalies; it evaluates their existence and possible explanations - both in case of the rational and behavioural spectre.
- Research on existing combined momentum-value studies.
- Data gathering from the internet, Datastream, etc.
- Writing a Python program for active stock selection for momentum, value and combined strategy.
- Performance of statistical analysis using Stata to evaluate strategy performance.
- Analysis and interpretation of results.

The existing literature on testing of the combined momentum-value strategy is relatively scarce. This study uses UK stock price data and contributes to the literature by investigating whether pure value, pure momentum and their combination can "beat the market" and whether any of these strategies yielded positive premium in the selected time period. The thesis also provides an insight into both anomalies and contributes to the ongoing debate on efficient markets.

The thesis is organized as follows. Chapter 1 provides a historical review of momentum and value existing literature. It starts with the efficient market hypothesis, followed by three subsections on momentum, value and combined strategies, where, main ideas, evidence of existence and theoretical explanations, both in terms of rational and behavioural views, are presented. Chapter 2 describes FTSE 100 index characteristics, retrieved data and risk performance measures used in the empirical analysis. The next chapter, Chapter 3, provides definition of strategies and methodologies applied in the empirical analysis. Chapter 4 outlines our empirical results and main findings.

1 LITERATURE REVIEW

In this chapter we present the literature review of momentum and value effect. We will start with the introduction of market anomalies and the definition of the efficient market hypothesis theory. We will continue with the characterization and main idea of both investment strategies separately. For both anomalies, there exist explanations that rely on rational (risk-based) explanations and explanations that explain the existence of a phenomenon on the basis of irrational behaviour of market participants, known as behavioural explanations. In this chapter, we will review the most important literature relating to momentum and value effect on the US market and internationally. In the last section, we will go through studies and findings of authors who investigated momentum and value in combination.

1.1 Market anomalies

Value and momentum are recognized as market anomalies because they are not in line with the traditional asset pricing theory, contradicting the efficient market hypothesis (Schwert, 2003). Market anomalies like momentum and value effect are a result of inefficiencies (profit opportunities) or the shortcomings of financial models (Schwert, 2003). Such anomalies are valid if they are persistent over long periods of time and yield positive premiums after controlling for risk, transaction costs and other factors.

There are several anomalies observed in financial markets. Latif, Arshad, Fatima and Farooq (2011) separate market anomalies into the following groups:

- **Calendar anomalies** are related to a calendar and are recognized as repetitive behaviour of asset movements due to the typical time period of the year, month or week. These anomalies are for example: day-of-the-week effect, holiday effect, weekend effect, January effect, etc.

- **Technical anomalies** are connected with analysing techniques used for forecasting returns on the basis of past indicators such as price or turnover. Among them are: short-term momentum, long-run return reversals, moving averages, low-volatility anomaly, turnover anomaly, etc.

- **Fundamental anomalies** are related to a company’s specific characteristics. For example, it has been shown that the company’s average return is associated with book-to-market ratio, earnings-to-book ratio, dividend yield, past sales growth, size, etc.

The main interests of this thesis are the momentum and value anomalies. Momentum anomaly is a technical anomaly, while value anomaly is categorized as fundamental. When market anomalies are identified, many investors try to use them to earn profits. However, Schwert (2013) quotes that after anomalies are documented and analysed, they often disappear, reverse or attenuate. In recent years it has been shown that many anomalies have weakened and average returns have decreased significantly due to increased liquidity and improved trading costs (Chordia, Subrahmanyam & Tong, 2014). Moreover, many argue that profits that an investor can achieve with investment strategies based on market anomalies are diminishing and causing financial markets to be more and more efficient. However, value and especially momentum seem to be persistent and have not disappeared despite increased recognition in recent years.

1.2 Efficient market hypothesis

Before reviewing the literature on momentum and value we place both into the perspective of the efficient market hypothesis (hereinafter: EMH). The EMH is an economic theory that has been a central proposition in finance for more than 30 years. The EMH puts forward that markets are rational and efficient, which means that, on the market, there is no security mispricing and that at any point in time securities "fully-reflect" all currently available information (Fama, 1970). Stock prices, on average, adjust quickly to new information as soon as they are available to market participates. This implies that assets on the market are priced correctly and there is no opportunity for excess return (also known as the risk premium). Besides, according to the EMH, prices adjust quickly and an investor is not able to use deviation from a true value and to gain benefit from the use of such information. Therefore, an investor cannot earn excess return (return adjusted for risk) using a technical or fundamental analysis without bearing extra risk.

Pioneer of the EMH is Eugene Fama (1970), who, in 1965, laid the foundation of **risk-based finance.** Fama (1970) distinguishes between 3 market efficiency forms:

- **Weak form efficiency:** also known as random walk theory, claims that asset prices follow a random walk. All available past information is already incorporated in the price and past prices cannot be used for future price predictions.

- **Semi-strong form efficiency:** states that prices reflect all available information and quickly adjust to new public information such as announcements on corporate earnings, dividends, etc. Only information that is not available to the public can lead to abnormal return; all other information is already included in the price.

- **Strong form efficiency:** Prices incorporate all information, public and also private, not accessible to the general public. Thus, even if the private information is available to the investor, he/she cannot earn excess return.

In the empirical part (Chapter 4), we will test semi-strong form efficiency on the major UK market – index FTSE 100. Semi-strong form of the EMH is tested using strategies that are built upon past stock returns (momentum strategy) and investing based on fundamental indicators (value strategy). If the FTSE 100 market is semi-strongly efficient we are not supposed to earn risk-adjusted return by any of the implemented strategies. Our first research question is, therefore:

- *Hypothesis 1: FTSE 100 market is semi-strongly efficient.*

Investors who are advocates of efficient markets and who believe that market anomalies are only temporary deviations from equilibrium, prefer to use passive investment strategies that track a market index or a market portfolio (Asness, Frazzini, Israel & Moskowitz, 2015). A **passive investor** buys securities and holds investments for a long time period. Passive investors are not seeking short-term earnings and are not interested in short-term price changes. They believe that the ongoing selling and buying activity in the short term is pointless.

Many passive market participants make use of instruments that closely follow market movements. One of the most popular passive investment instruments are the so-called exchange-traded funds (ETF) that follow price movements of the entire market. Passive investing is commonly known as a **buy-and-hold** strategy. In the empirical part of this thesis, the performance of the buy-and-hold strategy is shown in the example of the FTSE 100 and the buy-and-hold strategy serves as a benchmark.

As opposed to passive investing, in this thesis we focus on active investing trying to exploit momentum and value anomalies. An **active investor** buys and sells securities on an ongoing basis in the short run. According to Sharpe (1991) an active investor needs to trade rather frequently because he/she acts on perceptions of mispricing and such misperceptions change relatively frequently. The main goal of an active investor is to "beat the market" in the long run, doing so by actively changing the investment portfolio. For example, many investors use information by exploiting market anomalies, tracking repetitive patterns in prices or exploiting the irrational behaviour of other investors. One of the advantages of active investing is the ability of the investor to find ways to minimize risk. For example, with proper diversification.

Contradicting the EMH, many investors think that prices can be predicted based on historical data or by analysing behaviour patterns of other investors. For example, a new contemporary thought of finance, which stresses human behaviour and psychological patterns on the financial markets, has evolved in the last decades. The best-known authors of this stream of finance are for example: W. De Bondt, R. Thaler, A. Tversky, D. Kahneman and others. Besides, the aforementioned **behavioural finance** researchers believe that market anomalies are not just temporary aspersions from market efficiency but rather, systematic and significant deviations from the equilibrium. (Shleifer, 2000). Moreover, researchers have determined several ways to predict asset returns. One of the popular active methods is momentum investing, which is discussed in the next section.

1.3 Momentum investing

It has been more than 25 years since the first publication of Jagadeesh and Titman (1993) when the momentum strategy was first introduced. Among anomalies, momentum still remains a puzzle, opposing the EMH, which advocates the unpredictability of stock returns. One reason why momentum investing is so popular is the fact that the only input needed are historical prices, which are nowadays accessible to all investors. (Huynh, 2014).

Momentum effect in stocks' returns was extensively analysed in the last decades, but there is still an ongoing debate about the main forces behind it. The momentum anomaly seems to be persistent regardless of the time period and sample selection.

1.3.1 Basic idea of the momentum investment strategy

The momentum investment strategy, introduced by Jagadeesh and Titman (1993), is built upon the idea that if we buy stocks with best past returns over 3 to 12 past months and at the same time short sell stocks with worst past returns, we can earn excess return. Momentum anticipates that in the near future stocks with high past returns (known as **winners**) will persist to increase and stocks with low past returns (known as **losers**) will persist to decrease. Studies have shown that momentum is strongest in the time period up to 1 year and portfolios have to be rebalanced often to be efficient.

The classical method by Jagadeesh and Titman (1993) goes as follows. The momentum strategy at time period *t* sorts stocks according to their 3 - 12 past monthly returns into decile portfolios. In literature, this is known as the **formation period (*J*)**. According to the formation period, stocks are then ranked from those with the highest past returns to those with the lowest past returns and sorted into decile portfolios. After formation, strategy buys the top decile (known as **winner portfolio**) and shorts the bottom portfolio (known as **loser portfolio**). Both portfolios are then held for a short-term period (up to 12 months). The period when portfolios are held is known as the **holding period (*K*)**. Generally, the holding period ranges from 3–12 months. Jagadeesh and Titman (1993) and their successors propose that it is best to skip a month between the formation and holding period to bypass bid-ask spread, price pressure, and lagged reaction effects (Jagadeesh & Titman, 1993).

Momentum premium is defined as return generated as long position in past winner and short position in past loser portfolio, at the end of the holding period *K*. In literature, momentum strategy is most often denoted as the **winner-minus-loser (WML) strategy.**

Besides, momentum is a **zero-investment strategy**, meaning that as we simultaneously short-sell loser portfolio and buy winner portfolio, we create a zero net value. In the empirical part we will apply the above described classic momentum strategy, where we test the following hypothesis:

- *Hypothesis 2: Classic momentum strategies are profitable on the FTSE 100 stocks index in the period January 1996–February 2018.*

1.3.2 The evidence of momentum effect

Momentum has been observed internationally, and its existence was well documented over the last 25 years. Most of the studies have been made on the US market but there also exists some empirical evidence outside the US. In the following section, we will show some of the studies that prove that momentum is a persistent anomaly independent of the market, time period and sample size.

The first known study of the momentum investment strategy was made by Jagadeesh and Titman (1993) on the US market. The authors performed research on NYSE and AMEX in the time period from 1965 to 1989. They ranked securities into 10 portfolios (deciles) and created zero investment portfolios based on 3 to 12 months past returns. They reported that momentum strategy on the US market is profitable and leads to excess return. For example, their $J = 6$ / $K = 6$, where J is the formation period and K is the holding period, strategy earned more than 12% on a yearly basis. Moreover, most of momentum strategies were positive and statistically significant. The authors also analysed the causes of momentum premiums. They found that profitability does not result from systemic risk or delayed stock price reactions to common factors. They also showed that positive returns disappear within the next two years and that momentum strategies only work in the short term.

Soon after the pioneering article of Jagadeesh and Titman (1993), many authors, for example, Grinblatt, Titman and Wermers (1995), Chan, Jagadeesh and Lakonishok (1996) and Moskowitz and Grinblatt (1996) confirmed the existence of momentum profits on the US market. In response to the criticism, that momentum premium is due to data snooping, Jagadeesh and Titman (2001) provided new empirical evidence, where they replicated their original method and added 9 years of data and came to a similar conclusion.

In 1998, the research on momentum continued beyond the US market. Rouwenhorst (1998) used the same technique as Jagadeesh and Titman (1993) and conducted a study on international markets, namely on 12 European markets. His observed time frame was from 1978 to 1995. His average monthly momentum returns were in the range from 0.64% to 1.35% per month, after controlling for market risk and exposure to size factor. Momentum premium was present in all of the 12 markets and momentum returns were about 0.93% per month on average. Rouwenhorst (1998) also discovered that the best zero-investment portfolio was the portfolio with $J = 12$ months and $K = 3$ months. He showed that positive returns are negatively related to firm size. Additionally, he discovered that if the holding period of longer than 12 months is used, a reversal effect in stock returns occurs, exactly as in Jagadeesh and Titman (1993).

On the Asian continent, Chui, Titman and Wei (2000) explored the momentum effect in the period from 1975 to 1997. They conducted a study on 8 Asian markets (with low correlation to the US market) and discovered that the extent and prevalence of the momentum effect is weaker than in the US and is especially weak in Japan. Besides, momentum strategies have shown negative premiums in Korea and Indonesia. But, when Japan was excluded momentum strategies were profitable, earning a significantly positive momentum premium of 1.45% per month.

On the UK market, abnormal returns of momentum strategies were confirmed by Lui, Strong and Xu (1999). The authors performed an analysis of total and sub-periods, seasonal effects, etc. between 1977 and 1988. Lui, Strong and Xu. (1999) did a control for risk factors and confirmed the robustness of the momentum premium. Hon and Tonks (2003) examined momentum from 1955 to 1996 and again confirmed the presence of momentum premiums on the UK market. However, the authors argue that momentum on the UK market is not as persistent as on the US market and it only appeared in certain time periods, namely after 1977 but not before. Similarly, in a more recent study, Agyei-Ampomah (2007) included transaction costs and discovered that after controlling for transaction costs, UK momentum profits disappear for shorter horizons but remain for longer horizons.

All authors: Lui, Strong and Xu (1999), Agyei-Ampomah (2007), Siganos (2010), Hon and Tonks (2003) who examined the UK market used a large sample consisting of more than 500 stocks. In our case, we analysed the FTSE 100 index within 22 years where, in each month, we have approximately 100 of the largest stocks from different industries (see Appendix B for 2018 FTSE 100 constituents list). Hence, with our empirical analysis we add to the literature by analysing out-of-sample evidence of momentum effect on the UK market on a smaller sample.

In short, academics agree that empirical evidence of momentum’s existence cannot be overlooked and that momentum is not a unique phenomenon. Its existence was confirmed in different time periods and on almost all markets. The idea of data-snooping was quickly refuted and momentum became a well-established phenomenon as named by Asness, Frazzini and Moskowitz (2015). But the ongoing debate of what drives the momentum premium remains. In the next chapter, we will review a few interesting studies of rational and behavioural explanations of the momentum effect.

1.3.3 Theoretical explanations of momentum effect and momentum premiums

Two prevailing explanations of the momentum phenomenon have emerged among academia. The proponents of the risk-oriented explanation mostly argue that momentum profits are due to data-snooping, higher risk exposure, misspecified asset pricing models or use of different methodology. While, behavioural-oriented researchers argue that momentum profits arise from investors’ sentiment to news and events and occur because of psychological biases and market inefficiencies. In the following subchapters, we will review a few well-known studies of both streams.

1.3.3.1 *Risk-based explanations of momentum premiums*

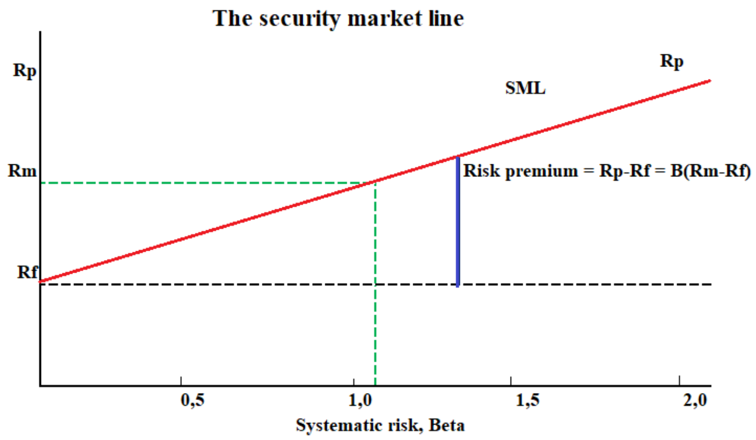
The theory of risk-based explanation argues that momentum premium is compensation for risk.

The Capital asset pricing model (CAPM), developed by Sharpe, Mossin and Lintner in the 1960s is a risk-based model that shows a relationship between expected risk and return. Equation (1) below describes that relation. With CAPM it is possible to decompose total risk into systematic risk (market risk), denoted as beta (*β*) and into non-systematic risk. With proper diversification, it is possible to minimize non-systematic risk almost to zero and the expected return of a portfolio is determined only by beta. A general CAPM equation is:

$$E(R_i) = \alpha^J + R_f + \beta\,[E(R_m) - R_f] \qquad (1)$$

Where $E(R_i)$ is the expected return, α^J is the intercept, R_f is the risk-free rate, β is the market risk, and $E(R_m)$ is the expected market return. The CAPM model anticipates that there is a linear relationship between expected return and risk, meaning that higher risk is associated with higher return. The relationship is further demonstrated in Figure 1. The risk premium ($R_p - R_f = \beta\,(R_m - R_f)$) of a portfolio changes linearly with the level of systematic risk – β.

Figure 1: The security market line



Adapted from Subach (2012, June 28).

The security market line (SML) in Figure 1 shows the expected rate of return as a function of systematic risk or beta. It is a graphical representation of the CAPM model (Subach, 2012). If beta is equal to 1, this indicates that the stock price (or portfolio price) is equally volatile as the market. If it is less than 1 it means that is less volatile (less risky) and if it is above 1 it means that is more volatile (riskier). Beta is, therefore, a risk measure and measures how the portfolio behaves in comparison to the benchmark, while alpha (see Section 3.3.3.) is a measure of performance. In an efficient market, the expected value of alpha is 0.

Relying on the CAPM theory, Jagadeesh and Titman (1993), Chan, Jegadeesh and Lakonishok (1996), Grundy and Martin (2001), Fama and French (1996) and many others have shown that momentum profits are not driven by market risk only. Persistent momentum profits in these studies have shown that there has to be something else causing abnormal returns.

The Fama-French three-factor model (1993) adds two new variables to CAPM to better explain the behaviour of stock returns. Fama and French (1993) claim that stocks with small capitalization and stocks with high a book-to-market ratio (hereinafter: B/M ratio) perform better than the overall market and that the two can better explain cross-sectional variation in stock returns than CAPM itself. Expected excess return in Equation (2) on the left side of the portfolio is captured by three risk factors in the following Fama-French (FF) model:

$$E(R_i)- R_f = \alpha^{FF} + \beta_{im} [E(R_m)- R_f]+ \beta_{is} E(SMB)+ \beta_{ih} E(HML) \qquad (2)$$

where $E(Ri)$ is the expected return, R_f is the risk-free rate, α^{FF} is the intercept of the multiple regression, β_{im} is the market risk, $E(R_m)$ is the expected market return, SMB is multiple regression factor (small-cap stocks - big-cap stocks) and HML is multiple regression factor (high B/M - low B/M). The investors are most interested in determination of alpha since it indicates how well the investor is capturing the expected returns, given the portfolio's exposure to the market risk, SMB and HML factors.

Although the idea that the momentum premium could be explained by adding additional factors to the CAPM model was attractive, the model was not able to explain it. In the next study, Fama and French (1996) again confirmed the assumption that their three-factor model is not able to explain the momentum returns documented by Jagadeesh and Titman (1993). However, Fama and French (1993, 1996) concluded that average stock returns are related to firm-specific risk factors like size and value.

A year later, Carhart (1997) introduced an extension of the Fama-French three-factor model where he added another factor, namely, 12-month momentum. In finance, this model is known as the **Carhart four-factor model**.

$$E(R_i)- R_f = \alpha^C + \beta_{im} [E(R_m)- R_f]+\beta_{is}E(SMB)+ h\beta_{ih} E(HML)+g_i\beta_{iw}(WML) \qquad (3)$$

As said, the difference between the Carhart four-factor model and the Fama-French three-factor model (Equation (3)) is in the additional regression factor – WML. WML (winner-minus-loser) is determined as equally weighted average of the best-performing stocks minus equally weighted average of the worst-performing stocks, lagged one month

(Carhart, 1997). With his model, Carhart (1997) tried to explain the perseverance of mutual fund average and risk-adjusted returns. He discovered that above mentioned common factors (size, value, market risk, momentum) in stock returns and transaction costs are able to explain mutual funds' returns to great extent. He argues that these results are in favour of efficient markets.

Some researchers believe that the existing models are incomplete and this the reason why positive alpha remains after controlling for traditional factors such as market risk, size, value and momentum. For example, Moskowitz and Grinblatt (1999) discovered that when industry momentum is taken into account, momentum investment strategies are significantly less profitable. Lee and Swaminathan (2000) argue that the magnitude and persistence of momentum are predictable by past trading volume. Chordia and Shivakumar, (2002) argue that earnings and price momentum are related and that zero investment momentum strategies can be explained by a set of macroeconomic activities such as GDP growth, consumption, labour income, etc.

Conrad and Kaul (1998) conducted a study on the US market between 1926 and 1989 with the aim to determine expected momentum profits. According to the authors, cross-sectional variation in the mean returns is an important determinant of momentum profitability. Meaning that momentum strategy equals purchasing securities with high unconditional expected returns (high-mean) and selling securities with low unconditional expected returns (low-mean). In other words, Conrad and Kaul (1998) are of the opinion that momentum profitability is just a reward for bearing extra risk, which is in line with the theory of efficient markets.

Further risk-based explanation is provided by Johnson (2002) who advocates the idea that: "stochastic growth rates are related to momentum profits, because stock prices are dependent on growth rates in a highly sensitive, non-linear way."

1.3.3.2 Behavioural explanations of momentum premiums

Behavioural finance provides an alternative explanation for abnormal momentum profits. In recent years, researchers turned to psychological experimental studies in the search for a possible explanation. According to the behavioural explanation, momentum is persistent because of behavioural biases like herding, anchoring, over and underreaction and confirmation biases of market participants. Through different irrational models, behaviourists show how these biases can explain the momentum effect. Most behavioural explanations argue that **underreaction** or/and **overreaction** to new information is the reason for momentum occurrence.

Existence of momentum premium could also be attributed to irrational behavioural characteristics of investors. For example, the disposition effect states that investors are inclined to sell stocks whose prices have increased and hold stocks whose prices have decreased. This theory goes hand in hand with the existence of momentum (Grinblatt & Han, 2002).

Jagadeesh and Titman (1993) argue that the profitability of momentum strategies is related to the market underreaction to firm-specific information. Chan, Jagadeesh and Lakonishok (1996) provide an alternative explanation of the underreaction theory and explore how the market reacts to new information. More specifically, the authors investigated market reactions to firm's earnings announcements. They observed that momentum effect is much more concentrated after earnings are released.

Based on behavioural models, Daniel, Hirshleifer and Subrahmanyam (1998) argue that underreaction and overreaction are consequences of two psychological biases. They argue that momentum effect occurs due to self-attribution bias and delayed overreaction which is a result of investor's overconfidence. Investor's biased self-attribution is a psychological action when someone attributes good results to his/her own skills, while bad results are assigned to bad luck. According to Daniel, Hirshleifer and Subrahmanyam (1998) overreaction is caused by the investor's overconfidence regarding his/her precision of private information.

Barberis, Shleifer and Vishny (1998) introduce a simple behavioural model of investor sentiment. With this model, they try to explain how investors form beliefs. Two psychological patterns, which could explain momentum effect, are presented. First is conservatism bias and the second is representativeness heuristic. Conservatism (or conservatism bias) used in the Barberis, Shleifer and Vishny (1998) model refers to human information processing when the investor will act conservatively (to slow) to new information. New information will, therefore, be only gradually incorporated in the security price. Underreaction in connection with conservatism could, therefore, be another explanation of the momentum effect. The second bias, representativeness (or representativeness heuristic), causes investors to underestimate the probability of change in the security price trend which results in momentum persistence.

Hong and Stein (1999) created a behavioural model of information diffusion in which market participants are segregated into: "newswatchers" and "momentum traders". The first type of agents relies on fundamental analysis and reacts only on private information, and the second type of agents is more prone to technical analysis. The model supposes that fundamental information diffuses gradually across "newswatchers", which leads to underreaction in the short run and gives "momentum traders" a signal to react. Momentum traders then push prices above or below their fundamental values. In the long run, prices become overvalued and convert to their equilibrium value, which is known as the reversal effect. Hong and Stein (1999) thus think that both overreaction and underreaction are causes for momentum effect.

In more recent studies, Cooper, Gutierrez and Hameed (2004) assign momentum premium to overconfidence of investors in good times.

Another interesting research done by Chui, Titman and Wei (2010) analysed how cultural differences are related to momentum returns. The authors discovered that individualism (which is related to overconfidence and self-attribution bias) is positively related to the magnitude of momentum profits. Moreover, the authors argue that momentum returns are positively connected with transaction cost, familiarity of the market to foreigners, analyst forecast dispersion and negatively to size and volatility.

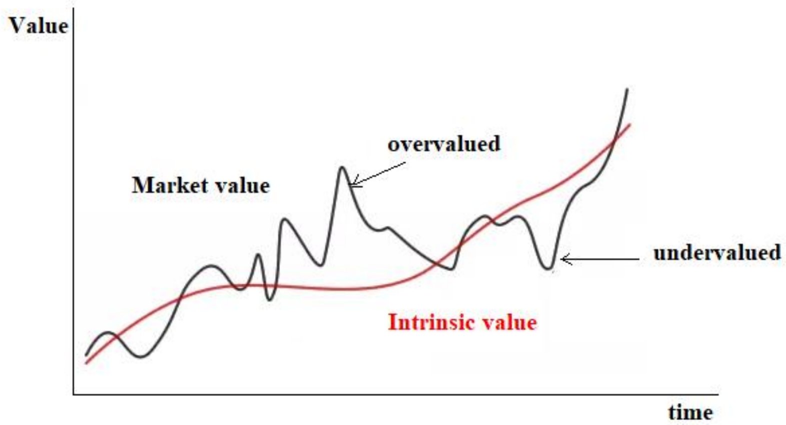
As we have seen in this section, there are different risk and behavioural explanations for the momentum effect, but there is still no absolute agreement about what is truly causing the persistence of the phenomenon in financial markets.

1.4 Value investing

Value investing is one of the oldest investment styles, which has been popular for more than 70 years. In 1934 Benjamin Graham and David Dodd first introduced the paradigm of value investing in their text called "Security Analysis". Nowadays, Asness, Frazzini, Israel and Moskowitz (2015) label the value premium as a well-established empirical fact, and they show that the value effect is one of the most extensively studied financial phenomenon in history.

By definition, value investing is an investment strategy where investors try to find stocks that are underpriced by the market. A value investor is looking for stocks whose intrinsic values deviate from their market values. An investor who believes he/she can earn with value investing will thus buy undervalued stocks and sell overvalued stocks. As shown in Figure 2, an investor will buy a stock that is below intrinsic value (marked with red) and short-sell stock that is above.

Figure 2: Graphical presentation of value investing



Adapted from Clau (2016, April 4).

Unlike momentum investing, value investing is more long-term oriented. Stocks are usually bought once a year and held for at least 12 months. A value portfolio does not have a need for constant rebalancing because companies usually publish financial reports quarter-yearly or annually.

Generally, the stock value characteristics to be considered are book-to-market ratio (B/M), earnings-to-price (E/P), cash flow-to-price (C/P) or dividends-to price (D/P). We distinguish between **value stocks** and **growth stocks**. The most used proxy to distinguish between the two types is B/M. Stocks with high B/M values are recognized as value stocks, while stocks with low B/M values are recognized as growth stocks. Value stocks are traded for less than indicated by their fundamentals and are undervalued by the market. A value investor thus acquires a value stock, because he/she believes that its price will increase when the market recognizes that it has been undervalued. It has been shown that in the long run, value stocks outperform growth stocks and this is known as the **value effect**. The basic idea of this style of investing is explained in the next subsection.

1.4.1 Basic idea of value investing strategy

Value investing is basically a really simple and intuitive investing strategy that looks for undervalued securities. Most of the literature uses the B/M ratio as a ranking factor, which is an inverse of the price-to-book ratio (P/B) (Fama & French, 1998). In the value investment strategy, stocks are sorted at the beginning of month *t* from the highest to the lowest according to their B/M ratios. Value stocks (those with the highest B/M ratios) are put in a portfolio, usually denoted as **High (*H*)** and growth stocks (those with the lowest B/M ratios) are put in a **Low (*L*)** portfolio. Stocks that are ranked in the highest portfolios are bought and those in the lowest portfolio shorted (sold), meaning, that just as momentum, value strategy is a zero-cost investment strategy that results in a high-minus-low (HML) strategy portfolio. Rebalancing is not as frequent as in the case of momentum, and portfolios are held for a longer time period (usually at least one year), and are usually rebalanced once or twice a year. Our next hypothesis that refers to value investing is:

- *Hypothesis 3: Value strategies are profitable on the FTSE 100 stocks index in the period January 1996–February 2018.*

The hypothesis is tested in Chapter 4, where B/M, E/P and D/P are used as ranking factors. In the next two subsections, however, we will first look at discoveries about value premium and possible explanations for it.

1.4.2 The evidence of value effect

In one of the first studies, Basu (1977) tested the efficient market hypothesis on the US market. His sample ran from 1956 to 1971 and consisted of NYSE constituents. He conducted an empirical study with the goal to determine the relationship between stock returns and their P/E ratios. He found out that, during the 14-year period, low P/E portfolios are more profitable than high P/E ratios and these portfolios have earned approximately 6% more per year (absolutely and risk-adjusted). A few years later, Basu (1983) implemented a similar study and examined the relationship between E/P ratio, size and returns on a similar NYSE sample in the time period 1962–1980. With this study, Basu confirmed that companies with high E/P ratios on average earn higher risk-adjusted returns than the ones with low E/P ratios.

Rosenberg, Reid and Lanstein (1985) examined the sample of 1400 US securities with high market capitalization in a period of 11 years. They created portfolios based on B/M ratios. Their zero-investment portfolio, with long positions in high B/M stocks and short positions in low B/M stocks, had an average return of 0.36% per month. The strategy achieved highly significant results, and the authors argue that this is a clear sign of market inefficiency.

Positive value premium was also documented by Fama and French (1993) in the period from 1963 to 1990 on the extensive US market sample. With one of the most know articles in finance literature titled “The Cross-Section of Expected Stock Returns” Fama and French (1993) showed that B/M stocks (value stocks) and additionally, small-capitalization stocks, outperform the market. They showed that the difference in the average monthly returns between high B/M portfolios and low B/M portfolios is almost 1%.

In Japan, Chan, Hamao and Lakonishok (1991) examined the relationship between average returns and their E/P ratio, size, B/M ratio and C/P ratio. They found a strong relationship between these variables and the expected average returns of Japanese stocks. For example, they discovered that high B/M (E/P) stocks have higher average returns than low B/M (E/P) stocks. On average high B/M portfolios earn 2.43% per month and low B/M portfolios earn 1.33% per month. Similar is true for E/P based portfolios. Chan, Hamao and Lakonishok (1991) provided clear evidence for the existence of profitability of value investment strategies in the Japan market.

In an international study, Fama and French (1998) used a sample running from 1975 to 1995, using MSCI firms with B/M, E/P, D/P and C/P ratios, with the purpose of differentiating value and growth stocks. Their goal was to check if there is a difference between value and growth stocks on international markets. The result showed that the difference between global value B/M portfolios and global B/M growth portfolios is more than 7% per year. Moreover, value-based portfolios outperformed growth-based portfolios in 12 out of 13 global markets. They also showed that the value premium exists in the emerging markets. Further international evidence of positive value premium is provided by Karolyi and Wu (2012), Arshanapalli, Coggin and Doukas, (1998) and Fama and French (2012).

Dimson, Nagel and Quigley (2002) conducted a study on the UK market, in a period from

1955 to 2001. They used a handcrafted dataset of the firm's specific information and merged it with stock price data. They found strong evidence for the existence of the value premium on the UK market. Additionally, they also provided some insight into the role of dividend yields. Moreover, they showed that the value premium could be found in both small and large capitalized UK stocks.

1.4.3 Theoretical explanations of value effect and value premiums

Just as for momentum effect, there are explanations based on risk models and explanations based on behavioural economics for the value effect. On the one hand, some believe that the value premium occurs due to human behaviour such as overreaction, overconfidence, self-attribution bias, etc. On the other hand, supporters of the rational approach claim that positive value returns are the result of greater risk, bad sampling, data-snooping or misspecification of asset pricing models.

1.4.3.1 Risk-based explanations of value premiums

Some authors have initially attributed positive returns of value strategies to sample biases or data-snooping. Among others, Kothari, Shanken and Sloan (1995) and Lo and MacKinlay (1990), argued that selection biases are associated with the data and that when sorting on firm-specific information like value, the positive premium can be a result of data-snooping. This statement is refuted by Chan, Hamao and Lakonishok (1991) and Fama and French (1996) who performed out-of-sample analysis and proved that value stocks perform better than growth stocks.

The rational theory assumes market efficiency, and the value premium is seen as a measure of risk, indicating a higher discount rate that compensates investors for carrying higher risk. (Fama & French, 1993). Furthermore, Fama and French (1996, 1998) argue that value stocks are more inclined to financial distress and are hence riskier and more likely to be more correlated with the business cycle than growth stocks. The same goes for Griffin and Lemmon (2002) and Campbell, Hilscher and Szilagyi (2008).

In recent years, researchers have turned to structural models that link value premium to firm-specific attributes and firm's risk management decisions. According to such models, higher risk premium is related to value firms that, on average, have similar firm-specific characteristics and, therefore, higher systematic risks. According to Wang and Yu (2013), these systematic risks are mostly: higher default probability, lower profitability, higher operating leverage, shorter cash flow duration or higher cash flow risk.

Zhang (2004) offers an explanation that value stocks are riskier than growth stocks because, in bad states, growth stocks can adjust more quickly to capital needs and are more flexible in that matter. Moreover, value firms (high B/M) are burdened with more useless capital than growth firms (low B/M). While for growth stocks, expanding capital is relatively easily accessible. A similar view is shared by Cooper (2006) who shows that value firms have restricted capital capacities that enable them to fully benefit from aggregate shocks without undertaking costly investments. In sum, value firms face less flexibility and have higher systematic risk and are therefore riskier.

Petkova and Zhang (2005) discovered that value stocks are riskier than growth stocks because: “Conditional market betas of value stocks covary positively with the expected market risk premium, and that value stocks are riskier than growth stocks in bad times when the expected market risk premium is high.”

Carlson, Fisher and Giammarino (2004) showed that operating leverage and B/M ratio are related and have an important role in cross-section of value returns. Specifically, value firms have high operating leverage and thus higher returns. Consistent with this finding, Doshi, Jacobs, Kumar and Rabinovich (2015) ran cross-sectional tests on the unlevered equity returns and found that the value premium disappears in the cross-section of unlevered equity returns, showing that leverage could be a reason why value stocks are riskier.

Another risk-based explanation links the expected rate of return to cash flow and discount rate events. Investors that act rationally are more prone to decrease of future cash flows than to discount-rate events. For example, a dynamic risk-based model by Lettau and Wachter (2007) shows that: “growth firms covary more with the discount rate than do value firms, which covary more with cash flows”. In the eyes of the investor, however, this is risky, and because of this, the return on value stocks is also higher. This was also confirmed by Da (2009), who argues that value and growth stock have significantly different durations of cash flows.

Even though there is a great contribution of rational literature on possible explanations, to date, there has been no conclusive evidence that distress factors provide an explanation.

1.4.3.2 Behavioural explanations of value premiums

Unlike rational models, behavioural models place the irrational behaviour of investors in association with behavioural patterns as the cause for asset mispricing. According to the behavioural explanation, investors tend to overprice growth stocks and underprice value stocks.

In one of the first studies of the value premium, Basu (1977) attributes positive premium of value portfolios to exaggerated investor expectations or overreaction. As reported by Basu (1977), companies with low P/E are mispriced because investors are too pessimistic after bad earnings announcements or when other bad information is released. When the true value of a company is recognized by the market, the price reverts.

In line with Lakonishok, Shleifer and Vishny (1992), the difference between growth and value stocks arises because of agency costs. Growth stocks are usually the ones that have had good performance in the past, and active investment managers can justify why these stocks were selected in their portfolio.

In response to the Fama and French (1993) paper, Lakonishok, Shleifer and Vishny (1994) argue that value strategies are profitable because of "the exploitation of suboptimal behaviour of typical investor". Authors argue that investors overestimate future growth rates of growth stocks, which is due to the judgment error of a typical investor. In other words, value premium according to this explanation is due to investors' extrapolation of past performance. Porta, Lakonishok, Shleifer and Vishny (1997) provide another article based on the irrational behaviour of market participants after companies' financial results are published. According to the authors, for value stocks there is a bright future because the surprises about earnings are more favourable to value than to growth stocks.

1.5 Value and momentum combined investing

1.5.1 Different nature of value and momentum investing

Momentum and value strategies are well documented in finance literature, as we have seen in the previous two sections. At first glance, combining momentum and value investing seems unusual, since they are diametrically opposite investment strategies (Carlson, 2016).

Momentum works well within the 3 to 12 months look-back period, and momentum portfolios need to be rebalanced frequently (typically monthly or quarterly) to work effectively, while the value strategy makes a bet on long-term mean reversion and needs to be rebalanced only once a year (Carlson, 2016).

Another difference is that momentum returns are inclined to be pro-cyclical while value returns are more prone to counter-cyclicality (Bird & Whitaker, 2004). Consequently, Babameto and Harris (2008) emphasize that combined value and momentum investment strategy's performance is less vulnerable to market movements. Because of these different value and momentum characteristics and a historically low correlation between the two, combining both in one strategy could be beneficial. Asness, Moskowitz and Pedersen (2013) found abnormally large positive return premiums for both strategies and also a negative correlation between them. The authors argue that the combined momentum and value portfolio is closer to an efficient frontier than pure value or pure momentum portfolio because such a portfolio exhibits less volatility and results in improved Sharpe ratios. One of the main questions of this thesis is set as follows:

- *Hypothesis 4: Momentum and value returns are negatively correlated and implementing both strategies at the same time can be beneficial.*

According to known analyses of value and momentum effect, the diversification benefit of combining both strategies is better in long-short combined strategies and not so much for long-only strategies. This is because the performance of long-short momentum and value strategies is not dependent on market movements since long-short strategies target absolute returns (Quantila, 2018).

To date, vast empirical literature exists, where value and momentum anomalies have been examined separately, but far fewer studies consider the value and momentum combined strategy due to the very different nature of both effects. Asness, Frazzini, Israel and Moskowitz (2015) declare that: »even experienced investors often seem to wrongly assume one cannot simultaneously believe in both value and momentum investing«. Value and momentum strategies implemented individually have proven to be effective and strong predictors of stock returns. An interesting question is if and how both strategies interact and how effective is the strategy, which implements both investing styles simultaneously.

In the next section, we review studies that address both phenomena simultaneously and discoveries connected with them.

1.5.2 A review of value and momentum combined studies

Asness (1997) was the first known researcher who studied value and momentum in combination. He discovered that: "momentum and value are negatively correlated across stocks, but are positively related to cross-section of average returns". He performed a value and momentum study on monthly data from 1963 through 1994 on the entire US equity universe. As one would expect, he discovered that: "value strategies are stronger among low-momentum (loser) stocks and weaker among high-momentum (winner) stocks". Conversely, momentum strategies are strongest among growth (low B/M) stocks. Asness' (1997) main conclusion is that negative correlation between the strategies can lead to portfolio improvements in terms of reduced risk and improved profitability.

A few years later, Daniel and Titman (1999) examined the performance of portfolios sorted on size, B/M and momentum created from the US common stock universe in the period from 1964 to 1997. First, they confirmed independent momentum and value effects on the US market. Then they showed that returns of the combined long-short strategy, which buys high B/M and high momentum stocks and at the same time sells low B/M and low momentum stocks, generates positive returns in 31 out of 34 years and realizes an average profit of 1.04% per month (and 12.64% per year). In line with overconfidence theory, they show that portfolio strategies realize extremely high and persistent abnormal returns. Also, as was the case in Asness (1997) momentum effect is much stronger for growth stocks. In Asia, Chui, Titman and Wei (2000) examined the relationship between expected returns and firm-specific factors such as size, value, momentum and turnover. They discovered that there is a positive relation between growth stocks and momentum, high turnover and momentum and negative relation between size and momentum.

Nagel (2001) conducted a study in the US and UK and showed that an important role in momentum reversal is played by value effect. He also argues that reversals in momentum is actually the value effect and that momentum profits disappear after adjusting for B/M factor, since in the long run high momentum stocks are inclined to become growth stocks and low momentum stocks tend to become value stocks and that when momentum runs out, WML portfolio is just growth minus value portfolio with negative return.

Cakici, Fabozzi and Tan (2013) examined both effects in 18 emerging equity markets in the period 1990–2011. They discovered that in emerging countries (with the exception of Eastern Europe) both momentum and value are present. A year later, Cakici and Tan (2014) presented another international study of momentum and value analysis. They examined 23 developed equity markets, namely countries in North America, Europe, Japan, and Asia Pacific, in the time period from January 1990 to March 2012. This time they were also interested in the correlation between momentum and value. They discovered a negative correlation between them within and across countries. Additionally, they found that when recession is close or in times when funding liquidity is bad, value returns are lower while momentum returns are not that sensitive to recession or funding restraints.

A very comprehensive study was made by Asness, Moskowitz and Pedersen (2013) in which authors examined value and momentum jointly across 8 equity markets and different asset classes (the US, the UK, Europe and Japan; country equity index futures; government bonds; currencies; and commodity futures), and offered a new insight into two market anomalies. Asness, Moskowitz and Pedersen (2013) found stable profits for both strategies in different countries and across different asset classes. They showed that value and momentum returns are negatively correlated and a simple equal-weighted combination of value and momentum produces a positive return premium, which is also more stable across markets. They also showed that the return premium cannot be explained by different risk factors, such as the CAPM beta or liquidity, and furthermore that there is no clear relationship between macroeconomic factors and returns.

The argument that the combination of both investment strategies is beneficial is also confirmed by Cooper, Mitrache and Priestley (2016), Fisher, Shah and Titman (2016) and Babameto and Harris (2008).

In a recent study, Cooper, Mitrache and Priestley (2016) tried to answer the question: »Can any asset pricing model explain the negative correlation of the value and momentum return premium and the fact that equally weighted combination strategy earns a positive average return?« The authors' main discoveries were as follows. First, the momentum and value premium across different asset classes and countries can be explained by loadings on the global risk factors. Second, they argue that with their simple model, a negative correlation between the return premium of individual momentum and value can be explained by their differing factor loadings. And third, their model can also explain the return premium in the combination of the value and momentum strategies.

De Groot, Pang and Swinkels (2010) examined frontier emerging markets from 1997 to 2008. Their data consisted of 24 emerging markets with more than 1.400 stocks. They showed that the momentum and value premium could be found on emerging markets and also that both effects are negatively correlated. Besides, with mean-variance spanning tests they proved that when value and momentum stocks from emerging markets strategies are added to the developed markets portfolios, combined portfolio becomes much more efficient because the mean-variance frontier is shifted outwards.

Blitz and Van Vliet (2008) analysed global tactical asset allocation (hereinafter: GTAA) strategies on 12 asset classes over the 1986–2007 period. They discovered that GTAA momentum and value strategies generate positive returns between 7–8% per year. Moreover, their combined "GTCAA" strategy tested over the years 1986 to 2007 delivered a yearly alpha of 12%. The combined "GTCAA" strategy remained profitable even after Fama and French or Carhart factors were taken into account. An important implication of this research is also that momentum and value were observed not only within asset classes but also across asset classes. Blitz and Van Vliet (2008) are of the opinion that their findings cannot be explained by risk-based explanations but that they are due to insufficient "smart money" and consequently inefficient markets.

In contrast to similar studies on larger samples, Franz and Regele (2016) examined different value and momentum strategies on the biggest German indices, namely on DAX, MDAX and SDAX in the period 1988–2015. They tested all strategies and critically examined their performance. Their findings were the following. Most of the strategies performed worse than the benchmarks. Next, momentum premium was observed only among small-cap stocks, namely on SDAX. None of the value strategies were profitable on the German market indices. However, their findings revealed negative correlation between momentum and value in DAX. In addition, they discovered that if both strategies are combined, the risk of a portfolio is reduced. The reason why momentum does not work might lie in the sample selection. All the before-mentioned indices contain companies with large capitalizations. Franz and Regele (2016) argue that momentum apparently only works for small stocks. Similar to Franz and Regele (2016), we analysed momentum and value and their combination on the equity index. But with the difference that our analysis was done on the UK market. In the next section, we will first present the data.

2 DATA

In Chapter 2, we will present the data and the methodology used in our empirical analysis.

First, we will briefly describe the FTSE 100 index characteristics, retrieved data and descriptive statistics of the sample, further we will describe problems and limitations that we encountered during data processing. We will continue with the description of performance metrics and risk factors, which are used in the assessment of individual strategies.

2.1 The FTSE 100 index

The FTSE 100 Index is the abbreviation for the Financial Times Stock Exchange 100 Index. The FTSE 100 (informally called "Footsie") is an equity index consisting of 100 companies listed on the London Stock Exchange (hereinafter LSE). FTSE was founded in 1984 with a base value of 1.000. At the end of February 2018, the value was approximately 7.490. As the name suggests FTSE 100 consists of 100 largest companies by market capitalization. However, today there are 101 index constituents since the company Royal Dutch Shell has 2 listed stocks (see Appendix B).

Interesting facts about the FTSE according to the London Stock Exchange (Ftserussell, 2018) are:

- ¾ of FTSE 100 companies' revenues are obtained out of the UK market
- FTSE 100 represents 78% of LSE market capitalization
- FTSE 100 companies employ more than 5.2 million people
- Out of 101 companies, only 16 companies make their revenue in the UK
- Royal Dutch Shell is the largest company by market capitalization listed on FTSE 100

Figure 3: FTSE 100 index performance 1996–2018

Source: own work.

With regard to market capitalization, every three months (March, June, September, December) it is determined whether a stock will be part of the FTSE 100 index or not. We had many problems with the creation of the database because some stocks were listed for a very short time period.

Figure 3 shows the FTSE performance from January 1996 to February 2018. We can see that the index fluctuated quite significantly in this period, reaching its peak in 2008. Major milestones shook the index through this period, one of them was the “dot-com crash”, which started in the late 1990s when all the capital accumulated around internet-based companies and hit the summit in 2000 when the FTSE 100 increased for almost 200 index points and was followed by a drastic decrease, which ended in 2003. The index reached the highest growth in the years 2003–2008, which ended with a global financial crisis. The global financial crisis started in autumn 2008 and prices hit bottom in 2009. In the years that followed, FTSE 100 gradually recovered and reached approximately the same level as in 2000 but was again deluded by the alleged departure of the UK from the European Union in 2015/2016 known as “Brexit”.

2.2 The sample selection

2.2.1 Motivation for the sample selection

Motivated by the study of Franz and Regele (2016), who did an analysis on the 3 biggest German indices, we examined the profitability of value and momentum strategies on the index FTSE 100. By selecting a sample, containing only the largest UK companies, we have provided a “rigorous test of the real-world profitability of strategies and actual feasibility of the strategies in practice with respect to firm size” (Franz & Regele, 2016). The sample selection is also based on the argument that the UK market is not as explored as the US market, where many momentum and value strategies have been carried out. Our sample, therefore, provides out-of-sample research of momentum and value in the international markets.

The stock universe of the FTSE 100 is very liquid and highly capitalized. The monthly market capitalization of all stocks in our sample ranged from 0.76 billion USD in 1996 to 3.12 billion USD in 2018. The data was obtained from Thomas Reuter Datastream (hereinafter: Datastream). All stocks in the sample are or were constituents of the FTSE 100 in the sample period running from January 1996 to February 2018. All together our sample consists of 266 months or more than 22 years.

2.2.2 Data gathering and processing

To retrieve the data from the Datastream we first used command LFTSE100 to get the constituent list for the current (February 2018) FTSE 100 list. Datastream only provides the oldest and most recent constituent list, therefore, we needed to edit the mnemonic to get the data for each month. For example, to retrieve the constituent list of FTSE 100 for 31st December 2005 we used the mnemonic LFTSE1001205 (Wordpress, 2018). We had to manually edit for each month to get all monthly lists for the FTSE 100. When we retrieved the codes for all stocks ever listed on FTSE 100 in the time period, we then used the time series request to get the historical prices for each stock in the sample. Our sample also includes stocks that were delisted because of bankruptcy, merger and acquisition or simply because their market capitalization fell to low. We did this to eliminate survivorship bias. All together we have historical data for 292 index constituents for 5 different variables, shown in Table 1. After we retrieved the data we checked at the vendor (Ftserussell, 2018) when a specific company was delisted from the index and manually edited the sample for each of the 292 companies to get the best proxy of the FTSE 100. When a company is excluded from the index, we replaced values with "*NA*" to reduce the errors in further data processing. For some stocks, we could not get the data, and those stocks were excluded from the sample. After the data has been consolidated, 283 stocks remained. An error, due to manual scanning and Datastream deficiency is possible nevertheless, it gives a sufficiently realistic state of the index changes over the past 22 years.

Table 1: Datastream data types

Search command	**Meaning**
P	Adjusted Price
PE	Price-to-Earnings ratio
PTBV	Price-to-book ratio
MV	Market Value
DY	Dividend Yield
FTSE100	FTSE 100 historical value
UKGBILL3	3-month UK Treasury Bills rate

Source: Datastream Database (2018).

Table 1 above shows Datastream commands used to create our data set. *P* represents the adjusted closing price on a specific date, *PE* is the price divided by earnings rate per stock at the required date (P/E ratio), *PTBV* is price divided by book value of equity (P/B ratio), *MV* is the stock price multiplied by the number of ordinary stocks and *DY* is dividend per share as a percentage of the share price (Datastream, 2017).

Table 2: Descriptive sample statistics

Variable		**Min**	**Max**	**Mean**	**Median**
Price (*P*)		0,17	25587,9	708,7	443
Market capitalization (*MV*)		0,07	205148,6	8012,6	3186,96
Price-to-Earnings ratio (*P/E*)		0,3	1051,2	22,7	16,3
Price-to-Book ratio (*P/B*)		-551,1	202,4	3,0	2,26
Dividend Yield (*DY*)		0,01	560,4	3,1	2,71
Number of observations (*n*)	**266**				
Number of total stocks in the sample (*N*)	**283**				
Number of created portfolios	**279**				

Source: own work.

Additionally, for further statistical analysis of returns and comparison to the benchmark, we obtained historical data for the FTSE 100 index (command FTSE100 in Datastream) and the data for the 3-month UK Treasury Bills rate (command UKGBILL3 in Datastream) which represents a proxy for our risk-free rate. The risk-free rate is adjusted to a monthly basis. A risk-free rate of return represents the interest an investor gets if he invests in a risk-free investment over a specified period of time. We used the 3-month UK Treasury Bill following the example of previous studies.

In the next step, we began cleansing the data in order to detect inconsistencies and irregularities and to ensure good data quality. We used different statistics such as maximum, minimum, median, mean in order to check the quality of the data and to deal with potential outliers. Unusual and strange variables were removed. In Table 2, we show the descriptive characteristics of the sample. The first row shows the variable name and abbreviation, Table 2 also shows minimum, maximum, mean and median for each variable. At the end of Table 2, we can see the number of monthly observations, number of stocks with which we operate in the analysis and the total number of portfolios created.

2.3 Risk and performance metrics

In this section, we will briefly describe the performance metrics used for strategy performance evaluation in the empirical part. We will present: excess return, standard deviation, Sharpe ratio, CAPM beta and Jensen's alpha. In the empirical analysis, for all of the 279 portfolios, the below performance and risk metrics are calculated.

Performance evaluation gives an insight into the balance between high returns and acceptable risks. Among investors there is always a question: »Can anyone consistently earn an "excess" return, thereby "beating" the market?«. (Jordan, Miller & Yüce, 2008). To answer this question, we need to introduce performance metrics that help us evaluate the investor's ability to beat the market while taking risk into consideration.

2.3.1 Excess return

For each portfolio, we first calculated the **raw return (R_p),** which is a naive performance measure since it does not take into account associated risk, and it is not compared to any benchmark. Such a measure does not give us an assessment of how successful our investment was and has limited usefulness (Jordan, Miller & Yüce, 2008).

The first important performance measure is **excess return (R_i - R_f)**, which measures the return of the strategy relative to the return on the risk-free investment. Excess return is compensation for the investor for bearing extra risk compared to a risk-free asset. It is calculated as a difference between raw return in month *t* and risk-free rate (UK Treasury Bill) in month *t*. Excess return is extensively used as a performance measure that gives us an insight into how much value is added by active investing.

2.3.2 Standard deviation

To evaluate riskiness of a particular strategy, we first calculate a **standard deviation**, which is calculated as:

$$Standard\ deviation\ (\sigma) = \sqrt[2]{Variance} \tag{4}$$

The standard deviation (σ) is the square root of the variance and measures variability or dispersion around the mean return. It is a measure of volatility and measures the total risk of a portfolio. If the standard deviation is high, it means that the volatility of a portfolio is high.

2.3.3 Sharpe ratio

Next, we will look at the Sharpe ratio. The Sharpe ratio (Sharpe 1966) measures the excess return per unit of deviation in a portfolio. It measures portfolio performance in relation to volatility. The Sharpe ratio is a reward-to-risk ratio that focuses on total risk. (Jordan, Miller & Yüce, 2008). It is calculated as:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma} \tag{5}$$

where, R_p is portfolio return; R_f is risk-free rate; and σ is standard deviation of a portfolio. In general, higher risk is compensated with higher return. If we, therefore, compare two or more different portfolios, we can easily see which of them is performing better when taking risk into consideration.

2.3.4 Beta

Another risk measure often used in the modern portfolio theory is the beta. Beta is a measure of volatility (or systematic risk) that gives insight into the riskiness of a portfolio in relation to the market. It is commonly referred to as the beta coefficient or measure of market sensitivity. Beta is estimated with the linear regression CAPM model. Equation (6) shows the formula for beta calculation. The denominator is the covariance between portfolio returns (R_p) and market returns (R_m) and the numerator is the variance of market returns.

$$\beta_p = \frac{Cov\ (R_p\ ;\ R_m)}{Var(R_m)} \tag{6}$$

In practice, beta greater than 1 indicates that a portfolio is riskier than the benchmark. Beta equal to 1 indicates that a portfolio has the same level of risk, and beta lower than 1 indicates that a portfolio is less risky than the benchmark. A negative beta indicates that returns move in the opposite direction than the benchmark.

2.3.5 Jensen's alpha

Jensen's alpha is used to determine the abnormal return of a security or portfolio of securities over the theoretical expected return (Jensen, 1968) and is usually denoted with α.

The theoretical return is predicted by CAPM. For each portfolio, we calculated Jensen's alpha (hereinafter: alpha), which measures the additional portfolio return when we adjust it for its "beta" risk. To calculate the alpha of a portfolio we first calculate the excess return (R_p - R_f) of each portfolio and excess return of the benchmark (R_m - R_f). We ran a regression (see Equation (7)) of (R_p - R_f) on the excess returns on the benchmark. With alpha, we estimated risk-adjusted returns from the following market model regression (Jagadeesh & Titman, 1993):

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p \left(R_{m,t} - R_{f,t}\right) + e_{i,t} \tag{7}$$

Furthermore, for each portfolio, we tested the null hypothesis H_0: $\alpha_p = 0$, H_1: $\alpha_p \neq 0$. We examined the alpha (intercept), and if it was positive and statistically significant, we could argue that the strategy has outperformed the market and if it was negative it has underperformed the selected benchmark.

2.3.6 Geometric average monthly return:

The geometric average is the most appropriate measure of return for measuring historical performance and for comparative performance among different strategies. It is calculated using the following formula:

$$R_p = \sqrt[n]{\prod_{i=1}^{n}(1+R_i)} - 1 \tag{8}$$

where R_p is geometric average monthly return, R_i is return in month t and n is the number of months in the holding period. When presenting the overall performance all portfolios were calculated using Equation (8).

For each portfolio, all the described risk and performance measures were calculated and will be presented in the last chapter. In the next chapter, we will describe the methodology of momentum and value investment strategies.

3 METHODOLOGY

3.1 Implementation issues

Before discussing each strategy in detail, we will describe a few implementation issues of usability of value and momentum investing in practice. As mentioned in the introduction, the idea of this thesis not a practical implementation but the evaluation of risk and return of different momentum and value investment strategies. In the analysis, we did not take into account transaction costs, we neglected short-selling constraints and taxes. In addition, we assumed that liquidity issues are minimized due to sample selection since trading costs are highest among small stocks which are costly and difficult to short (Israel & Moskowitz, 2013). Because of these technical reasons we also included financial firms.

3.1.1 Short sale constraints

According to Lamont (2004), short-selling constraints include risks and costs connected with shorting as well as institutional and legal constraints. Portfolios can be mispriced (usually they are overpriced) if short sale constraints bind.

To minimize risk, investors can resort to the long-short investment method. The long-short method is constructed to make a profit from stocks with positive expected returns and also from stocks with negative expected returns. Such strategies are attractive because they are neutral to market risk. Since opposite positions are taken simultaneously, portfolio correlation to the market decreases the systematic risk. Long-short portfolios are also known as **market-neutral portfolios** or **zero-beta portfolios**. They are a great diversification mechanism and long-short portfolios tend to have low betas (usually around 0) and higher Sharpe ratios than long-only portfolios which is, of course, desirable for investors.

Still, investors are usually more prone to long-only investing because short-selling is connected with liquidity constraints and higher transaction costs. Israel and Moskowitz (2013) found that the importance of shorting is irrelevant if we look at raw returns. In their opinion, most returns on size, value and momentum derive from long positions. Shorting is important only if the yields are compared with a benchmark. In their study, for example, they found that if returns are adjusted for market risk, long positions contributed most of the returns of portfolios based on size, 60% of value strategies and about 50% of momentum strategies. Moreover, according to the authors, the profits of these strategies are dependent on company size. More specifically, Israel and Moskowitz (2013) state that: "Shorting becomes less important for momentum and more (less) important for value strategies as firm size decreases (increases)." But as Thomas (2006) points out, it is not difficult to short-sell most of the highly capitalized stocks. Therefore, in this thesis, we assume that short selling is possible and feasible given that we operate only with the largest stocks in the UK market.

3.1.2 Transaction cost

Following past studies, we neglected the impact of transaction costs. However, it should be noted that, due to the frequency of trading (at least with momentum), transaction costs may have a major impact on the strategy performance. Given that the portfolios are rebalanced often, such costs could considerably reduce the overall profitability. However, Frazzini, Israel and Moskowitz (2012) showed that transaction costs of these strategies are smaller than previous studies have shown and that transaction costs for institutional investors are robust, implementable and sizeable and that these investment strategies still generate abnormal returns. The empirical analysis of this thesis is performed under assumptions of zero transaction costs.

3.1.3 Small-cap effect

As already said, profitability is related to the size of the company. Large companies tend to bring lower returns than small companies. Previous studies (e.g., Jegadeesh and Titman (1993) and Fama and French (1992)) have shown that momentum and value are stronger among companies with small market capitalization (small-caps). However, Israel and Moskowitz (2013) show that momentum and size are not related, but value premium is weaker among larger stocks.

In general, small-caps are usually connected with higher cost and liquidity issues. Hon and Tonks (2003) argue that the bid-ask spread is usually wider for small-cap stocks. Small-cap stocks also have bigger fluctuations in price, on average, and are thus riskier. To eliminate this issue, we restricted our stock universe to the index FTSE 100 of the 100 largest UK companies.

3.1.4 Financial firms and value investing

It is common practice to exclude financial stocks from the dataset (Fama & French, 1992). Financial firms are highly leveraged, and the financial sector is under high regulations. Besides, financial stocks tend to have lower P/E ratios when compared to growth rates of other industries. Despite all of the differences, we decide to include financial firms in our analysis to be consistent with other studies of combined momentum and value, such as the studies of Franz and Regele (2016); Asness, Moskowitz and Pedersen (2013) and others.

3.1.5 Size of a portfolio

Our stock universe was relatively small, each month we could select from 100 stocks, approximately. Therefore, we decided to modify all strategies so that an arbitrary number of stocks could be selected into a portfolio, rather than dividing the stock universe into deciles, quartiles or quantiles. We formulated strategies of 3 different portfolio sizes – portfolio of 4, 10 and 20 stocks. We did this in order to examine how statistical characteristics of portfolios change if they consist of larger/smaller number of stocks. We assume that by increasing the amount of stocks the exposure to risk is reduced because of the diversification effect.

In the next section, we will determine momentum, value and combined strategy methods used in the empirical part.

3.2 Pure momentum strategy

Our first strategy, named pure momentum, closely follows the original work of Jagadeesh and Titman (1993). With this strategy, we analysed the stock universe of the FTSE 100, and we first tried to determine if a difference existed difference between “winner” and “loser” portfolios. Secondly, we implemented the long-short momentum strategy named WML (winner-minus-loser). We applied the zero-cost strategy in order to examine if momentum premium has been historically present on the UK market.

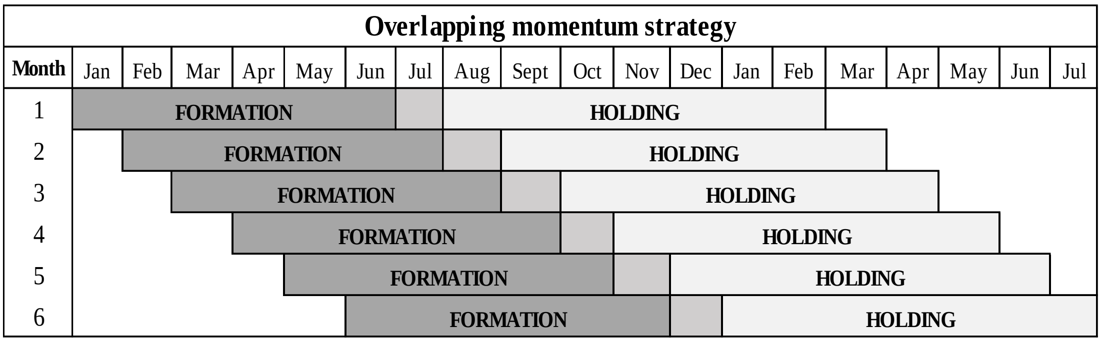
3.2.1 Momentum method

Our momentum strategy is defined as follows. In month *t*, we sorted stocks based on their returns over the past 1, 3, 6, 9 or 12, known as the **formation period (*F*)**. According to the formation period, best (worst) *n* performing stocks are selected into the Winner (Loser) portfolio. In month *t*, we formed equally-weighted winner and loser portfolios on the basis of their past returns. The number of stocks in both winner and loser portfolios, is always the same. We anticipated that stock prices would continue to persist in the same direction in the short-term (up to 12 months). After portfolio formation, in month $t + 1$, “winner” stocks were bought, and “loser” stocks were sold-short. This way we created a long-short WML portfolio. Portfolios were then held for 1, 3, 6, 9, or 12 months depending on the strategy. The period when we are holding stocks in a portfolio is called the **holding period** (denoted with *H)*. In order to avoid the bid-ask spread, price pressure and lagged reaction effects (Jagadeesh and Titman, 1993) and to deal with a potential implementation lag between the ranking of the stocks and the actual investment (De Groot, Pang & Swinkels, 2010), we skipped a month between the formation and holding period.

Based on the formation and holding period, two different strategies are possible. In the so-called **non-overlapping strategy**, as the name suggests, the formation and holding period do not overlap, while in the second, the two periods overlap, as shown in Figure 4. We chose the **overlapping strategy** because it increases the number of observations and thus the power of statistical tests (Jagadeesh & Titman, 1993). To illustrate, in Figure 4, overlapping momentum strategy with formation period $F = 6$ and holding period $H = 6$ is presented. At the end of each month, portfolios are were rebalanced. With the overlapping method, we created a series of overlapping portfolios, where each month a new portfolio is created.

To illustrate further (Figure 4), for example, with momentum strategy ($F = 6$ / $H = 6$), starting with end of June 1996, we formed two portfolios: winner and loser that are based on 6-month prior return and consist of *n* best (worst) performing stocks. We skipped a month (July) to avoid before mentioned problems. The two portfolios (long position in winner portfolio and short position in loser portfolio) were then held from August to February. While we were already holding one portfolio, a new portfolio was created at the end of July 1996 and was held from September to March 1996, the third portfolio was created at the end of August 1996 and so on, until February 2018. In the pure momentum strategy, we rebalanced portfolios every month, as is common in momentum literature. Monthly return is calculated as the average return of all portfolios held at time *t*.

Figure 4: Overlapping momentum strategy (F = 6 / H = 6)



Source: own work.

As a result, we got 25 different long-short WML strategies with different holding and formation periods ranging from 1 to 12 months. The procedure was implemented for 3 different portfolio sizes, namely for 4, 10 and 20 stocks.

3.3 Pure value strategy

To investigate the value effect on the FTSE 100, we created three different value strategies. We used variables that incorporate firm-specific characteristics: price-to-book ratio (P/B), price-to-Earnings ratio (P/E) and price-to-dividends (P/D).

Table 3: Price and inverse price ratios

Price Ratio	**Inverse Price Ratio**	**Formula**
Price-to-earnings (P/E)	Earnings yield (E/P)	= Earnings per Share/Share price
Price-to-book (P/B)	Book-to-market (B/M)	= Book value of Equity/Share price
Price-to-dividends (P/D)	Dividend yield (D/P)	= Dividend per Share/Share price

Source: CFA Program Curriculum 2017 Level II (2016, p. 380).

In most studies, authors use the inverses of these price ratios. The inverses of multiples are used to ensure consistent ranking because price is never negative. We also used the inverses in order to compare results with previous studies. Table 3 shows formulas for all three value variables and their inverses denoted as book-to-market (B/M), earnings yield (E/P) and dividend yield (D/P). We applied the same strategy for all 3 measures, but the strategy method is further explained on the example of B/M.

3.3.1 Value method

For value strategies, we followed the methodology of Asness, Moskowitz and Pedersen (2013) and Fama and French (1992) with some modifications.

To create value portfolios, we used the B/M ratio in order to differentiate between value stocks and growth stocks. Each March, starting with March 1996, we ranked stocks according to their current B/M values from highest to lowest. Asness, Moskowitz and Pedersen (2013) suggest that we should use lagged B/M values to ensure accounting data availability to investors. Fama and French (1992) used lagged book values and current market values when calculating ratios. However, we decided to use non-lagged B/M values to ensure greater consistency for all strategies. Besides, Asness, Moskowitz and Pedersen (2013) show that for the purpose of this kind of research it is not so important to use lagged book values, the only difference is that the value premium is slightly reduced, but the overall result is almost the same. Therefore, we decided to use current B/M values.

Next, *n* number of stocks with the highest B/M values were selected into the High portfolio, and *n* stocks with the lowest B/M values were selected into the Low portfolio. Portfolios were rebalanced annually and were equally-weighted. Long-short HML (high-minus-low) portfolio was created in the same manner as momentum portfolio, meaning that *n* stocks in a High portfolio are bought, and *n* stocks in Low portfolio are shorted simultaneously. For example, in 4-stocks portfolio we bought 2 stocks and simultaneously 2 stocks were shorted.

Again, we applied the methodology for 3 different portfolio sizes, namely for 4, 10, and 20 stocks, resulting in 3 different long-short HML portfolios for B/M, E/P and D/P value investment strategies.

3.4 Combined strategy

The combined strategy is created in a way that both investment styles, momentum and value, are incorporated into one strategy. The combined strategy is based on the idea of the following papers: Asness, Moskowitz and Pedersen (2013) and Franz and Regele (2016).

The strategy goes as follows: Each March, starting with March 1997, the strategy sorts stocks according to two signals: momentum and value. Momentum is defined as the 12-month formation period and value as current B/M, E/P or D/P measure.

Most authors who studied the momentum and value effect in combination, chose a 6-month formation (Franz & Regele, 2016; Babameto & Harris, 2008) or a 12-month formation period (Asness, 1997; Asness, Moskowitz & Pedersen, 2013; Fisher, Shah & Titman, 2016; Daniel & Titman, 1999) with monthly rebalancing. In line with previous studies in the field, we analysed combined strategies with a 12-month holding period and monthly rebalancing. Additionally, two more strategies for each combination (momentum & B/M; momentum & E/P and momentum & D/P) that are rebalanced annually and semi-annually are created to see if rebalancing has any impact on combined strategy performance. All together we generated 9 different combined strategies.

Long-short combined strategy buys (sells) stocks with the highest (lowest) 12 months cumulative return and buys (sells) value stocks with the highest (lowest) price ratios for the current month. Stocks are selected by criterion function, first on momentum and then on value. When a portfolio consists of an uneven number of stocks, for example, when there are 10 stocks in a portfolio, priority is given to momentum, meaning that long position is taken in 3 stocks with the best 12 months past cumulative return and 2 stocks with best price ratio value. Simultaneously short position is taken in 3 stocks with worst past cumulative return and 2 stocks are shorted. If the stock is selected, both in terms of momentum and value, we buy/sell it twice. Meaning that one stock can be duplicated in a particular portfolio.

We tested portfolios with different rebalancing: monthly, annually and semi-annually, as well as portfolios with different number of assets (4, 10 and 20). The goal was to evaluate if the combined strategy is superior to pure momentum and pure value strategy, as suggested by the literature. Results of combined strategy are presented at the end of the following chapter.

4 EMPIRICAL RESULTS

In the last chapter, empirical results of 3 different investment strategies will be presented. The observed sample is the UK market – the FTSE 100, running from January 1996 to February 2018.

To evaluate the profitability of the momentum, value and combined investment strategy we calculated returns, volatilities and performance metrics for each of the 279 created portfolios. We will start with momentum, continue with value and conclude with combined strategy results. At the end of this chapter, all three strategies are compared in order to assess whether the combined strategy is superior to both individual strategies.

As discussed in Chapter 3, for each strategy, we used 3 different portfolio sizes (n), a portfolio of 4, 10 and 20 stocks. We focused on excess monthly returns of equally weighted long-short portfolios created according to momentum, value and their 50/50 weighted combination. For the combined strategy we will only present results for zero-investment strategy. The combined strategy was created as long position in best-performing stocks, and short position in worst performing stocks, according to both value and momentum.

We examined if strategies remained profitable after accounting for systematic risk.

Excess return is defined as a strategy's monthly geometric average return minus the risk-free rate, where the risk-free rate is the 3-month UK Treasury Bill. We also investigated correlations between different investment strategies and the benchmark FTSE 100. Using the CAPM model we assessed the trade-off between risk and expected return for each portfolio. Portfolio beta coefficients were estimated to observe correlations to the market movements. In this respect, beta serves as a proxy for systematic risk and is used to examine how risky a portfolio is relative to the benchmark. With the CAPM model, we estimated another measure – alpha. Reported alphas show how profitable the portfolio is relative to the benchmark. Positive and statistically significant alpha indicates by how much the strategy outperformed the benchmark, negative alpha shows the opposite. We also report annualized standard deviations and Sharpe ratios which were computed from monthly return series in the period from January 1996 to February 2018. We will conclude with a summary of our empirical findings.

4.1 FTSE 100 momentum strategy results

Tables 4–7, 13–16 (Appendix C) and 17–20 (Appendix D) show our main findings regarding momentum effect on the UK market. Tables 4–7 report results for portfolios consisting of 10 stocks, Tables 13–16 for portfolios consisting of 4 stocks and Tables 17–20 for 20 stocks in a portfolio. The pure momentum strategy, as described in Chapter 3, follows Jaagadesh and Titman (1993).

Momentum effect is evaluated by calculating the average monthly return in the holding period (period starting one month after formation period). Returns are calculated for overlapping momentum strategies with formation periods F = 1, 3, 6, 9, 12 months and holding periods H = 1, 3, 6, 9, 12 months. The evaluation period is dependent on the length of the formation period – the longer the formation period the shorter the period where we measure returns. Namely, returns of strategies with formation period F = 1 are calculated based on 263 months, strategies with F = 3 on 261 months, strategies with F = 6 on 258 months, strategies with F = 9 on 255 months and strategies with F = 12 on 252 months. Therefore, to properly evaluate returns on different strategies Tables 4, 13 (Appendix C) and 17 (Appendix D) report geometric monthly excess returns for 25 different F / H strategies.

4.1.1 FTSE 100 monthly excess returns

We first need to investigate if momentum strategies are profitable on the UK market. This is the case if the zero-investment WML (winner-minus-loser) portfolio yields positive excess return and is statistically significant at the same time. Excess return (momentum premium) is defined as monthly raw return minus the risk-free rate, while the market risk premium is defined as monthly market return minus the risk-free rate (buy-and-hold strategy).

Table 4 shows results for portfolios consisting of 10 stocks (*n* denotes a portfolio size). Momentum portfolios are created by selecting stocks into a portfolio based on *F*- month past return. The Loser portfolio consists of *n* worst-performing stocks, while the Winner portfolio consists of *n* best-performing stocks based on the formation period. The stocks are held for *H* - months. WML portfolios reported below Winner and Loser portfolio results, are zero-investment strategies created as long-short positions in *n/2* best and *n/2* worst-performing stocks in the formation period and are also held for *H* - months. Winner, Loser and zero-investment portfolios are equally weighted and the overlapping method was used.

Table 4: Momentum monthly excess returns (n = 10)

Momentum Strategy (n = 10)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	Winner	1,19%	1,12%	1,12%	1,04%	1,03%
	Loser	0,16%	0,22%	0,23%	0,22%	0,21%
F = 1	**WML**	**0,02%**	**0,38%**	**0,27%**	**0,18%**	**0,25%**
	(t-stat)	**0,89**	**1,95**	**1,87**	**1,95**	**2,27**
	Winner	1,60%	1,65%	1,41%	1,37%	1,26%
	Loser	0,15%	0,26%	0,17%	0,10%	0,04%
F = 3	**WML**	**0,71%**	**0,72%**	**0,58%**	**0,57%**	**0,51%**
	(t-stat)	**1,30**	**1,90**	**1,99**	**2,40**	**2,47**
	Winner	2,11%	1,84%	1,68%	1,57%	1,37%
	Loser	0,12%	0,02%	-0,06%	-0,07%	-0,02%
F = 6	**WML**	**1,07%**	**0,95%**	**0,74%**	**0,64%**	**0,54%**
	(t-stat)	**2,24**	**2,25**	**2,43**	**2,49**	**2,19**
	Winner	2,12%	2,02%	1,77%	1,60%	1,45%
	Loser	0,14%	0,06%	-0,06%	-0,03%	0,02%
F = 9	**WML**	**1,16%**	**1,07%**	**0,84%**	**0,67%**	**0,60%**
	(t-stat)	**2,12**	**2,29**	**2,28**	**2,11**	**2,11**
	Winner	2,13%	1,80%	1,53%	1,43%	1,38%
	Loser	0,14%	0,09%	-0,03%	0,03%	0,12%
F = 12	**WML**	**0,92%**	**0,72%**	**0,66%**	**0,63%**	**0,57%**
	(t-stat)	**2,11**	**1,88**	**1,76**	**1,76**	**1,55**

Note. Table 4 reports monthly excess returns for strategies consisting of 10 stocks (*n* indicates number of stocks) in the period January 1996 - February 2018. Table displays 25 different strategies that are based on formation periods (denoted with *F)* reported in columns and holding periods (denoted with *H)* reported in rows. Table gives results for Winner, Loser and long-short WML portfolio returns respectively. Long-short portfolios and corresponding t-statistics (*t-stat*) are reported in bold. The t-statistics are based on standard t-test: $H_0 \neq 0$.

Source: own work.

The rows in Table 4 indicate different formation periods (*F*) and the columns different holding periods (*H*). Table 4 shows monthly excess returns for Winner, Loser and zero-investment (WML) portfolios. WML portfolios consist of 10 stocks (5 stocks are bought and 5 stocks short sold). Since the zero-investment strategy is our main interest, Table 4 reports its corresponding t-statistics. T-statistics for Winner and Loser portfolios are not presented, but in general, Winner returns are statistically different from zero, while Loser returns are not.

From Table 4, we can observe that in absolute terms Winner portfolios generated higher returns than Loser portfolios in all cases. Both Winner and Loser portfolios are following the trend predicted by momentum theory. This gives the potential for the creation of a zero-investment WML strategy. We can notice that almost all Winner portfolios exhibit strong positive monthly excess return above 1%, while loser portfolios generate average monthly returns ranging from -0.07% to 0.23%. A similar trend can be observed in portfolios with 4 and 20 stocks (see Appendix C and D), with the difference that portfolios with 4 stocks display an even greater difference between Winner and Loser returns (Table 13, Appendix C). Moreover, Winner portfolios consisting of 4 stocks seem to be particularly effective, some portfolios (e.g. $F = 6 / H = 1$ and $F = 9 / H = 1$) achieve risk premium above 2.5%, but are associated with higher risk as will be shown in the following subsections.

When considering long-short WML strategy (marked in bold, Table 4), we can see that all strategies yield a positive average monthly return, ranging from 0.02% to 1.16%, demonstrating positive momentum returns on the UK market. The most profitable zero-investment strategy (n = 10) on the UK market is the strategy with the formation period F = 9 and holding period H =1, with a 1.16% monthly excess return. Furthermore, 22 of the 25 zero-investment strategies are statistically different from zero at the 5% significance level.

The average long-short momentum strategy returns for different portfolio sizes, where n represents a portfolio size, are 0.64% for $n = 10$; 0.99% for $n = 4$; and 0.47% for $n = 20$. In comparison, Jaagadesh and Titman (1993) reported momentum returns (not corrected for risk-free rate) ranging from 0.32% for ($F = 3 / H = 3$) to 1.31% for ($F = 12 / H = 3$). Positive returns are in line with previous literature. For example, Asness, Moskowitz and Pedersen, (2013) who used a 12-month cumulative raw return, reported momentum results for the UK Market in the period 1972–2011, and the average momentum return was 6% per year which is roughly 0.5% per month. Our positive momentum returns on the UK market are also consistent with the results of Hon and Tonks (2003), who reported positive momentum premiums in the period from January 1955 to December 1996.

If we compare momentum returns with market returns in the range from 0,52%–0,54% depending on the length of the formation period), we can conclude that at first glance our momentum strategies perform similarly or better than the benchmark, except for strategies with a formation period of 1 month (F = 1). Generally, portfolios based on the past 6 to 9 months outperform the market, but we cannot draw a bigger conclusion before risk and CAPM estimates are discussed.

We also analysed correlations between momentum returns and the benchmark, represented by the FTSE 100 excess returns. As stated by Franz and Regele (2016) "The degree of diversification benefits strongly depends on the correlation, that is, the smaller the correlation between strategies the higher is the diversification potential." We found that our long-short momentum portfolios have weak negative correlations with the FTSE 100. For example, the correlation for long-short WML portfolios with 10 stocks (Table 4) ranges between -0.16 and -0.28, and the average correlation for this portfolio size is -0.22. For the other 2 portfolio sizes, we noted that the correlations are also negative and weak and do not exceed -0.30. Weak negative correlations are desirable and show one of the advantages of using a long-short strategy, as they improve stability and are more insensitive to the fractures of markets than long-only strategies. However, the returns of long-short strategies are a bit lower, as indicated in Tables 4, 13 (Appendix C) and 17 (Appendix D).

For all long-short momentum strategies, we also observed that the worst returns are generated by strategies created in the 1-month formation period. These results match those mentioned in earlier studies, testifying that momentum will not appear until after 3 months. Excess momentum returns of Tables 4, 13 (Appendix C) and 17 (Appendix D) show that momentum is particularly strong with formation and holding periods ranging from 6 to 12 months, which is consistent with the literature (Jegadeesh & Titman, 1993; Rouwenhorst, 1998; Hong & Stein, 1999, Li, Brooks & Miffre, 2009 and others).

For further momentum performance evaluation, we continue the analysis by introducing CAPM betas, alphas, volatility and performance measures, explained in section 2.3., starting with CAPM betas.

4.1.2 FTSE 100 momentum betas

In Table 5, we report CAPM betas of Winner, Loser and long-short WML portfolios for portfolios consisting of 10 stocks. Betas were estimated with the CAPM model, where we regressed excess returns of the momentum portfolio against excess returns of the market portfolio. Betas are also estimated for 2 additional portfolio sizes, namely for n = 4 and n = 20 (Table 14, Appendix C and Table 18, Appendix D).

We found that according to observed beta values, losers are riskier than winners. Betas of Winner portfolios are around 1 which indicates that winner portfolios have approximately a similar level of risk as the market, while Loser portfolios exhibit betas above 1.4. The results further indicate slightly negative betas for zero-investment portfolios. Similar to portfolios with 4 and 20 stocks (Table 14, Appendix C and Table 18, Appendix D). Negative beta coefficients are not that surprising and are similar to those of Jaagadesh and Titman (1993), who reported negative betas for zero-cost momentum with formation period F = 6 and holding period H = 6. The reason is that Loser betas are higher than the Winner betas, and the beta of the zero-cost WML is consequently negative. Grundy and Martin (2001) agree that winners are stocks with low betas, and losers are stocks with high betas. The same discovery is found by Daniel and Moskowitz (2015). They also argue that "when the market rebounds, momentum strategies crash because of these negative betas and that most of the up versus down beta asymmetry in bear markets is driven by the past losers".

Table 5: Beta coefficients (n = 10)

Beta Coefficients - Momentum strategy (n = 10)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	β (W)	1,04	1,21	1,14	1,12	1,13
	β (L)	1,60	1,67	1,48	1,42	1,38
F = 1	**β (WML)**	**-0,28**	**-0,23**	**-0,18**	**-0,16**	**-0,12**
	(t-stat)	**-3,90**	**-3,29**	**-3.63**	**-3.98**	**-3.26**
	β (W)	1,09	1,07	1,08	1,07	1,07
	β (L)	1,65	1,54	1,54	1,42	1,42
F = 3	**β (WML)**	**-0,30**	**-0,35**	**-0,21**	**-0,24**	**-0,24**
	(t-stat)	**-3,90**	**-4,01**	**-4,23**	**-3,83**	**-3,41**
	β (W)	0,94	0,96	0,98	1,01	1,03
	β (L)	1,73	1,62	1,54	1,47	1,43
F = 6	**β (WML)**	**-0,29**	**-0,20**	**-0,30**	**-0,14**	**-0,18**
	(t-stat)	**-4,16**	**-3,73**	**-3,29**	**-1,35**	**-2,31**
	β (W)	0,98	1,01	1,02	1,05	1,06
	β (L)	1,69	1,59	1,54	1,46	1,41
F = 9	**β (WML)**	**-0,27**	**-0,31**	**-0,25**	**-0,19**	**-0,15**
	(t-stat)	**-3,78**	**-2,70**	**-2,44**	**-1,89**	**-1,66**
	β (W)	1,00	1,02	1,04	1,06	1,08
	β (L)	1,70	1,62	1,58	1,50	1,47
F = 12	**β (WML)**	**-0,32**	**-0,30**	**-0,20**	**-0,16**	**-0,13**
	(t-stat)	**-3,33**	**-2,57**	**-1,88**	**-1,55**	**-1,35**

Note. Table 5 reports beta values of Winner (*β(W)*), Loser (*β(L)*) and long-short WML (*β(WML)*) portfolios for 25 different *F* / *H* momentum strategies consisting of 10 stocks (*n* = 10). Formation periods (*F*) are reported in columns and holding periods (*H*) are reported in rows. Betas are estimated with the CAPM model, where we regressed excess returns in each of the 25 momentum portfolios against excess returns of the market portfolio represented by the FTSE 100. T-statistics (*t-stat*) are reported for WML portfolios only. Beta values and corresponding t-statistics (t-stat) for 25 long-short portfolios are reported in bold.

Source: own work.

Long-short WML betas are in the range from -0.12 to -0.35 for portfolio size *n* = 10, 0.02 to -0.37 for portfolio size *n* = 4 and -0.12 to -0.34 for portfolio size *n* = 20. Nevertheless, we can argue that betas of our market-neutral portfolios are around 0, as expected by the theory. This finding further supports the argument that with the implementation of a long-short strategy, the systematic risk of a portfolio is reduced. Long-short portfolios are more stable and less volatile, as is further shown in the next subsection when we look at standard deviations and Sharpe ratios.

4.1.3 FTSE 100 momentum standard deviations and Sharpe ratios

Next, we will analyse momentum standard deviations and Sharpe ratios for all 3 portfolio sizes. The results, as shown in Table 6, Table 15 (Appendix C) and Table 19 (Appendix D) indicate that, in general, the most effective in terms of low volatility are portfolios of 20 stocks, where the average standard deviation is 19.89% for Winner portfolio, 30.46% for Loser portfolio and 17.32% for long-short WML portfolio. The most volatile on average are portfolios with 4 stocks, where the average standard deviations for winner, loser and WML portfolio are, 28.02%, 42.30% and 28.19%, respectively. We observed an inverse relationship between the number of stocks and the standard deviation, meaning that when more stocks are added into a portfolio standard deviation decrease.

Table 6: Standard deviations & Sharpe ratios (n = 10)

Standard Deviations & Sharpe ratios - Momentum strategy (n = 10)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	Sdev (W)	25,0%	23,7%	21,1%	20,2%	20,3%
	Sdev (L)	35,8%	31,9%	30,5%	28,5%	27,3%
F = 1	**Sdev (WML)**	**23,6%**	**16,4%**	**12,1%**	**10,0%**	**22,8%**
	Sharpe (WML)	**0,23**	**0,43**	**0,53**	**0,59**	**0,69**
	Sdev (W)	26,6%	24,5%	22,0%	20,4%	20,3%
	Sdev (L)	39,2%	35,6%	33,5%	30,5%	29,1%
F = 3	**Sdev (WML)**	**25,0%**	**32,8%**	**17,7%**	**14,9%**	**13,6%**
	Sharpe (WML)	**0,46**	**0,56**	**0,57**	**0,66**	**0,68**
	Sdev (W)	25,4%	23,3%	21,2%	20,8%	20,8%
	Sdev (L)	41,8%	38,7%	35,5%	33,4%	32,0%
F = 6	**Sdev (WML)**	**28,7%**	**25,7%**	**22,0%**	**19,5%**	**18,0%**
	Sharpe (WML)	**0,55**	**0,55**	**0,54**	**0,55**	**0,52**
	Sdev (W)	24,3%	23,3%	22,7%	22,9%	22,4%
	Sdev (L)	29,1%	39,2%	37,0%	34,7%	33,0%
F = 9	**Sdev (WML)**	**29,7%**	**26,5%**	**24,0%**	**22,7%**	**20,9%**
	Sharpe (WML)	**0,29**	**0,27**	**0,24**	**0,47**	**0,47**
	Sdev (W)	25,5%	24,5%	24,2%	24,2%	23,7%
	Sdev (L)	42,2%	40,2%	38,6%	35,9%	34,1%
F = 12	**Sdev (WML)**	**29,1%**	**26,6%**	**24,6%**	**22,9%**	**21,1%**
	Sharpe (WML)	**0,46**	**0,42**	**0,43**	**0,44**	**0,44**

Note. Table 6 reports Standard Deviations (*Sdev*) and Sharpe ratios (*Sharpe*) of Winner (*W*), Loser (*L*) and long-short (*WML*) portfolios for 25 different momentum strategies consisting of 10 stocks ($n = 10$), where in columns, *F* denotes the formation period and in rows, *H* denotes the holding period. Statistics are computed from monthly return series in the period from January 1996 to February 2018 and are annualized. Results for long-short WML portfolios are reported in bold.

Source: own work.

In comparison with the volatility of the FTSE 100 index returns, where yearly volatility is 14.46%, our momentum strategies display higher volatilities on average. Most volatile portfolios are those with formation and holding periods between 1–3 months for all portfolio sizes.

Sharpe ratios range from 0.23 to 0.69. The most effective, according to Sharpe ratio values, are portfolios consisting of 4 stocks, which accumulated to 0.56 on average, followed by portfolios with n = 20 with average Sharpe ratio of 0.52 and portfolios with n = 10 with an average Sharpe ratio of 0.48.

Interestingly, we can observe that for all portfolio sizes, the Sharpe ratio values increased with the length of a holding period. This is due to decreased volatility in portfolios that are held for longer periods (e.g. 12 months). However, volatility increased with the length of the formation period. The results show that the most volatile momentum portfolios are those that are based on the 12-month past cumulative returns, regardless of portfolio size.

4.1.4 FTSE 100 momentum alphas

To evaluate market efficiency and profitability of momentum strategies on the UK market, as discussed in previous Chapters, we will next look at the sizes and significances of alphas.

Alphas in Table 7 (Table 16, Appendix C; and Table 20, Appendix D) are reported in percentages, demonstrating the percentage by which the portfolio out-or-underperformed the market on a risk-adjusted basis. We can observe that all WML alphas are positive for all combinations of formation and holding periods, regardless of the portfolio size. Alphas are significant for formation and holding periods between 3–9 months. From the data in Table 7, where alphas for 10-stock portfolios are presented, it can be seen that momentum profits are mostly produced by winners, which is also the case for strategies with 4 and 20 stocks in a portfolio. As expected, abnormal returns, defined as the difference between the portfolio's excess returns and risk-adjusted market returns predicted by the CAPM model, are positive for Winner portfolios and negative for Loser portfolios.

With the momentum strategy, in the portfolio with size n = 10, winners generated an average alpha of 1.17% per month, while losers generated an average alpha of -0.43%. Similarly, for portfolio size n = 20 average winners' alpha is 0.78% and average losers' alpha is -0.39%. While for momentum strategy consisting of 4 stocks n = 4, average winners' alpha is a bit higher 1.45% and average losers' alpha is -0.57%.

If we look at risk-adjusted long-short WML portfolios for different portfolio sizes, we can see that zero-cost portfolios with a smaller number of stocks (n = 4) are more efficient; they yield alpha of 1.37%, while 20-stocks portfolios produce alpha of 0.61%. The average alpha of a portfolio consisting of 10 stocks is 0.76%.

The results for all three portfolio sizes show that momentum investment strategies generated positive returns with significant positive alphas, suggesting that the FTSE 100 market is not semi-strong efficient. Moreover, the existence of positive alphas indicates that momentum premiums cannot be explained entirely as a risk premium. In conclusion, our results confirm the existence of the momentum premium on the UK market.

Table 7: Jensen's alphas (n = 10)

Jensen's Alpha - momentum strategy (n = 10)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	α (W)	0,80%	0,68%	0,70%	0,62%	0,61%
	α (L)	-0,43%	-0,34%	-0,06%	-0,30%	-0,31%
F = 1	**α (WML)**	**0,39%**	**0,46%**	**0,34%**	**0,28%**	**0,30%**
	(t-stat)	**0,85**	**1,37**	**1,35**	**1,36**	**1,54**
	α (W)	1,20%	1,26%	1,02%	0,98%	0,86%
	α (L)	-0,15%	-0,30%	-0,40%	-0,43%	-0,47%
F = 3	**α (WML)**	**0,85%**	**0,85%**	**0,70%**	**0,66%**	**0,58%**
	(t-stat)	**1,27**	**1,86**	**1,97**	**2,32**	**2,21**
	α (W)	1,75%	1,47%	1,31%	1,18%	1,18%
	α (L)	-0,54%	-0,59%	-0,65%	-0,63%	-0,63%
F = 6	**α (WML)**	**0,90%**	**0,80%**	**0,86%**	**0,68%**	**0,68%**
	(t-stat)	**2,39**	**2,38**	**2,48**	**2,45**	**1,99**
	α (W)	1,77%	1,65%	1,40%	1,21%	1,06%
	α (L)	-0,23%	-0,52%	-0,62%	-0,31%	-0,50%
F = 9	**α (WML)**	**1,32%**	**1,18%**	**0,93%**	**0,74%**	**0,66%**
	(t-stat)	**2,24**	**2,33**	**2,20**	**1,92**	**1,67**
	α (W)	1,78%	1,45%	1,17%	1,07%	1,01%
	α (L)	-0,44%	-0,47%	-0,57%	-0,48%	-0,38%
F = 12	**α (WML)**	**1,06%**	**0,82%**	**0,73%**	**0,68%**	**0,61%**
	(t-stat)	**2,21**	**1,86**	**1,60**	**1,39**	**1,35**

Note. Table 7 displays estimated Jensen's alphas (α) for Winner (*W*), Loser (*L*) and long-short (*WML*) portfolios for 25 different momentum strategies consisting of 10 stocks (*n* = 10), where *F* denotes the formation period (in columns) and *H* denotes the holding period (in rows). T-statistics (*t-stat*) are reported for WML portfolios only. Momentum alpha values and corresponding t-statistics for long-short portfolios are reported in bold.

Source: own work.

Next, we will look at the results of the value investment strategy in the period 1996–2018.

4.2 FTSE value strategy results

Table 8 displays the FTSE value strategy results. Performance and risk statistics of value strategies for 3 portfolio sizes (*n* = 4, *n* = 10 and *n* = 20) are reported. Average monthly excess returns of value strategies, namely returns of High, Low and long-short HML (High-minus-Low) portfolios formed either on B/M, E/P or D/P criteria are reported. Value strategy performance is evaluated in the period of January 1996–February 2018. High (Low) portfolios are formed as long positions in stocks, formed on the highest (lowest) values of each ratio. Long-short (reported in bold) HML strategy is defined as long (short) investment in stocks with the highest (lowest) price ratios. Portfolios were rebalanced annually and are equally weighted. R_p values in Table 8 display average monthly excess return (raw return minus risk-free rate). The beta (*β)*, alpha (*α)* and corresponding t-statistics (*t-stat*) are estimated through the CAPM model for each portfolio excess return on the FTSE 100 returns. Additionally, Table 8 reports standard deviations (*Sdev*) and Sharpe ratios (*Sharpe*) for all 3 value strategies and the 3 portfolio sizes.

As with momentum strategies, there is a notable difference between High and Low portfolios for B/M and E/P strategies, while the D/P strategy results are not in line with expectations. Portfolios build on stocks with high B/M and E/P measures, consisting of value stocks, yield a positive excess return of at least 0.70% and are statistically significant in 4 out of 6 cases. Results from Table 8 indicate that investing in value stocks on the FTSE 100 is profitable. In contrast, Low B/M and E/P portfolios show poor performance in the observed period.

Moreover, we can see that portfolios consisting of fewer stocks, i.e. $n = 4$ seem to be the most effective in the case of excess returns, however, they are much more volatile, as indicated by higher standard deviation values. Reported standard deviations for long-short HML portfolios show decreased volatility. For all HML portfolios, without exception, volatilities are lower than for High or Low portfolios, ranging from 12.4% to 24.1% on an annual basis.

From Table 8, we can see that positive excess return of long-short portfolios is evident for strategies B/M and E/P, while D/P shows negative return for all 3 portfolio sizes. Corresponding t-statistics (stated in the rows below portfolio returns) indicate that returns for long-short HML value strategies are not statistically significant.

Investing in value stocks according to high B/M (E/P) yields a return of 1.49% (1.49%), 1.14% (0.97%) and 0.93% (0.77%) for portfolios containing 4, 10 and 20 stocks respectively. Portfolios constructed on low B/M (E/P) generate returns in a range of -0.11% to 0.37% per month for B/M and E/P value strategies.

Correlations with the market for long-short value investment strategies are not reported but are as weak as before with momentum. The correlations with the benchmark FTSE 100, are in the range from 0.25 to 0.28 for B/M value strategy, -0.03 to 0.06 for E/P value strategy and 0.03 to 0.05 for D/P value strategy.

Reported beta coefficients in Table 8 give an insight into the riskiness of value portfolios in relation to the market. All High portfolio betas are above 1, indicating higher volatility compared to the market, however they are not as high as in the case of momentum. Similarly, we can find that most of the Low portfolio betas are around or slightly above/below 1. Long-short HML strategies' betas are around 0, which is expected since these portfolios were created as market-neutral portfolios. Compared to momentum, Sharpe ratios are lower, which is probably due to lower excess returns achieved by these strategies.

Table 8: Value returns on FTSE 100

B/M		**n = 4**			**n = 10**			**n = 20**	
	High	Low	**HML**	High	Low	**HML**	High	Low	**HML**
Rp	1,49%	-0,11%	**1,19%**	1,14%	0,29%	**0,55%**	0,93%	0,31%	**0,20%**
t-stat	2,79	0,29	**2,49**	2,56	1,22	**1,68**	2,44	1,31	**1,31**
β	1,39	0,78	**0,30**	1,32	0,85	**0,31**	1,24	0,89	**0,24**
t-stat (β)	9,81	8,92	**3,24**	13,05	14,03	**4,24**	16,34	19,33	**4,71**
α	1,50%	-0,14%	**0,56%**	0,98%	0,13%	**0,57%**	0,71%	0,10%	**0,17%**
t-stat (α)	2,48	-0,38	**1,4**	2,26	0,5	**1,81**	2,18	0,52	**0,78**
Sdev	39,0%	23,5%	**22,4%**	30,8%	19,0%	**17,6%**	25,5%	16,9%	**12,4%**
Sharpe	0,46	-0,05	**0,64**	0,44	0,19	**0,37**	0,44	0,22	**0,19**
E/P		**n = 4**			**n = 10**			**n = 20**	
	High	Low	**HML**	High	Low	**HML**	High	Low	**HML**
Rp	1,49%	0,21%	**0,37%**	0,97%	0,27%	**0,23%**	0,77%	0,37%	**0,03%**
t-stat	2,80	1,06	**1,36**	2,27	1,11	**0,88**	2,07	1,38	**0,46**
β	1,16	1,27	**-0,15**	1,15	1,15	**-0,05**	1,19	1,09	**0,01**
t-stat (β)	8,13	11,39	**-1,47**	10,74	14,78	**-0,59**	14,16	18,37	**0,10**
α	1,51%	0,18%	**0,63%**	0,86%	0,11%	**0,41%**	0,59%	0,16%	**0,12%**
t-stat (α)	2,48	0,39	**1,46**	1,88	0,34	**1,07**	1,64	0,64	**0,41**
Sdev	37,4%	32,1%	**23,6%**	30,3%	24,8%	**20,8%**	26,3%	21,3%	**15,5%**
Sharpe	0,48	0,08	**0,19**	0,38	0,13	**0,13**	0,35	0,21	**0,02**
D/P		**n = 4**			**n = 10**			**n = 20**	
	High	Low	**HML**	High	Low	**HML**	High	Low	**HML**
Rp	0,65%	0,40%	**-1,04%**	0,20%	0,84%	**-0,81%**	0,58%	0,71%	**-0,39%**
t-stat	1,73	2,78	**-1,25**	2,36	2,10	**-0,41**	1,87	2,04	**-0,95**
β	1,24	1,15	**0,00**	1,19	1,15	**0,05**	1,16	1,07	**0,02**
t-stat (β)	10,08	8,69	**-0,03**	13,5	10,77	**0,53**	19,45	13,68	**0,33**
α	0,65%	1,40%	**-0,72%**	0,76%	0,76%	**-0,63%**	0,35%	0,53%	**-0,26%**
t-stat (α)	1,24	2,47	**-1,63**	2,01	1,67	**-1,55**	1,4	1,59	**-0,85**
Sdev	34,1%	35,2%	**24,1%**	27,0%	30,1%	**22,2%**	22,0%	24,2%	**16,7%**
Sharpe	0,23	0,14	**-0,52**	0,09	0,34	**-0,44**	0,32	0,35	**-0,28**

Note. Table 8 shows results for 3 different value investment strategies evaluated in the period from January 1996 to February 2018. First, the results for the B/M strategy are presented, followed by the results for the E/P strategy and, finally, the table shows results for the D/P value strategy. High (Low) portfolio results are reported in columns and results of long-short strategies (HML) are presented in last columns (in bold). For each of the 3 value strategies we report results for 3 portfolio sizes (*n*) with 4, 10 and 20 stocks in a portfolio, displayed in panels. For each strategy, the following statistics are reported in rows: average monthly excess return (*Rp*), beta (*β*), alpha (*α*) and their corresponding t-statistics (*t-stat*, *t-stat (β)* and *t-stat (α)*, respectively). Additionally, Table 8 reports standard deviations (*Sdev*) and Sharpe ratios (*Sharpe*) for all 3 value strategies.

Source: own work.

Observed alpha values (Table 8) demonstrate positive abnormal returns for the zero-investment B/M and E/P strategy and negative abnormal returns for the D/P strategy.

However, most of the estimated alphas are not statistically different from zero. Strategies B/M and E/P are profitable on average in the period 1996–2018, while the strategy created on the D/P ratio is not profitable for any of the portfolio sizes. The most successful is the zero-investment B/M strategy consisting of 4 stocks $n = 4$, which yields 1.19% on a monthly basis and is statistically significant.

Based on the results presented in Table 8, we cannot confirm the presence of the value premium on the FTSE 100 in the sample period, because only 2 out of 9 HML strategy returns are statistically significant. Therefore, we cannot draw an unambiguous conclusion regarding the existence of the value premium on the FTSE 100 stocks index in the period 1996–2018.

4.3 Correlation of value and momentum strategies

The main conclusion from Asness (1997) is the negative correlation between value and momentum strategies, which can lead to portfolio improvements in terms of reduced risk and improved profitability. To test this, we performed an analysis of the correlation between value and momentum portfolios created out of FTSE 100 constituents. Table 9 shows Pearson correlation matrix of zero-investment (long-short) value and momentum strategies containing 10 stocks ($n = 10$). The correlation was tested between long-short value portfolios formed on B/M, E/P and D/P and long-short momentum strategies with formation and holding periods: $H = 1$ / $F = 1$, $H = 6$ / $F = 6$ and $H = 12$ / $F = 12$. Table 9 also shows correlations with the market.

Correlation with the market, represented by the FTSE 100, is slightly negative or low for momentum and moderately positive for value, however, it is not statistically significant for value portfolios. This result is not in line with the statement of Bird and Whitaker (2004) who argue that momentum returns are inclined to be pro-cyclical, whereas returns for value strategies are more prone to counter-cyclicality. The correlation between the market returns and pure momentum or pure value returns is low, ranging from -0.24 to 0.28, indicating a weak linear relationship.

In line with Asness (1997), Asness, Moskowitz and Pedersen (2013) and Franz and Regele (2016), we found a negative correlation between momentum and value. Asness (1997) documents a negative correlation of -0.53 between momentum and B/M, ours is slightly lower around -0.40. E/P and momentum are similarly negatively correlated. Again, we are surprised by the results of the D/P strategy. D/P is positively correlated with momentum. Interestingly, D/P was shown to be negatively correlated with both value variables (Correlation E/P: -0.67; Correlation B/M: -0.44) and positively correlated with momentum (Correlation Momentum: 0.61).

Although the D/P strategy deviates from the expected correlation results, we can partially confirm Hypothesis 4 and argue that value and momentum are negatively correlated and that our idea of combining both strategies has the potential to deliver superior results.

Table 9: Correlation matrix of value and momentum portfolios and FTSE 100

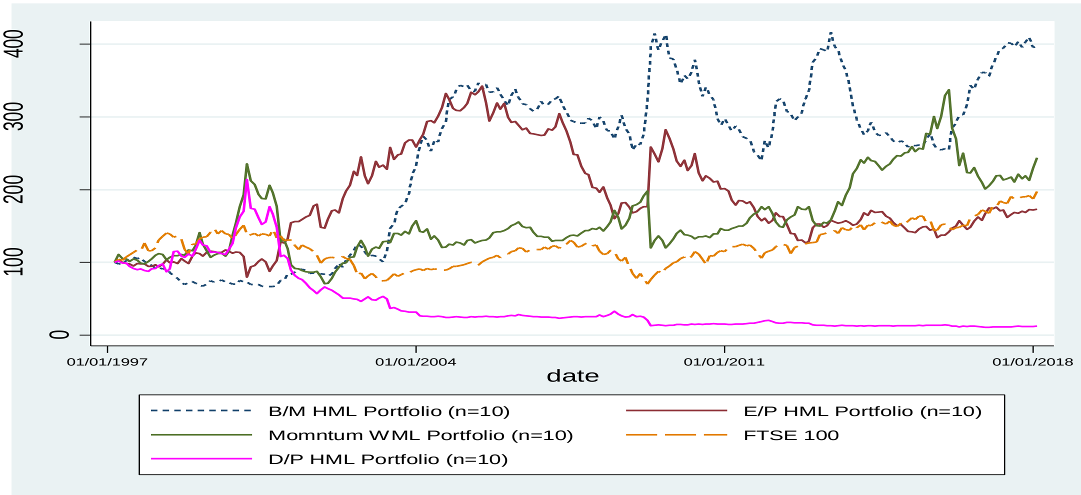
	Value			Momentum			
	B/M	**E/P**	**D/P**	**(F = 1/F = 1)**	**(F=6/F=6)**	**(F=12/F=12)**	**FTSE**
B/M	1						
E/P	0,384*	1					
D/P	-0,449**	-0,676**	1				
(F=1/F=1)	-0,187**	-0,109**	0,203*	1			
(F=6/F=6)	-0,373**	-0,344*	0,428	0,519**	1		
(F=12/F=12)	-0,364**	-0,526**	0,611	0,338**	0,711**	1	
FTSE	0,2842	0,0041	0,0192	-0,2392	-0,2419	-0,1589	1

Note. Table 9 shows Pearson correlation matrix for long-short portfolios consisting of 10 stocks (n = 10). Last row of Table 9 shows correlation relative to the benchmark FTSE 100. *, ** and *** indicate statistical significance at 10 %, 5 % and 1 % respectively.

Source: own work.

For illustrative reasons, we included Figure 5, which displays cumulative returns for long-short strategies consisting of 10 stocks with the same starting date – February 1997 and with the same ending date – February 2018. The graph shows the development of value and momentum strategies and their volatilities. Negative correlation can be observed between momentum (marked with green) and value (B/M marked with dashed blue and E/P marked with violet).

Figure 5: Cumulative returns of long-short momentum and value strategies, 1997–2018



Source: own work.

Regardless of the different strategies' paths (Figure 5), we can observe a couple of milestones that have rocked the path of all strategies. The most notable are declines around period 2000–2003 (dot-com bubble) and of course around 2008–2011 when the global financial crisis took place. At both points in time, the returns of strategies were reduced regardless of the fact that they were built on the basis of long-short investing.

In this section, we have confirmed (at least partially) a negative correlation between value and momentum. We will continue by evaluating strategies where momentum and value are combined. As stated in Hypothesis 4, because of the negative correlation, the combined strategy might generate better risk and return performance than pure momentum or pure value strategy (Asness, Moskowitz & Pedersen, 2013).

4.4 FTSE 100 combined strategy results

In this subsection we will examine the strategies, where a simple 50/50 weighted combination of value and momentum was applied. Results of the combined strategy are presented in Table 10, where combinations of 3 long-short strategies: momentum and B/M, momentum and E/P and momentum and D/P, are presented in rows. Strategies were created as long positions in best performing stocks according to two criteria (high momentum and value stocks) and short position in worst performing stocks (low momentum and growth stocks). The evaluation period ran from January 1997 to February 2018.

The columns of Table 10 shows monthly average excess returns (R_p) with their corresponding t-statistics, standard deviations (*Sdev*), CAPM betas (β), and alphas (α) and Sharpe ratios (*Sharpe*) for portfolios consisting of 4, 10 and 20 stocks, reported in columns. Momentum is based on the formation period of 12 months (F = 12), where winners (losers) are stocks with the highest (lowest) cumulative returns in the past 12 months.

Value is defined as undervalued (overvalued) stocks formed on the highest (lowest) B/M, E/P and D/P ratios. Portfolios were rebalanced either monthly, semi-annually or annually depending on the strategy. The holding period was 12 months. The last row of Table 10 presents correlations (*Corr*) with the FTSE 100 index.

From the results in Table 10, we can observe that the long-short combined portfolio performance improved relative to the results of pure strategies. The performance analysis of combined strategies shows that momentum and B/M and momentum and E/P achieved comparable results. Momentum and D/P strategy generated positive excess return (with insignificant alphas) and deviate from the performance of two other strategies, both in case of risk and return.

Results show that the most profitable in trade-off between risk-and-return are portfolios rebalanced semi-annually, followed by portfolios rebalanced annually. A monthly rebalanced portfolio does not improve in performance, which is good because transaction costs are much higher if rebalancing is done more frequently.

Table 10 on the next page reports main findings of our empirical research.

Table 10: Combined strategy (long-short) performance, 1997–2018

Monthly rebalancing

	Momentum & B/M			**Momentum & E/P**			**Momentum & D/P**		
	n=4	n=10	n=20	n=4	n=10	n=20	n=4	n=10	n=20
Rp	**0.90%**	**0.88%**	**0.65%**	**1.03%**	**0.58%**	**0.52%**	**0.98%**	**0.63%**	**0.56%**
t-stat	1.92	2.38	1.96	2.78	1.55	1.51	1.44	0.97	0.90
β	0.43	0.16	0.06	0.24	-0.04	-0.08	0.28	0.03	-0.03
t-stat (β)	5.85	2.58	3.18	3.78	-0.85	-2.06	2.42	0.33	-0.43
α	0.50%	0.57%	0.38%	0.69%	0.33%	0.29%	0.63%	0.36%	0.31%
t-stat (α)	1.57	2.19	1.86	2.54	1.61	1.68	1.25	0.94	0.93
Sdev	18.5%	14.3%	11.2%	15.2%	11.3%	9.4%	27.6%	20.9%	18.3%
Sharpe	0.59	0.73	0.70	0.81	0.61	0.66	0.43	0.36	0.37
Corr	0.32	0.35	0.26	0.36	0.06	0.00	0.14	-0.01	-0.02

Semi-annually rebalancing

	Momentum & B/M			**Momentum & E/P**			**Momentum & D/P**		
	n=4	n=10	n=20	n=4	n=10	n=20	n=4	n=10	n=20
Rp	**1.01%**	**1.21%**	**0.88%**	**1.06%**	**0.81%**	**0.57%**	**1.02%**	**0.83%**	**0.65%**
t-stat	2.13	3.38	2.93	2.41	2.69	1.76	1.52	1.58	1.20
β	0.25	0.10	0.08	0.14	-0.11	-0.07	0.2	-0.03	-0.06
t-stat (β)	2.35	3.34	2.45	1.46	-1.76	-1.37	1.35	-0.33	-0.66
α	0.94%	0.57%	0.55%	0.92%	0.29%	0.33%	0.33%	0.02%	0.25%
t-stat (α)	2.11	1.74	2.3	2.22	1.04	1.53	0.53	0.05	0.67
Sdev	20.1%	17.5%	12.9%	22.3%	14.9%	11.4%	33.3%	22.5%	20.4%
Sharpe	0.50	0.83	0.81	0.57	0.65	0.60	0.37	0.44	0.38
Corr	0.44	0.34	0.30	0.33	0.10	0.11	0.15	0.05	0.01

Annually rebalancing

	Momentum & B/M			**Momentum & E/P**			**Momentum & D/P**		
	n=4	n=10	n=20	n=4	n=10	n=20	n=4	n=10	n=20
Rp	**1.20%**	**0.80%**	**0.78%**	**1.15%**	**0.48%**	**0.52%**	**0.60%**	**0.24%**	**0.46%**
t-stat	2.25	1.83	2.40	2.31	0.93	1.43	0.62	0.02	0.62
β	0.35	0.14	0.07	0.27	-0.03	-0.05	0.29	0.04	-0.02
t-stat (β)	4.3	2.11	1.36	3.44	-0.6	-1.04	2.44	0.43	-0.29
α	0.67%	0.94%	0.62%	0.74%	0.58%	0.34%	0.70%	0.58%	0.42%
t-stat (α)	1.89	3.25	2.83	2.21	2.72	1.83	1.35	1.55	1.22
Sdev	19.8%	15.9%	11.9%	18.6%	11.5%	10.1%	28.4%	20.5%	18.6%
Sharpe	0.72	0.61	0.79	0.74	0.50	0.62	0.25	0.14	0.30
Corr	0.31	0.27	0.30	0.20	-0.04	0.06	0.08	-0.03	0.08

Note. Table 11 shows results for 3 combined long-short strategies for 3 different rebalancing methods, evaluated in the period 1997–2018. Combinations of momentum and B/M, momentum and E/P and momentum and D/P are presented. For each of the 3 combined strategies, we report results for 3 portfolio sizes. Furthermore, for each strategy, the following statistics are reported in rows: average monthly excess return (denoted with *Rp*), beta (denoted with *β*), alpha (denoted with *α*) and their corresponding t-statistics (denoted with *t-stat*, *t-stat (β)* and *t-stat (α)*, respectively). Additionally, Table 8 reports standard deviations (*Sdev*), Sharpe ratios (*Sharpe*) and correlations with the FTSE 100 (*Corr*) for all strategies.

Source: own work.

According to portfolio size (averaged by all strategies), the best performing are 4-stocks portfolios with an average excess return of 0.99%, followed by 10-stocks portfolios with an average return of 0.72% and 20-stocks portfolios with an average return of 0.62% per month. In this regard, results are comparable to those obtained by pure value and momentum strategies, where average return decreased with size.

The CAPM betas (β) of combined strategies are mainly around 0, with the exception of 4-stock portfolios, which have slightly positive betas ranging from 0.14 to 0.43. Some betas of portfolios consisting of 10 stocks are slightly negative, and this could be due to the fact that an uneven number of high momentum (value) stocks was bought and sold. The 10-stocks portfolios are mostly driven by momentum, and a similar pattern can be observed in momentum portfolios.

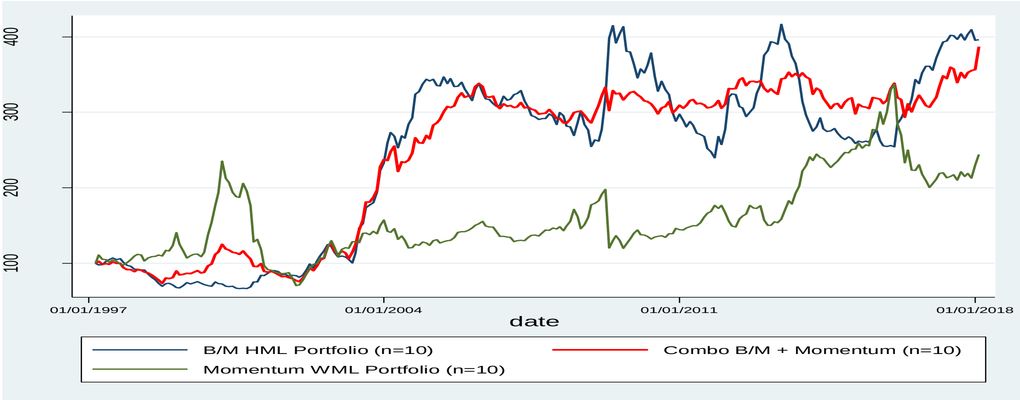
Reported alphas signal that 2 out of 3 combined strategies deliver abnormal returns. This is the case for combinations of momentum and B/M (E/P). Especially large and significant alphas can be observed for the combined momentum and B/M strategy. Furthermore, combined portfolios outperformed the benchmark, which achieved 0.52% return.

Regarding volatility, our long-short combined strategies are more volatile than the benchmark FTSE 100 (calculated standard deviation of 14.5%). However, compared to pure momentum or pure value, a major change is detected. The standard deviations for momentum and B/M and momentum and E/P are much lower and decrease with portfolio sizes. In the case of long-short strategies momentum and B/M and momentum and E/P, the results of Table 10 suggest a major risk improvement. For example, momentum and B/M strategy displays average standard deviations in a range from 20.1% (for smaller portfolios, $n = 4$) to 11.2% (for larger portfolios, $n = 20$). The decrease in volatility can be attributed to a negative correlation between value and momentum returns. Furthermore, increases in performance (Sharpe ratio) is evident for momentum and B/M and momentum and E/P. Sharpe ratio values of these two combinations are above 0.5 for all portfolio sizes, which is in line with the results of Asness, Moskowitz and Pedersen (2013) who reported a Sharpe ratio of 0.77 for their combined momentum and B/M strategy on the UK market.

Lastly, we analysed correlations of our combined long-short strategies with the benchmark FTSE 100. Correlations are reported in the last rows of Table 10. We can observe that correlations are the highest for B/M strategies ranging from 0.26 to 0.44. Still, they indicate a weak or moderate correlation with the FTSE 100. By comparing strategies in regard to the portfolio size, we can see that the highest correlation with the market is observed for portfolios with 4 stocks. We can also notice that momentum and D/P strategies have the lowest correlation with the market, ranging from -0.02 to 0.15.

For illustrative reasons, we included Figure 6. Figure 6 shows comparison of pure value (denoted as B/M HML Portfolio), pure momentum (denotes as momentum WML Portfolio) and combined strategy (denoted as Combo B/M + momentum) consisting of 10 stocks (n = 10). Figure 6 shows how the volatility of combined momentum and B/M decreased relative to both pure strategies while maintaining the performance level of momentum.

Figure 6: Combined strategy (momentum & B/M) performance, 1997–2018



Source: own work.

From results disclosed in Table 10, it can be seen that a combination of momentum and value leads to improved performance, at least when considering the risk and return trade-off. In summary, we found that 2 out of 3 combined strategies outperformed the benchmark FTSE 100 and both pure strategies. To further defend this statement, we will next present summarized findings of the results.

4.5 Comparison of investment strategies

The summary results of tested long-short pure momentum, long-short pure value and long-short combined strategies are presented in Table 11. Tested strategies are reported in rows and are classified by portfolio sizes (n = 4, n = 10 and n = 20). The columns of Table 11 report monthly excess returns, Jensen's alphas, volatilities, Sharpe ratios and correlations to the FTSE 100. Excess return is defined as monthly raw return minus the risk-free rate. Stocks in portfolios are equally weighted and portfolios were rebalanced either monthly or annually. Momentum was rebalanced monthly, while reported pure value strategies and combined strategies were rebalanced annually. Jensen's alpha was estimated through the CAPM model, where the portfolio's monthly excess returns are regressed on market excess returns. Volatility was measured with the yearly standard deviation. The Sharpe ratio was calculated from the monthly return series and is annualized. Correlation is the measure relative to the benchmark – FTSE 100. Bold values show the best performing strategy in each of the following categories: excess return, alpha, volatility, Sharpe and correlation.

Table 11: Summary results for different investment strategies, 1996–2018

Long-short strategy (n = 4)	**Excess return**	**Jensen's Alpha**	**Volatility**	**Sharpe ratio**	**Correlation FTSE 100**
Buy-and-hold	0,52%	-	**14,5%**	0,43	-
Momentum (H=6/F=6)	1,10%	**1.22%*** **	25,68%	0,63	-0,18
Momentum (H=12/F=12)	0,99%	0.97%**	32,3%	0,53	**0,02**
Pure value B/M	1,19%	0.56%**	22,4%	0,64	0,26
Pure value E/P	0,37%	0,63%	23,6%	0,19	-0,04
Pure value D/P	-1,04%	-0,72%	24,1%	-0,52	0,03
Combined Momentum & B/M	**1,20%**	0.67%*	19,8%	0,72	0,31
Combined Momentum & E/P	1,15%	0.74%**	18,6%	**0,74**	0,20
Combined Momentum & D/P	0,60%	0,70%	28,4%	0,25	0,08
Long-short strategy (n = 10)	**Excess return**	**Jensen's Alpha**	**Volatility**	**Sharpe ratio**	**Correlation FTSE 100**
Buy-and-hold	0,52%	-	14,5%	0,43	-
Momentum (H=6/F=6)	0,74%	0,86%**	22,0%	0,54	-0,24
Momentum (H=12/F=12)	0,57%	0,61%	21,1%	0,44	-0,16
Pure value B/M	0,55%	0,57%	17,6%	0,37	0,28
Pure value E/P	0,23%	0,41%	20,8%	0,13	**0,00**
Pure value D/P	-0,81%	-0,63%	22,2%	-0,44	0,02
Combined Momentum & B/M	**0,80%**	**0.94%*** **	15,9%	**0,61**	0,27
Combined Momentum & E/P	0,48%	0.58%***	**11,5%**	0,50	-0,04
Combined Momentum & D/P	0,24%	0,58%	20,5%	0,14	-0,03
Long-short strategy (n = 20)	**Excess return**	**Jensen's Alpha**	**Volatility**	**Sharpe ratio**	**Correlation FTSE 100**
Buy-and-hold	0,52%	-	14,5%	0,43	-
Momentum (H=6/F=6)	0,63%	0.45%	17,1%	0,61	-0,25
Momentum (H=12/F=12)	0,37%	0,43%	17,7%	0,41	-0,16
Pure value B/M	0,20%	0,17%	12,4%	0,19	0,27
Pure value E/P	0,03%	0,12%	15,5%	0,02	0,06
Pure value D/P	-0,39%	-0,26%	16,7%	-0,28	**0,06**
Combined Momentum & B/M	**0,78%**	**0.62%*** **	11,9%	**0,79**	0,30
Combined Momentum & E/P	0,52%	0.34%*	**10,1%**	0,62	0,06
Combined Momentum & D/P	0,46%	0,42%	18,6%	0,30	0,08

Note. Table 11 shows results for long-short strategies for 3 different portfolio sizes, namely for portfolios consisting of 4, 10 and 20 stocks respectively. Combined strategies results are for strategies with annual rebalancing. Returns are measured in the period from January 1996 to February 2018. Buy-and-hold strategy reports average monthly return for the FTSE 100 in the same period. Rows in the table show the following statistics: average monthly excess return, Jensen's alpha, annualized Sharpe ratio and the last column presents correlation with the FTSE 100, adjusted for risk. * indicates significance at the 10 % level, ** indicates significance at the 5 % level, and *** indicates significance at 1 % level.

Source: own work.

The compared results, in the period from January 1996 to February 2018, have shown that the 3 best-performing strategies according to excess returns are: combined momentum and B/M (n = 4), pure value B/M (n = 4) and combined momentum and E/P

(n = 4). In comparison, the buy-and-hold strategy on the FTSE 100 yields approximately 0.50% per month. The 3 highest statistically significant alpha values can be observed for momentum strategies (n = 4), followed by combined momentum and B/M (n = 10). Pure value D/P is the worst-performing strategy, as reported by Table 11.

It turns out that it is important which proxy is used for value and growth stock separation. The D/P strategy shows the worst performance and deviates from the overall results. However, it is possible that the results are due to the analysed data, because many FTSE 100 companies do not pay dividends, therefore, the data for this proxy was limited.

In the case of volatilities, winners are again combined strategies with volatilities below 12%. The portfolio with the lowest standard deviation is combined momentum and E/P (n = 20) with 10.1%. In contrast, the portfolio with the highest standard deviation is momentum (H = 12 / F = 12, n = 4) with 32.3% annual volatility. For comparison, the annualized volatility of the market index is 14.5%. In this regard, combined strategies (combined momentum & E/P and combined momentum & B/M) show improved results which could be explained by the negative correlation between momentum and value. Also, Franz and Regele (2016) argue that negative correlation is the prime cause for the substantial decrease of the combined portfolio's risk.

Correlations with the benchmark FTSE 100 of long-short strategies reported in Table 11 are in the range from -0.25 to 0.31. Low correlations of the benchmark and long-short portfolios are in line with the financial theory and prove that returns are not explained by the performance of the benchmark.

Finally, the best Sharpe ratios can be observed for combined strategies, namely, combined momentum & B/M (n = 20), combined momentum & E/P (n = 4), combined momentum & B/M (n = 4) and are 0.79, 0.74 and 0.72, respectively. Largely due to lower volatilities, the 50/50 combination of value and momentum generates higher Sharpe ratios. From this comparison, we can conclude that combined strategies are in general superior to individual value and momentum strategies in the case of decreased volatility and increased Sharpe ratios. The results are comparable to those of Asness, Moskowitz and Pedersen, (2013) who reported a 13.4% volatility for combined momentum & B/M strategy and a Sharpe ratio of 0.33 on the UK market. We found that the most profitable risk-adjusted strategy among all strategies is strategy momentum & B/M, which is the overall winner in almost all categories.

CONCLUSION

Momentum and value are well-established phenomena observed on many markets and in different time periods. The main goal of this master thesis was to apply and test the pure momentum, pure value and combined investment strategy on the FTSE 100 stocks index. We handcrafted a data set, consisting of FTSE constituents in the period from January

1996 to February 2018. All three investment strategies were implemented and tested to evaluate the efficiency of the UK market and to assess the profitability of the pure momentum and pure value strategy relative to combined strategy and also relative to the benchmark in the observed time period.

Our results indicate that the UK market is not semi-strong efficient since many of the presented active zero-investment strategies have earned statistically significant positive monthly excess returns supported by positive alphas. We showed that it is possible to "beat the market" without bearing extra risk using a simple investment strategy. Our results indicate that it is even better to use a combination of two strategies with opposite characteristics. Outperformance was supported by positive Jensen's alphas and low betas at least in case of the momentum and combined strategy.

We tested portfolios of different sizes and confirmed that adding more stocks in a portfolio decreases risk, due to diversification effect. Furthermore, we found that portfolios with a smaller number of stocks are more profitable but are associated with higher risk.

Through our analysis, we also show one of the advantages of using the long-short method. By creating long-short positions, systemic risk was reduced and lower volatilities were observed in almost all portfolios. We, therefore, argue, that using the long-short method is preferable than using the long-only method at least on a highly capitalized and liquid market such as the FTSE 100.

Our analysis of the momentum effect on the FTSE 100 shows that long-short momentum strategies yield a positive monthly return, in addition to being statistically significant in most cases. Most volatile momentum portfolios are those with the formation and holding periods between 1–3 months for all portfolio sizes. For momentum strategies we also found that the worst returns are generated by strategies with the formation period of 1 month. Excess momentum returns showed that momentum is particularly strong with the formation and holding periods ranging from 6 to 12 months, which is consistent with the literature (Jegadeesh & Titman, 1993; Rouwenhorst, 1998; Hong & Stein, 1999, Li, Brooks & Miffre, 2009).

Secondly, the analysis shows that value investment strategies performed worse than pure momentum strategies. Long-short value strategy monthly excess returns were positive for strategies created based on B/M and E/P and negative for D/P. The best performing value strategy was B/M strategy with a 0.64% average monthly return. Investing only in value stocks proved to be profitable, while many long-short value strategies underperformed relative to the benchmark. Moreover, returns for long-short value strategies were not statistically significant, therefore, we cannot unambiguously argue that the positive value premium can be observed on the UK market in the period 1996–2018.

Following findings of Asness (1997), Asness, Moskowitz and Pedersen (2013), Cooper, Mitrache and Priestley (2016) and Franz and Regele (2016), we found a negative correlation between value and momentum. Asness (1997) documented a negative correlation of -0.53 between momentum and B/M, ours was slightly lower, around -0.40.

Furthermore, we found a low correlation between all long-short strategies and the FTSE 100. Weak negative correlation with the market is desirable and shows another advantage of using the long-short strategy. Long-short portfolios bring stability and are more insensitive to the fractures of markets than long-only strategies.

Moreover, increases in performance (Sharpe ratio) were evident for combined strategies of momentum & B/M and momentum & E/P. The Sharpe ratio values of these two combinations were above 0.5 for all portfolio sizes, which is consistent with the results of Asness, Moskowitz and Pedersen (2013). We can conclude that building an investment strategy based on two very different anomalies has a diversification benefit since it lowers risk and increases Sharpe ratios.

In summary, the main purpose of this thesis was to evaluate if the combined strategy is superior to pure momentum and pure value strategy. We found that even though the returns of combined strategies did not increase much, there was a major improvement in decreased risk. The decrease in volatility can be attributed to the negative correlation between value and momentum returns. Since a majority of combined strategies improved in performance, we conclude that combined strategies perform better than pure momentum or pure value strategies on the UK market. Our findings are in line with previous research and suggest that there exists a diversification benefit when combining momentum and value into one investment strategy.

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APPENDICES

Appendix A: Povzetek v slovenskem jeziku

Ena najbolj vročih tem na finančnih trgih so različne investicijske strategije, s katerimi želijo vlagatelji "premagati trg". Za "premagovanje trga" vlagatelji uporabljajo informacije z izkoriščanjem tržnih anomalij, sledenjem ponavljajočih se vzorcev cen ali z izkoriščanjem neracionalnega vedenja drugih tržnih udeležencev. Med najpomembnejšimi in najpogosteje uporabljenimi metodami, ki konsistenčno premagujejo trg, sta investicijski strategiji oblikovani na podlagi trenda rasti (ang. momentum effect) ter učinka vrednosti (ang. value effect). Pretekle študije so pokazale, da lahko investiranje na podlagi teh dveh tržnih anomalij privede do nadpovprečnih donosov.

Glavni cilj te magistrske naloge je bila uporaba investicijske strategije trenda rasti, strategije vrednosti ter njune kombinacije v praksi, na primeru delniškega indeksa FTSE 100. Analiza obeh strategij ter njune kombinacije je bila narejena v obdobju od januarja 1996 do februarja 2018. Vse tri naložbene strategije so bile implementirane in preizkušene, z namenom, da bi ocenili učinkovitost britanskega delniškega trga. Prav tako sem z analizo želela preveriti donosnost strategij glede na donosnost samega trga. Zanimalo me je tudi, ali kombiniranje obeh strategij v eno, vodi do višjih donosov oziroma do nižjega tveganja. Raziskave namreč kažejo, da zaradi nasprotnih značilnosti obeh strategij (strategiji sta negativno korelirani), obstajajo diverzifikacijske koristi, če strategiji združimo v eno (Asness, 1997; Asness, Moskowitz & Pedersen, 2013).

V magistrski nalogi sem za vse tri strategije preizkusila portfelje različnih velikosti in potrdila, da dodajanje večih delnic v portfelj zmanjšuje tveganje zaradi učinka diverzifikacije. Poleg tega sem ugotovila, da so portfelji z manjšim številom delnic bolj donosni, vendar so povezani z večjim tveganjem.

Rezultati magistrske naloge so pokazali, da britanski delniški trg FTSE 100, v preučevanem obdobju ni srednje močno učinkovit, saj je veliko strategij doseglo statistično značilne pozitivne mesečne donose. Empirična analiza je pokazala tudi, da je možno premagati donosnost celotnega trga brez dodatnega tveganja.

Skozi analizo sem pokazala tudi eno od prednosti uporabe t.i. kratko-dolge pozicijske metode. Z ustvarjanjem dolgo-kratkih pozicij se je zmanjšalo sistematično tveganje, portfelji pa so imeli manjše volatilnosti v skoraj vseh primerih. Ugotovila sem, da je raba dolgo-kratke pozicijske metode bolj zaželena kot uporaba dolge pozicijske metode, vsaj na visoko kapitaliziranem in likvidnem delniškem trgu kot je FTSE 100. Analiza strategije trenda rasti na delniškem indeksu FTSE 100 je pokazala, da dolgo-kratke "momentum" strategije prinašajo pozitivne mesečne donose. Strategije na podlagi "value" so prinesle nižje, a še vedno pozitivne mesečne donose pri večini ustvarjenih portfeljev.

Podobno kot Asness (1997), Asness, Moskowitz in Pedersen (2013), Cooper, Mitrache in Priestley (2016) ter Franz in Regele (2016) sem ugotovila negativno korelacijo med obema strategijama. Rezultati so pokazali tudi, da imajo portfelji ustvarjeni na podlagi kratko-dolge pozicijske metode zelo nizko korelacijo s trgom, kar je zaželjeno, saj so taki portfelji bolj stabilni in manj občutljivi na gibanje trga.

V magistrski nalogi sem želela tudi oceniti, ali je kombinirana strategija boljša od obeh individualnih strategij. Ugotovila sem, da čeprav se donosi kombiniranih strategij niso bistveno povečali, so kombinirane stategije privedle do zmanjšanega tveganja pri skoraj vseh portfeljih. Povečanje učinkovitosti je bilo očitno pri večini kombiniranih strategij. Zmanjšanje tveganja je tako mogoče pripisati negativni korelaciji med obema strategijama. Naše ugotovitve so v skladu s prejšnjimi raziskavami in kažejo, da zaradi negativne korelacije in diverzifikacijskega učinka obstaja korist kombiniranja obeh strategij v eno investicijsko strategijo.

Appendix B: List of 2018 FTSE 100 constituents

Table 12: FTSE 100 constituents – 2018

#	Company	Ticker	FTSE sector
1	3i	III	Financial Services
2	Admiral Group	ADM	Nonlife Insurance
3	Anglo American plc	AAL	Mining
4	Antofagasta	ANTO	Mining
5	Ashtead Group	AHT	Support Services
6	Associated British Foods	ABF	Food Producers
7	AstraZeneca	AZN	Pharmaceuticals & Biotechnology
8	Aviva	AV.	Life Insurance
9	BAE Systems	BA.	Aerospace & Defense
10	Barclays	BARC	Banks
11	Barratt Developments	BDEV	House Goods & Home Construction
12	Berkeley Group Holdings	BKG	House Goods & Home Construction
13	BHP	BLT	Mining
14	BP	BP.	Oil & Gas Producers
15	British American Tobacco	BATS	Tobacco
16	British Land	BLND	Real Estate Investment Trusts
17	BT Group	BT.A	Fixed Line Telecommunications
18	Bunzl	BNZL	Support Services
19	Burberry	BRBY	Personal Goods
20	Carnival Corporation & plc	CCL	Travel & Leisure
21	Centrica	CNA	Gas, Water & Multi-utilities
22	Coca-Cola HBC AG	CCH	Beverages
23	Compass Group	CPG	Support Services
24	CRH plc	CRH	Construction & Materials
25	Croda International	CRDA	Chemicals
26	DCC plc	DCC	Support Services
27	Diageo	DGE	Beverages
28	Direct Line Group	DLG	Nonlife Insurance
29	easyJet	EZJ	Travel & Leisure
30	Evraz	EVR	Industrial Metals & Mining
31	Experian	EXPN	Support Services
32	Ferguson plc	FERG	Support Services
33	Fresnillo plc	FRES	Mining
34	GlaxoSmithKline	GSK	Pharmaceuticals & Biotechnology
35	Glencore	GLEN	Mining
36	GVC Holdings	GVC	Travel & Leisure
37	Halma	HLMA	Electronic & Electrical Equipment
38	Hargreaves Lansdown	HL.	Financial Services
39	HSBC	HSBA	Banks
40	Imperial Brands	IMB	Tobacco
41	Informa	INF	Media
42	InterContinental Hotels Group	IHG	Travel & Leisure
43	International Airlines Group	IAG	Travel & Leisure
44	Intertek	ITRK	Support Services
45	ITV plc	ITV	Media
46	Johnson Matthey	JMAT	Chemicals
47	Just Eat	JE.	General Retailers
48	Kingfisher plc	KGF	General Retailers
49	Land Securities	LAND	Real Estate Investment Trusts
50	Legal & General	LGEN	Life Insurance

(*Table continues*)

Table 13: FTSE 100 constituents – 2018 (continued)

51	Lloyds Banking Group	LLOY	Banks
52	Lloyds Banking Group	LLOY	Banks
53	London Stock Exchange Group	LSE	Financial Services
54	Marks & Spencer	MKS	General Retailers
55	Melrose Industries	MRO	Automobiles & Parts
56	Micro Focus	MCRO	Software & Computer Services
57	Mondi	MNDI	Forestry & Paper
58	Morrisons	MRW	Food & Drug Retailers
59	National Grid plc	NG.	Gas, Water & Multiutilities
60	Next plc	NXT	General Retailers
61	NMC Health	NMC	Health Care Equipment & Services
62	Ocado	OCDO	Food & Drug Retailers
63	Paddy Power Betfair	PPB	Travel & Leisure
64	Pearson plc	PSON	Media
65	Persimmon plc	PSN	H. Goods & Home Construction
66	Prudential plc	PRU	Life Insurance
67	Quilter	QLT	Financial services
68	Randgold Resources	RRS	Mining
69	Reckitt Benckiser	RB.	H. Goods & Home Construction
70	RELX Group	REL	Media
71	Rentokil Initial	RTO	Support Services
72	Rio Tinto Group	RIO	Mining
73	Rolls-Royce Holdings	RR.	Aerospace & Defense
74	Royal Bank of Scotland Group	RBS	Banks
75	Royal Dutch Shell	RDSA	Oil & Gas Producers
76	Royal Mail	RMG	Industrial transportation
77	RSA Insurance Group	RSA	Nonlife Insurance
78	Sage Group	SGE	Software & Computer Services
79	Sainsbury's	SBRY	Food & Drug Retailers
80	Schroders	SDR	Financial Services
81	Scottish Mortgage Investment Trust	SMT	Equity Investment Instruments
82	Segro	SGRO	Real Estate Investment Trusts
83	Severn Trent	SVT	Gas, Water & Multiutilities
84	Shire plc	SHP	Pharmaceuticals & Biotechnology
85	Sky plc	SKY	Media
86	Smith & Nephew	SN.	Health Care Equipment & Services
87	Smith, D.S.	SMDS	General Industrials
88	Smiths Group	SMIN	General Industrials
89	Smurfit Kappa	SKG	General Industrials
90	SSE plc	SSE	Electricity
91	Standard Chartered	STAN	Banks
92	Standard Life Aberdeen	SLA	Financial Services
93	St. James's Place plc	STJ	Life Insurance
94	Taylor Wimpey	TW.	H.Goods & Home Construction
95	Tesco	TSCO	Food & Drug Retailers
96	TUI Group	TUI	Travel & Leisure
97	Unilever	ULVR	Personal Goods
98	United Utilities	UU.	Gas, Water & Multiutilities
99	Vodafone Group	VOD	Mobile Telecommunications
100	Whitbread	WTB	Retail hospitality
101	WPP plc	WPP	Media

Source: FTSE Russell (2018, April 4).

Appendix C: Empirical results for momentum strategy (n = 4)

Table 14: Momentum monthly excess returns (n = 4)

Momentum Strategy (n = 4)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	Winner	1,20%	1,34%	1,37%	1,27%	1,33%
	Loser	0,18%	0,05%	0,29%	0,29%	0,29%
F = 1	**WML**	**0,46%**	**0,68%**	**0,35%**	**0,13%**	**0,25%**
	(t-stat)	**0,89**	**1,95**	**1,87**	**1,95**	**2,27**
	Winner	2,07%	2,14%	1,66%	1,64%	1,48%
	Loser	0,13%	0,17%	-0,04%	-0,03%	-0,08%
F = 3	**WML**	**0,78%**	**1,12%**	**0,92%**	**0,84%**	**0,78%**
	(t-stat)	**1,30**	**1,90**	**1,99**	**2,40**	**2,47**
	Winner	2,84%	2,22%	1,90%	1,75%	1,49%
	Loser	0,20%	-0,17%	-0,08%	-0,03%	-0,08%
F = 6	**WML**	**1,77%**	**1,48%**	**1,10%**	**0,93%**	**0,81%**
	(t-stat)	**2,24**	**2,25**	**2,43**	**2,49**	**2,19**
	Winner	2,77%	2,57%	2,14%	1,90%	1,77%
	Loser	-0,06%	-0,08%	-0,06%	0,04%	0,05%
F = 9	**WML**	**1,69%**	**1,53%**	**1,12%**	**0,99%**	**0,87%**
	(t-stat)	**2,12**	**2,29**	**2,28**	**2,11**	**2,11**
	Winner	2,37%	2,00%	1,74%	1,67%	1,50%
	Loser	0,30%	0,32%	-0,08%	-0,08%	-0,12%
F = 12	**WML**	**1,74%**	**1,35%**	**0,96%**	**1,00%**	**0,99%**
	(t-stat)	**2,11**	**1,88**	**1,76**	**1,76**	**1,55**

Note. Table 13 reports monthly excess returns for strategies consisting of 4 stocks (*n* indicates number of stocks) in the period January 1996 - February 2018. The table displays 25 different strategies that are based on formation periods (denoted with *F)* reported in columns and holding periods (denoted with *H)* reported in rows. The table gives results for Winner, Loser and long-short WML portfolio returns respectively. Long-short portfolios and corresponding t-statistics (*t-stat*) are reported in bold. The t-statistics are based on standard t-test: $H_0 \neq 0$.

Source: own work.

Table 15: Beta coefficients (n = 4)

Beta Coefficients - Momentum Strategy (n = 4)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	β (W)	1,13	1,21	1,21	1,18	1,19
	β (L)	1,89	1,67	1,58	1,51	1,44
F = 1	**β (WML)**	**-0,37**	**-0,29**	**-0,24**	**-0,16**	**-0,15**
	(t-stat)	**-4,10**	**-4,07**	**-3,79**	**-4,77**	**-3,12**
	β (W)	1,09	1,02	1,04	1,05	1,07
	β (L)	1,91	1,73	1,67	1,53	1,46
F = 3	**β (WML)**	**-0,38**	**-0,36**	**-0,42**	**-0,36**	-0,21
	(t-stat)	**-3,67**	**-4,12**	**-3,94**	**-4,12**	**-3,09**
	β (W)	1,05	1,04	1,07	1,09	1,12
	β (L)	2,05	1,85	1,68	1,54	1,48
F = 6	**β (WML)**	**-0,38**	**-0,43**	**-0,32**	**-0,20**	**-0,15**
	(t-stat)	**-4,07**	**-3,40**	**-2,94**	**-2,11**	**-1,67**
	β (W)	1,05	1,11	1,11	1,13	1,06
	β (L)	1,99	1,74	1,62	1,62	1,14
F = 9	**β (WML)**	**-0,35**	**-0,19**	**-0,08**	**-0,08**	**0,06**
	(t-stat)	**-2,01**	**-1,21**	**-0,59**	**1,20**	**1,54**
	β (W)	1,01	1,09	1,15	1,16	1,14
	β (L)	1,86	1,69	1,56	1,48	1,39
F = 12	**β (WML)**	**-0,36**	**-0,19**	**-0,19**	**0,02**	**0,04**
	(t-stat)	**-2,10**	**-1,31**	**-1,21**	**1,12**	**1,34**

Note. Table 14 reports beta values of Winner (*β(W)*), Loser (*β(L)*) and long-short WML (*β(WML)*) portfolios for 25 different momentum strategies consisting of 4 stocks (*n* = 4). Formation periods (*F*) are reported in columns, while holding periods (*H*) are reported in rows. Betas are estimated with the CAPM model, where we regressed excess returns on the each of 25 momentum portfolios against excess returns of a market portfolio represented by the FTSE 100. T-statistics (*t-stat*) are reported for WML portfolios only. Beta values and corresponding t-statistics (*t-stat*) for 25 long-short portfolios are reported in bold.

Source: own work.

Table 16: Standard deviations & Sharpe ratios (n = 4)

Standard Deviations & Sharpe ratios - Momentum Strategy (n = 4)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	Sdev (W)	30,7%	28,4%	24,7%	23,4%	23,2%
	Sdev (L)	47,3%	38,2%	34,8%	32,4%	30,4%
F = 1	**Sdev (WML)**	**33,4%**	**23,3%**	**14,9%**	**18,4%**	**21,6%**
	Sharpe	**0,26**	**0,49**	**0,49**	**0,59**	**0,55**
	Sdev (W)	32,8%	27,9%	24,7%	23,1%	22,9%
	Sdev (L)	51,0%	43,9%	39,8%	35,9%	33,7%
F = 3	**Sdev (WML)**	**31,4%**	**25,8%**	**21,1%**	**15,9%**	**15,9%**
	Sharpe	**0,39**	**0,64**	**0,67**	**0,75**	**0,78**
	Sdev (W)	32,6%	29,3%	25,7%	25,0%	24,8%
	Sdev (L)	55,7%	50,5%	44,2%	40,1%	37,8%
F = 6	**Sdev (WML)**	**34,5%**	**30,3%**	**25,7%**	**22,3%**	**20,9%**
	Sharpe	**0,70**	**0,68**	**0,63**	**0,63**	**0,60**
	Sdev (W)	33,6%	31,0%	29,0%	28,8%	27,8%
	Sdev (L)	53,9%	49,6%	45,2%	42,5%	39,5%
F = 9	**Sdev (WML)**	**41,5%**	**36,0%**	**31,9%**	**29,3%**	**40,2%**
	Sharpe	**0,55**	**0,58**	**0,51**	**0,50**	**0,49**
	Sdev (W)	27,8%	31,3%	30,5%	30,7%	30,7%
	Sdev (L)	39,5%	44,9%	43,7%	41,6%	41,6%
F = 12	**Sdev (WML)**	**40,2%**	**34,2%**	**31,5%**	**32,3%**	**32,3%**
	Sharpe	**0,57**	**0,52**	**0,44**	**0,50**	**0,53**

Note. Table 15 reports Standard deviations (*Sdev*) and Sharpe ratios (*Sharpe*) of Winner (*W*), Loser (*L*) and long-short (*WML*) portfolios for 25 different momentum strategies consisting of 4 stocks (*n* = 4), where in columns, *F* denotes formation period and in rows, *H* denotes holding period. Statistics are computed from monthly return series in the period from January 1996 to February 2018 and are annualized. Results for long-short WML portfolios are reported in bold.

Source: own work.

Table 17 Jensen's alphas (n = 4)

Jensen's Alphas - Momentum Strategy (n = 4)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	α (W)	0,78%	0,89%	0,92%	0,83%	0,88%
	α (L)	-0,53%	-0,57%	-0,30%	-0,27%	-0,24%
F = 1	**α (WML)**	**0,67%**	**0,83%**	**0,94%**	**0,19%**	**0,30%**
	(t-stat)	1,61	2,70	2,76	3,29	2,87
	α (W)	1,67%	1,76%	1,27%	1,25%	1,09%
	α (L)	-0,57%	-0,47%	-0,65%	-0,60%	-0,62%
F = 3	**α (WML)**	**0,95%**	**1,28%**	**1,05%**	**0,93%**	**0,85%**
	(t-stat)	2,20	3,57	3,41	3,57	3,97
	α (W)	2,48%	1,86%	1,52%	1,36%	1,09%
	α (L)	-0,57%	-0,87%	-0,72%	-0,61%	-0,64%
F = 6	**α (WML)**	**1,99%**	**1,65%**	**1,22%**	**1,00%**	**0,86%**
	(t-stat)	**3,71**	**3,55**	**3,22**	**3,16**	**2,98**
	α (W)	2,39%	2,16%	1,74%	1,48%	1,35%
	α (L)	-0,78%	-0,72%	-0,65%	-0,51%	-0,48%
F = 9	**α (WML)**	**1,82%**	**1,59%**	**1,14%**	**0,98%**	**0,85%**
	(t-stat)	**2,77**	**2,83**	**2,42**	**2,31**	**2,24**
	α (W)	2,06%	1,65%	1,37%	1,30%	1,14%
	α (L)	-0,57%	-0,50%	-0,61%	-0,58%	-0,60%
F = 12	**α (WML)**	**1,86%**	**1,41%**	**0,97%**	**0,99%**	**0,97%**
	(t-stat)	**2,85**	**2,52**	**2,50**	**2,31**	**2,44**

Note. Table 16 displays estimated Jensen's alphas (*α*) for Winner (*W*), Loser (*L*) and long-short (*WML*) portfolios for 25 different *F* / *H* momentum strategies consisting of 4 stocks (*n* = 4), where *F* denotes formation period (in columns) and *H* denotes holding period (in rows). T-statistics (*t-stat*) are reported for WML portfolios only. Momentum alpha values and corresponding t-statistics for long-short portfolios are reported in bold.

Source: own work.

Appendix D: Empirical results for momentum strategy (*n* = 20)

Table 17: Momentum monthly excess returns (n = 20)

Momentum Strategy (n = 20)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	Winner	1,10%	1,02%	1,00%	0,95%	0,98%
	Loser	0,48%	0,43%	0,37%	0,39%	0,35%
F = 1	WML	**0,16%**	**0,32%**	**0,16%**	**0,13%**	**0,15%**
	(t-stat)	**0,52**	**0,98**	**0,94**	**0,92**	**1,15**
	Winner	1,22%	1,28%	1,18%	1,17%	1,11%
	Loser	0,44%	0,40%	0,25%	0,21%	0,20%
F = 3	**WML**	**0,32%**	**0,46%**	**0,40%**	**0,42%**	**0,37%**
	(t-stat)	**0,93**	**1,57**	**1,57**	**1,95**	**1,89**
	Winner	1,55%	1,46%	1,41%	1,35%	1,22%
	Loser	0,25%	0,19%	0,17%	0,16%	0,22%
F = 6	**WML**	**0,75%**	**0,67%**	**0,63%**	**0,58%**	**0,44%**
	(t-stat)	**1,92**	**1,94**	**2,05**	**2,07**	**1,67**
	Winner	1,58%	1,56%	1,45%	1,32%	1,24%
	Loser	0,11%	0,11%	0,76%	0,13%	0,20%
F = 9	**WML**	**0,76%**	**0,55%**	**0,67%**	**0,55%**	**0,44%**
	(t-stat)	**2,24**	**2,33**	**2,20**	**1,92**	**1,67**
	Winner	1,52%	1,41%	1,23%	1,20%	1,13%
	Loser	0,06%	0,14%	0,15%	0,20%	0,22%
F = 12	**WML**	**0,78%**	**1,01%**	**0,51%**	**0,23%**	**0,37%**
	(t-stat)	**1,87**	**1,55**	**1,34**	**1,16**	**1,14**

Note. Table 17 reports monthly excess returns for strategies consisting of 20 stocks (*n* indicates number of stocks) in the period January 1996 - February 2018. The table displays 25 different strategies that are based on formation periods (denoted with *F)* reported in columns and holding periods (denoted with *H)* reported in rows. The table gives results for Winner, Loser and long-short WML portfolio returns respectively. Long-short portfolios and corresponding t-statistics (t-stat) are reported in bold. The t-statistics are based on standard t-test: H0 ≠ 0.

Source: own work.

Table 18: Beta coefficients (n = 20)

Beta Coefficients - Momentum Strategy (n = 20)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	β (W)	1,04	1,18	1,14	1,12	1,13
	β (L)	1,60	1,53	1,48	1,42	1,38
F = 1	**β (WML)**	**-0,25**	**-0,22**	**-0,17**	**-0,15**	**-0,12**
	(t-stat)	**-3,61**	**-4,14**	**-4,32**	**-4,66**	**-4,07**
	β (W)	1,09	1,07	1,08	1,28	1,08
	β (L)	1,65	1,54	1,54	1,44	1,38
F = 3	**β (WML)**	**-0,30**	**-0,26**	**-0,24**	**-0,24**	**-0,16**
	(t-stat)	**-3,66**	**-3,65**	**-4,14**	**-3,72**	**-3,39**
	β (W)	0,94	0,96	0,98	1,01	1,01
	β (L)	1,73	1,62	1,54	1,47	1,47
F = 6	**β (WML)**	**-0,30**	**-0,34**	**-0,29**	**-0,24**	**-0,24**
	(t-stat)	**-4,54**	**-4,35**	**-4,16**	**-3,73**	**-3,30**
	β (W)	0,98	1,01	1,02	1,05	1,06
	β (L)	1,69	1,59	1,54	1,46	1,41
F = 9	**β (WML)**	**-0,27**	**-0,31**	**-0,27**	**-0,21**	**-0,18**
	(t-stat)	**-3,91**	**-3,53**	**-3,27**	**-2,73**	**-2,56**
	β (W)	1,00	1,02	1,04	1,06	1,08
	β (L)	1,70	1,62	1,58	1,50	1,47
F = 12	**β (WML)**	**-0,25**	**-0,31**	**-0,27**	**-0,22**	**-0,19**
	(t-stat)	**-3,72**	**-3,45**	**-3,10**	**-2,72**	**-2,50**

Note. Table 18 reports beta values of Winner (*β(W)*), Loser (*β(L)*) and long-short WML (*β(WML)*) portfolios for 25 different momentum strategies consisting of 20 stocks (*n* = 20). Formation periods (*F*) are reported in columns and holding periods (*H*) are reported in rows. Betas are estimated with the CAPM model, where we regressed excess returns on the each of 25 momentum portfolios against excess returns of a market portfolio represented by FTSE 100. T-statistics (*t-stat*) are reported for WML portfolios only. Beta values and corresponding t-statistics (*t-stat*) for 25 long-short portfolios are reported in bold.

Source: own work.

Table 19: Standard deviations & Sharpe ratios (n = 20)

Standard Deviations & Sharpe ratios - Momentum Strategy (n = 20)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	Sdev (W)	21,3%	21,3%	19,2%	19,2%	18,6%
F = 1	Sdev (L)	28,4%	28,4%	25,8%	25,8%	23,9%
	Sdev (WML)	**19,0%**	**17,0%**	**9,6%**	**9,6%**	**7,1%**
	Sharpe	**0,30**	**0,38**	**0,53**	**0,59**	**0,69**
	Sdev (W)	22,9%	21,0%	19,1%	18,3%	18,4%
F = 3	Sdev (L)	31,9%	30,1%	29,0%	27,4%	26,3%
	Sdev (WML)	**19,4%**	**16,8%**	**14,2%**	**12,1%**	**11,1%**
	Sharpe	**0,36**	**0,51**	**0,55**	**0,67**	**0,68**
	Sdev (W)	20,4%	19,5%	18,4%	18,3%	18,4%
F = 6	Sdev (L)	34,4%	32,2%	31,3%	29,8%	28,7%
	Sdev (WML)	**21,6%**	**19,2%**	**17,1%**	**15,7%**	**14,8%**
	Sharpe	**0,55**	**0,57**	**0,61**	**0,64**	**0,56**
	Sdev (W)	20,2%	20,2%	19,9%	20,0%	19,8%
F = 9	Sdev (L)	35,6%	34,0%	32,5%	30,9%	29,7%
	Sdev (WML)	**22,7%**	**21,0%**	**19,5%**	**18,3%**	**16,9%**
	Sharpe	**0,53**	**0,57**	**0,56**	**0,52**	**0,49**
	Sdev (W)	20,5%	20,9%	20,7%	20,6%	20,4%
F = 12	Sdev (L)	35,8%	34,5%	33,4%	31,8%	30,0%
	Sdev (WML)	**22,8%**	**20,8%**	**22,8%**	**26,4%**	**17,7%**
	Sharpe	**0,53**	**0,44**	**0,43**	**0,40**	**0,41**

Note. Table 19 reports Standard Deviations (*Sdev*) and Sharpe ratios (*Sharpe*) of Winner (W), Loser (L) and long-short WML (WML) portfolios for 25 different momentum strategies consisting of 20 stocks (*n* = 20), where in columns, *F* denotes formation period and in rows, *H* denotes holding period. Statistics are computed from monthly return series in the period from January 1996 to February 2018 and are annualized. Results for long-short WML portfolios are reported in bold.

Source: own work.

Table 18: Jensen's alphas (n = 20)

Jensen's Alpha - Momentum Strategy (n = 20)						
		Holding period (months)				
Formation period (months)		**H = 1**	**H = 3**	**H = 6**	**H = 9**	**H = 12**
	α (W)	0,72%	0,62%	0,60%	0,55%	0,57%
	α (L)	0,20%	-0,09%	-0,14%	-0,10%	-0,13%
F = 1	**α (WML)**	**0,25%**	**0,44%**	**0,22%**	**0,19%**	**0,19%**
	(t-stat)	0,85	1,37	1,35	1,36	1,54
	α (W)	0,83%	0,90%	0,81%	0,79%	0,73%
	α (L)	-0,12%	-0,13%	-0,28%	-0,29%	-0,30%
F = 3	**α (WML)**	**0,43%**	**0,55%**	**0,49%**	**0,49%**	**0,43%**
	(t-stat)	1,27	1,86	1,97	2,32	2,21
	α (W)	1,20%	1,10%	1,05%	0,98%	0,57%
	α (L)	-0,35%	-0,37%	-0,39%	-0,38%	-0,57%
F = 6	**α (WML)**	**0,90%**	**0,80%**	**0,45%**	**0,68%**	**0,52%**
	(t-stat)	2,39	2,38	2,48	2,45	1,99
	α (W)	0,98%	0,95%	0,83%	0,69%	0,60%
	α (L)	-0,73%	-0,71%	-0,74%	-0,64%	-0,56%
F = 9	**α (WML)**	**0,90%**	**0,87%**	**0,77%**	**0,63%**	**0,51%**
	(t-stat)	2,24	2,33	2,20	1,92	1,67
	α (W)	0,93%	0,81%	0,63%	0,60%	0,52%
	α (L)	-0,74%	-0,64%	-0,61%	-0,54%	-0,51%
F = 12	**α (WML)**	**0,90%**	**1,19%**	**0,60%**	**0,48%**	**0,43%**
	(t-stat)	2,21	1,86	1,60	1,39	1,35

Note. Table 20 displays estimated Jensen's alphas (*α*) for Winner (*W*), Loser (*L*) and long-short (*WML*) portfolios for 25 different momentum strategies consisting of 20 stocks (*n* = 20), where *F* denotes formation period (in columns) and *H* denotes holding period (in rows). T-statistics (*t-stat*) are reported for WML portfolios only. Momentum alpha values and corresponding t-statistics for long-short portfolios are reported in bold.

Source: own work.