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Combining value, momentum, and low volatility

Evidence from the German stock market

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ABSTRACT:
This thesis examines the risk and return characteristics of different long-only and long-short smart beta strategies in the German stock markets. The aim of this thesis is to explore the risk-adjusted returns of multi-factor portfolios created by mixing and integrating value, momentum, and low volatility strategies.

Earlier research has examined multi-factor smart beta strategies as long-only, and generally in the U.S. or international equity markets. Hence, this thesis adds to the existing literature on smart beta investing by focusing on a novel geography and studying long-short returns in addition to the long-only strategies.

The findings indicate that both long-only and long-short strategies outperform the German stock market regardless of using single-factor strategies or constructing multi-factor strategies by mixing or integrating. The long-short portfolios perform overall significantly better compared to the long-only portfolios, and multi-factor portfolios perform better compared to single-factor portfolios. The integrating approach generates superior risk-adjusted returns for long-only strategies, while the mixing approach is preferred for long-short strategies.

KEYWORDS: Smart beta, multi-factor investing, value, momentum, low volatility

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TIIVISTELMÄ:
Tämä tutkielma tarkastelee erilaisten smart beta -sijoitusstrategioiden riski- ja tuotto-ominaisuuksia Saksan osakemarkkinoilla. Tutkielman tavoitteena on tutkia multifaktoriportfolioiden riskikorjattuja tuottoja, kun portfoliot on muodostettu yhdistämällä ja integroimalla arvo-, momentum- ja matalan volatiliteetin portfolioita.

Aikaisemmissa tutkimuksissa on tarkasteltu multifaktori smart beta -strategioita ilman lyhyeksi myymistä, ja yleensä Yhdysvaltojen tai kansainvälisillä osakemarkkinoilla. Täten tämä tutkielma täydentää olemassa olevaa kirjallisuutta smart beta -sijoittamisesta keskittymällä uudelle maantieteelliselle alueelle ja tutkimalla lyhyeksi myynnin lisäämisen vaikutusta tuottoihin.

Tulokset osoittavat, että sekä pitkien että pitkien/lyhyiden sijoitusten strategiat ylittävät Saksan osakemarkkinoiden tuoton riippumatta siitä, käytetäänkö yksittäisiä riskifaktoristrategioita vai luodaanko multifaktoristrategioita yhdistämällä tai integroimalla useampia riskifaktoristrategioita. Pitkien/lyhyiden sijoitusten portfoliot suoriutuvat kokonaisuudessaan merkittävästi paremmin verrattuna pelkästään pitkien sijoitusten portfolioiden tuottoihin, ja multifaktoriportfoliot suoriutuvat paremmin verrattuna yksittäisiin faktoriportfolioihin. Strategioiden integroiminen tuottaa parempia riskikorjattuja tuottoja kun osakkeita ei myydä lyhyeksi, kun taas strategioiden yhdistäminen on parempi tapa kun osakkeiden ostamisen lisäksi hyödynnetään lyhyeksi myymistä.

AVAINSANAT: Smart beta, multifaktorisijoittaminen, arvo, momentum, matala volatiliteetti

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1 Introduction

Previous literature has provided clear evidence of different risk factors, including size, value, momentum, quality, low beta, and low volatility, that have been proven to drive returns within asset classes (see e.g. Banz, 1981; Carhartt, 1997; Fama & French, 1993, 2015, 2018; Jegadeesh & Titman, 1993). These persistent drivers of returns can be used to construct investment portfolios that aim to generate increased risk-adjusted returns. The proven effectiveness of these factors has motivated researchers and practitioners to combine these factors by constructing multi-factor smart beta portfolios. These smart beta portfolios strive to achieve superior performance compared to capitalization-weighted market indices by employing alternative rules-based weighting approaches that place significant emphasis on selected factors and investment styles (Jacobs & Levy, 2014). So, smart beta strategies assume that these capitalization-weighted indices are inefficient, and investors can increase risk-adjusted returns by weighting certain investment styles and factors, that are known to generate excess returns.

The phenomenon of style premium, which refers to the differential returns associated with specific factors and investment styles, has garnered considerable attention from academic researchers over the past few decades. Notably, Eugene Fama and Kenneth French have emerged as influential figures in this field. During the early 1990s, Fama and French (1992, 1993) introduced the renowned three-factor model, which expands upon the traditional capital asset pricing model (CAPM) by incorporating two additional factors, value and size. Through their pioneering research, Fama and French observed a noteworthy relationship between the cross-section of equity market returns and these newly introduced factors. Specifically, they discovered a negative correlation between firm size and expected returns, as well as a positive correlation between the book-to-market (B/M) ratio and expected returns. These findings implied that investing in small value stocks could potentially generate higher risk-adjusted returns than what would be predicted by the conventional CAPM. Their findings have paved the way for further exploration and refinement of factor-based investment strategies aimed at capturing these style premiums and enhancing investment performance (Carhartt, 1997; Fama & French, 1993, 2015, 2018).

Unlike traditional factor models, that are typically market neutral zero cost long-short portfolios, multi-factor smart beta strategies are generally long-only, meaning that they also have higher correlation with market indices (Bender & Wang, 2016; Fitzgibbons et al., 2017). Both long-only and long-short multi-factor strategies are examined in this thesis, to better understand the differences between the two ways of implementing factor investing. However, these long-only smart beta strategies can also have significant advantages: lower transaction fees and volumes, transparency, and accessibility for investors, like most noninstitutional investors who face restrictions or constrains on short selling and leverage (Jacobs & Levy, 2014). Furthermore, traditional factor models produce excess returns on average, but are subject to times of extremely poor performance. For instance, momentum is renowned for its crashes (Barroso & Santa-Clara, 2015). The multi-factor smart beta strategies aim to avoid these periods of extremely poor returns by diversifying risk exposure to multiple risk factors within portfolios.

1.1 Purpose of the study

Smart beta portfolios are designed to achieve superior risk-adjusted returns compared to conventional capitalization-weighted indexes by using alternative weighting methods. One approach is to construct portfolios that tilt towards specific factors such as value, momentum, or low volatility. This thesis examines the historical performance of long-only and long-short smart beta multi-factor portfolios that have been constructed using these risk factors in the German stock market by regressing the returns of these portfolios against those of the market index and Fama-French 6-factor model, to determine whether the use of smart beta strategies has resulted in superior risk-adjusted returns over a longer time period, and which risk factors contribute most to the performance.

1.2 Hypothesis development

This thesis studies whether value, momentum, and low volatility factors exist in the German stock market. More importantly, the main research question of the study is whether long-only and long-short smart beta strategies consisting of value, momentum, and low volatility have provided statistically significant excess returns over the CAPM and 6-factor model in the German stock market during the research period. Hanauer et al. (2013) provided evidence of significant positive value and momentum premiums in the German stock market, and several other studies have shown evidence of these premiums in European equity markets (see e.g., Asness et al., 2013, 2015; Fama & French, 2012, 2015, 2018; Grobys & Kolari, 2022). Perras et al. (2020) sorted stocks in quintiles based on past volatility and found that the low volatility anomaly is present in the German stock market. Similarly, the evidence of a positive and significant low volatility premium also exists in Europe (Blitz & Van Vliet, 2007, 2013; Frazzini & Pedersen, 2014). Thus, the first hypothesis is as follows:

H1: Investing to value, momentum, and low volatility stocks is expected to provide excess returns compared to the German stock market index.

Integrating value, momentum, and low volatility factors into a single portfolio is anticipated to yield higher risk-adjusted returns than portfolios focused on any factor alone, due to the cumulative benefits of strategy diversification which are expected to enhance stability and performance. Previous novel and up-to-date studies have provided evidence of achieving superior risk-adjusted returns by combining different risk factors, compared to single-factor strategies (see e.g. Amenc et al., 2017; Bender & Wang, 2016; Blitz & Vidojevic, 2018; Chow et al., 2018; Clarke et al., 2016; Fitzgibbons et al., 2017; Leippold & Rueegg, 2018). Accordingly, the second hypothesis is:

H2: Smart beta portfolios constructed by combining value, momentum, and low volatility generate superior excess returns compared to any single-factor portfolios.

Bender and Wang (2016) present findings that the correlations between the excess returns of value, size, quality, momentum, and low volatility risk factors are generally weak, often below 0.5, and can even be negative over extended periods. Additionally, the correlations between any long-only single-factor portfolios and the market are significantly higher due to lack of the short (hedging) part of each portfolio. That leads to long-short multi-factor portfolios being expected to perform better due to enhanced diversification benefits and abilities to gain returns when the overall market goes down. However, previous literature has studied multi-factor portfolios mainly as long-only, but like for single-factor portfolios, adding the short part should yield better risk-adjusted returns. Thus, the third hypothesis is as follows:

H3: Long-short portfolios generate superior risk-adjusted returns compared to the corresponding long-only portfolios.

Similarly, the two most common and practical methods for merging these risk factors into multi-factor portfolios are known as mixing and integrating. Among others, Bender and Wang (2016), Clarke et al. (2016) and Fitzgibbons et al. (2017) found that the integrated portfolios are more efficient, because those include only stocks with wanted factor exposures, compared to simply mixing together portfolios using single-factor strategies.

H4: The integrated approach to building multi-factor smart beta strategies provides better risk-adjusted returns than the mixing approach.

The last research question studies the factor exposures of these multi-factor smart beta strategies, aiming to examine which factors provide most of these superior risk-adjusted returns by performing CAPM and multi-factor regressions. Asness et al. (2018) and Esakia et al. (2019) find that the size effect can explain some part of the returns of different risk factor portfolios, and that other risk factors are usually most prominent among small stocks. So, the last hypothesis is presented below:

H5: The size factor can explain some of the risk-adjusted excess returns of different portfolios consisting of value, momentum, and low volatility.

1.3 Intended contribution

Most multi-factor studies focus on the U.S. markets (Amenc et al., 2017; Chow et al., 2018; Clarke et al., 2016; Fama & French, 2015, 2018; Ghayur et al., 2018; Leippold & Rueegg, 2018) or consider Europe as a whole (Fama & French, 2017; Grobys & Kolari, 2022). The German stock market is an extremely interesting market to study, since it represents alone the majority of the European equity markets. Furthermore, in terms of nominal GDP, Germany's economy ranks fourth in the world and is also the largest in Europe. Furthermore, Silvasti et al. (2021) studied long-only multi-factor strategies consisting of value, momentum, and low beta in the Nordic equity markets. Their study lacked the comparison between long-only and long-short strategies, and they suggested that future research could investigate the different risks of these strategies by using traditional multi-factor regressions. Silvasti et al. focused on the Nordic markets (Finland, Sweden, Norway and Denmark), but the German market can be seen as even more interesting due to bigger size, implying better liquidity and implementation of these multi-factor strategies.

Additionally, while many multi-factor strategies include value and momentum (see eg. Asness et al., 2013; Bender & Wang, 2016; Clarke et al., 2016; Fama & French, 2018; Fitzgibbons et al., 2017; Silvasti et al., 2021), to the best of the author’s knowledge, low volatility is not covered in many multi-factor strategies, even though the low volatility factor clearly exists individually (Ang et al., 2006; Baker et al., 2011; Baltussen et al., 2019; Blitz & van Vliet, 2007; Blitz et al., 2013; Frazzini & Pedersen, 2014). Thus, this study aims to contribute to the existing literature by providing a comprehensive study of multi-factor smart-beta portfolios consisting of value, momentum, and low volatility, in the novel German market, where existing evidence is very limited. Furthermore, this study aims to understand different dimensions of risks between mixed and integrated portfolios by performing 6-factor regressions.

2 Theoretical background

The theoretical part first presents the modern portfolio theory by Markowitz (1952) that examines the methods by which risk-averse investors can construct portfolios to maximize expected return given a specific level of risk. The theoretical part also covers the efficient market hypothesis (Fama, 1970; Kendall, 1953) and discusses some controversies regarding the actual efficiency of the markets presented by previous empirical literature. Additionally, CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966) and the multi-factor asset pricing models that made factor and smart beta investing possible are presented (Carhart, 1997; Fama & French, 1992, 1993, 2015, 2018).

2.1 Modern portfolio theory

Modern portfolio theory (MPT) is the term used to describe the framework for investment analysis as well as rules for optimal portfolio formation developed by Harry Markowitz (1952) is his Nobel Prize-winning paper "Portfolio Selection." According to the modern portfolio theory, investors should concentrate on choosing portfolios rather than individual securities by using mean-variance analysis. Furthermore, when given the same level of return, investors would rather take a less risky portfolio than a riskier one because they are risk averse, thus maximizing risk-adjusted returns. The weighted average of the expected returns on each financial instrument held in the portfolio is used to determine the expected returns on the portfolio. So, the formula for the expected returns of the portfolio is as follows:

$$E\left(r_p\right) = \sum_{i=1}^{n} w_i r_i, \; where \; \sum_{i=1}^{n} w_i = 1 \tag{1}$$

where n is the number of securities held in portfolio and w is the weight of each security. On the other hand, the portfolio risk can be represented as the portfolio variance, which can be computed as follows for a pair of securities:

$$\sigma_p^2 = w_a^2\sigma_a^2 + w_b^2\sigma_b^2 + 2w_a w_b \sigma_a \sigma_b p_{ab} \quad (2)$$

where w_a is the portfolio weight and σ_a is the standard deviation security a, w_b is the weight and σ_b is the standard deviation security b, and p_{ab} is the correlation coefficient between the two securities. The correlation coefficient is interpreted as $|p| \leq 1$, symbolizing values between -1 and 1. A perfect positive correlation, denoted by a correlation coefficient of 1, occurs when the returns of a and b develop in the same direction. A perfect negative correlation indicates the opposite direction of movement for a and b, whereas a zero correlation suggests no relationship at all. Thus, investors can control the correlation coefficient by changing its value (by changing weights between individual securities), which impacts the combination variance, by adjusting the portfolio's structure and weight for individual securities within portfolios.

By using the appropriate correlation coefficient relationship, Markowitz (1952) asserts that there are optimal portfolios that provide the best risk-return relationship. A rational investor should to choose a portfolio from this particular set that offers the ideal balance between risk and return. Figure 1 below provides a graphic representation of this, with σ representing the standard deviation and $E(r)$ representing the expected return. The efficient frontier is the curve that plots the expected return against the risk and has a positive slope. It illustrates the trade-off between risk and return, and localizes the efficient portfolios, global minimum variance portfolio and inefficient portfolios. The reason why the inefficient portfolios below the graph are meaningless is that investors could receive a higher return at the same level of risk.

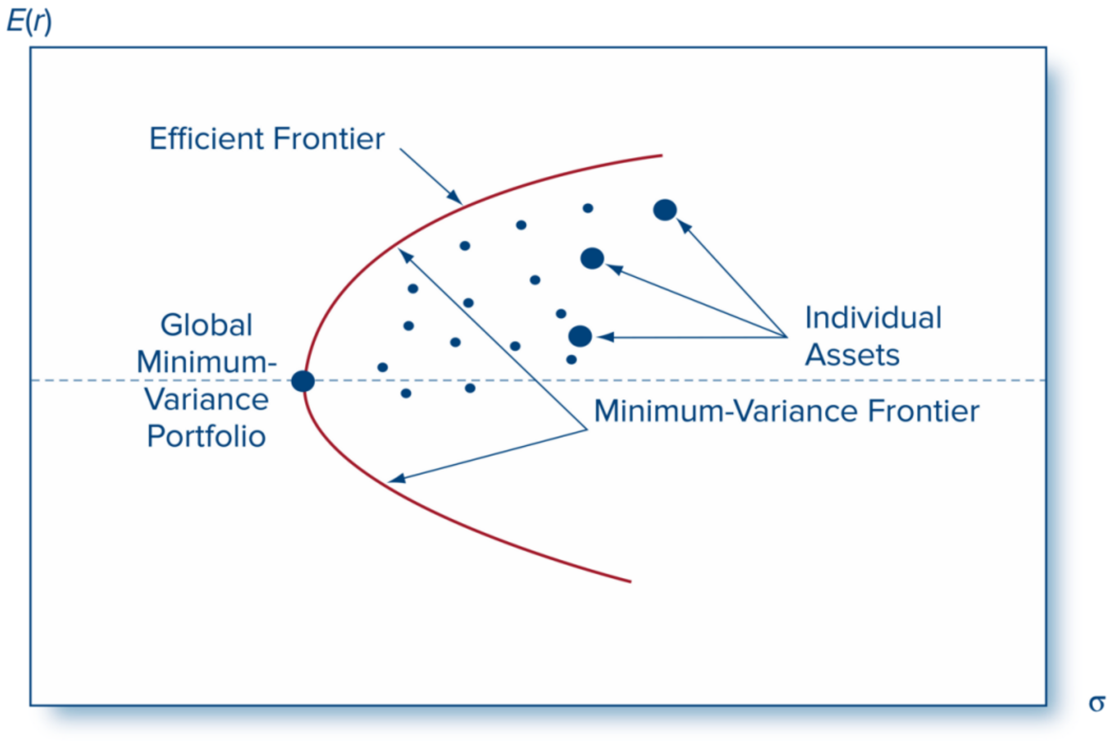

Figure 1: Efficient frontier (Bodie et al., 2023)

In Markowitz’s (1952) modern portfolio theory, two factors make up a portfolio's total risk: systematic risk and unsystematic risk. Systematic risk is an undiversified component of overall risk that impacts all stocks in the market. Conversely, diversification of unsystematic risk can be achieved by adding more stocks to the portfolio, which lowers the portfolio's overall risk as well as its unsystematic risk. The main idea of modern portfolio theory is to optimize the relationship between total risk and expected returns. The portfolios on the efficient frontier are the portfolios constructed by the most optimal way, and they yield the highest possible return for a given level of risk, leading to the highest possible Sharpe ratios.

So, according to Markowitz (1952), the modern portfolio theory is used to optimize the risk-return trade-off between different portfolios. The correlation coefficient between different securities makes it possible for investors to optimize their risk-adjusted returns, and the benefits are higher if correlations between securities are lower. While Markowitz used individual securities for constructing portfolios, the same idea applies for factor investing. Bender and Wang (2016) showed evidence of low, or even negative correlations between value, size, momentum and low volatility factors for extended periods of time, and the low correlations were the main driver for the superior risk-adjusted returns for smart beta multi-factor portfolios. Similarly, Hanauer et al. (2013) found marginally positive, or negative, correlations between size, value and momentum, that were the main explanation for enhanced risk-adjusted returns.

2.2 Efficient market hypothesis

The efficient market hypothesis (EMH) has been one of the primary interests of academic studies since it was first presented, and it is a base assumption for many theories in finance. Kendall (1953) studied stock prices expecting to find regular price cycles, but his study did not find evidence of them existing. In contrast, Kendall found that stock prices seemed to follow a random walk, meaning that successive price changes are independent, indicating that the stock market is irrational and has no logical rules. Many researchers contributed to Kendall's findings and suggested that random stock price movements demonstrate an efficiently functioning market rather than an irrational one. One of these researchers was Eugene Fama, who created the theoretical framework for the efficient market hypothesis, stating that in an efficient market, all information is always immediately incorporated into stock prices (Fama, 1970).

Fama (1970) presents three different versions of the efficient market hypothesis based on the level of information that is immediately included in market prices when made available. The weak-form hypothesis states that stock prices must reflect all past information from prices and patterns. Thus, historical prices, trends, or technical analysis cannot predict future returns. The semi-strong hypothesis claims that stock prices always reflect all publicly available information, meaning that future returns cannot be predicted by looking at annual reports, earnings forecasts, or fundamental analysis. The strong-form hypothesis states that stock prices reflect all information, also private or insider information. In effective markets, stock prices accurately represent all information, and it is impossible to find expected returns greater than the risk-adjusted opportunity cost of capital (Fama, 1970). Nevertheless, it is essential to note that the EMH does not assume complete rationality on the part of investors, which creates the potential for mispricing. An investor can behave arbitrarily, but the market as a whole is always correct.

So, according to the EMH, stocks should always trade at their fundamental value, which is “efficient” and reflects the company’s future cash flows and risk. Fundamental analysis also considers different macroeconomic factors, like expectations for future interest rates and inflation, as well as political, country, and exchange rate risk. The EMH theory assumes that the market knows the fundamental value of every security. However, that is difficult to know in practice because the market price can often differ from the fundamental price level. Furthermore, while the strong-form hypothesis assumes that all information is always incorporated in prices, it seems highly unlikely that, for example, financial fraud could be incorporated into prices.

Furthermore, in the context of factor models, the discovery that relatively straightforward investment strategies produce statistically significantly better risk-adjusted returns compared to the overall market has called into question the theory of efficient markets (Blitz & van Vliet, 2007). Value, size, and momentum strategies are well-known examples of risk factors, whose return premiums have been demonstrated in international stock markets by previous literature. If a straightforward investment strategy yields a return comparable to that of the market portfolio but at a consistently reduced risk level, market efficiency is also put to the test.

2.3 Asset pricing models

The most commonly used asset pricing models are covered in this chapter in chronological order, starting with the CAPM developed by Sharpe (1964), Lintner (1965), and Mossin (1966), to the six-factor model developed by Fama and French (2018).

2.3.1 Capital asset pricing model

The capital asset pricing model (CAPM) is among the pillars of modern financial economics. It was independently developed by Sharpe (1964), Lintner (1965), and Mossin (1966). The foundation of CAPM is a theory of market equilibrium for asset prices under conditions of risk, and it has its foundation on the modern portfolio theory by Markowitz in 1952. The CAPM includes several underlying assumptions, which arguably simplify and distinct the model from the practical side of finance. First, investors have unlimited access to risk-free borrowing and lending. Also, in line with the strong form of the efficient market hypothesis (Fama, 1970), all relevant information is made available to the public, and consequently all investors have comparable expectations. Additionally, markets are in equilibrium, and all investors have access to the same types of investments. Lastly, investors allocate the same time frame to hold their investments.

The CAPM is essentially a single-factor model that accounts for expected stock or portfolio returns using only the market risk factor and specific exposure β. It is commonly used to determine the required rate of return of a security. The CAPM formula can be written as follows:

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

where $E(R_i)$ is the expected return of security or portfolio i, R_f is the risk-free interest rate, $E(R_M)$ is the expected market return. β_i is the market beta of security or portfolio i, which can be composed as:

$$\beta_i = \frac{COV(R_i,R_m)}{\sigma^2(R_m)} \tag{4}$$

where R_i is the return of security or portfolio i, R_m is the market return, σ^2 $(R\mathrm{m})$ is the variance of the return of the market, and $COV(R_iR_m)$ is the covariance between the return of the market and the return of the security or portfolio i. The volatility or systematic risk of a security or portfolio in relation to the market is measured by β_i. So, according to the CAPM, an asset's exposure to changes in economic activity, also known as the systematic risk, can be used to determine the expected return of the asset. The expected return is proportional to β, or systematic risk, and securities with high correlations with the excess return of the market have higher β, and the CAPM predicts higher expected return, as the security has higher systematic risk. The opposite applies to securities with low correlations with the excess return of the market. So, the CAPM rewards only for taking more systematic risk, since the CAPM's assumes that unsystematic risk can be completely removed by effective diversification.

The CAPM has limitations, just like many other scientific models. Academics have been troubled by the CAPM's irrational assumptions and poor performance for a long time. For instance, a number of studies have shown that using market beta as the only variable has limitations and that there are numerous other factors that can also account for the cross-section of expected returns. For example, Black, Jensen, and Scholes (1972) demonstrate that security returns are not always directly proportional to their betas. They used data between 1931 and 1965, and formed portfolios based on their market beta. Their findings indicate that portfolios with high β yielded lower returns than was predicted by the CAPM, and vice versa for portfolios with low β. This indicates that the CAPM is too flat and inefficient, in comparison to the security market line (SML), which visually illustrates the theoretical CAPM, by drawing a line between multiple CAPM efficient portfolios of different levels of risk. Multiple other CAPM contradictions were found in the 1980s, including the size factor (Banz, 1981) and the value factor (Stattmann, 1980).

Additionally, according to Frazzini and Pedersen (2014) one main explanation for the low volatility anomaly is that certain investors have limitations on borrowing and must thus include higher beta stocks in their portfolio, to achieve the optimal risk-return relationship. Consequently, low-beta (low volatility) stocks are systematically undervalued, presenting an opportunity for investors who can leverage to "arbitrage" this mispricing. This discrepancy between theoretical frameworks, like the CAPM, and the empirical side of finance successfully illustrate why different risk-factor models are important, and how investors can utilize them to make better decisions.

Also, the CAPM assumption that every investor has access to the same types of investments is often considered unrealistic in practice. For example, institutional investors are better equipped to implement multi-factor smart beta strategies by computer algorithms compared to retail investors. On the other hand, while retail investors typically commit smaller amounts of capital, institutional investors, managing larger pools of funds, may encounter liquidity constraints. The substantial scale of the funds under institutional management can lead to challenges in quickly entering or exiting positions without impacting the market, or paying significant premiums compared to prices available for smaller investments. Together, these results show that the cross-section of variation of average stock returns can be explained by a variety of factors other than the CAPM market factor and a particular exposure β.

2.3.2 Three-factor model

Several empirical contradictions of CAPM's ability to explain the full cross-section of average stock returns (see e.g. Banz, 1981; Stattmann, 1980) motivated Fama and French (1992; 1993) to create a three-factor model, that, in addition to the CAPM β, could more accurately capture the risk exposure of common stocks. Fama and French (1992) found that size and book-to-market can explain the majority of the variation in average stocks returns. In their three-factor model, Fama and French (1993) show that size, measured by total market capitalization, and value, measured by book-to-market ratio, are consistent risk factors that are able to capture risk exposure beyond the CAPM β over extended periods of time. According to the Fama and French's three-factor model, the risk factors of size and value can be calculated as SMB (small minus big) and HML (high minus low). Thus, the three-factor model can be written as:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + \varepsilon_{it} \quad (5)$$

where according to Fama and French (1993), R_{it} is the return of security or portfolio i for period t, R_f is the risk-free interest rate and R_{mt} is the return on the market portfolio. SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on diversified portfolios of high and low book-to-market stocks. ε_{it} is a zero-mean residual error term, which is created when the regression model fails to accurately represent the dependence between the independent and dependent variables. Consequently, the error term indicates the degree to which the regression model may vary during empirical studies if the relationship is not complete. β_i, s_i, and h_i represent the sensitivities of a portfolio or security to the market factor, size factor, and value factor. α_i is the intercept, which is 0, if the factors successfully capture all of the variation of expected returns of securities or portfolios. In other words, if intercept α_i is not 0, the model cannot fully explain the cross-section of expected returns.

In summary, the significance of the three-factor model is based on its ability to broaden our understanding of the factors driving stock market returns as well as improving our capacity to develop investment strategies that align with an investor's risk and return objectives. Acknowledging these premiums therefore has significant implications for asset allocation and portfolio construction, and it has encouraged other researchers and practitioners to identify additional factors that can explain stock returns.

By considering these factors, investors and portfolio managers can construct portfolios that potentially enhance returns by targeting stocks that score highly on these dimensions. Furthermore, factor models help investors understand and manage the risks they are taking. For example, if a portfolio is heavily weighted towards high book-to-market (value) stocks, it's more exposed to the value factor, and the three-factor model helps to quantify this exposure to make adjustments to get the ideal exposure to each risk factor.

2.3.3 Carhart four-factor model

Carhart (1997) looked at the performance of mutual fund managers and discovered that their success was not based on their extraordinary abilities in stock selection, but on a few common risk factors that stock valuation methods at that time did not consider. He found that adding Jegadeesh and Titman's (1993) momentum factor could improve Fama and French's (1993) three-factor model to better explain the cross section of risk-adjusted returns. The Carhart four-factor model can be written as follows:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{it} \tag{6}$$

where, in addition to the three-factor model, MOM_t is the difference in returns of diversified portfolios of stocks that are considered as winners and losers based on past performance, and m_i is the sensitivity of security or portfolio to momentum factor.

2.3.4 Five-factor model

After the publication of the renowned Fama and French (1993) three-factor model, several other factors were found that could explain the average stock returns. Novy-Marx (2013) found that the ratio of firm's profitability, measured by gross profit, divided by total assets could explain the cross-section of average stock returns as well as book-to-market. Additionally, it appeared that value stocks and high profitability stocks had a negative correlation, which is generally useful in portfolio management. Aharoni et al. (2013) found that companies with lower investment have higher risk-adjusted returns, in comparison to companies that invest more. Fama and French (2015) argue that the five-factor model is better suited to explain stock returns compared to the three-factor model due to the empirical evidence of a strong correlation between profitability and investment factors and stock returns. Additionally, they claim that the three-factor model fails to account for a significant portion of the variation in average returns associated with profitability and investment factors. Fama and French (2015) added these two factors, and formed the five-factor model, which is as follows:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it} \quad (7)$$

where, in addition to the three-factor model, RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA_t is the difference between the returns on diversified portfolios of stocks of low, or conservative, and high, or aggressive, investment companies. Again, r_i and c_i are the sensitivities to profitability factor and investment factor, respectively.

2.3.5 Six-factor model

Finally, Fama and French (2018) added the momentum factor to their five-factor model and formed the six-factor model. Based on previous literature, the six-factor model seems to most accurately capture the variation of average stock returns. The six-factor model can be denoted as follows:

$$E(R_{it}) - R_{ft} = \alpha_i + \beta_i\left[E(R_{mt}) - R_{ft}\right] + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + m_i MOM_t + \varepsilon_{it} \quad (8)$$

which is the five-factor model (Fama & French, 2015), added with the momentum factor (Carhart, 1997). In conclusion, the six factors are market, size, value, profitability, investment, and momentum. The respective sensitivities to these factors are β_i, s_i, h_i, r_i, c_i, and m_i. If these sensitivities, or factor loadings, can fully explain the cross-section of average stock returns, intercept α_i is 0, otherwise not.

The development of Fama and French's (1993, 2015, 2018) models over time reflects the evolving understanding of different risk factors that drive stock returns. When Fama and French first introduced their 3-factor model in 1993, it was a significant advancement from the single-factor CAPM, incorporating size and value factors in addition to market risk. The 3-factor model was based on their observation that these factors historically explained a significant portion of the differences in returns between diversified portfolios. Later, as further empirical evidence evolved, multi-factor models became better known and accepted even by researchers. Finally, the six-factor model, which includes momentum, was a subsequent development. This inclusion indicates a recognition of the robustness of the momentum effect in empirical data and possibly a concession that an asset pricing model that aims to be comprehensive cannot ignore the momentum factor. In conclusion, these asset pricing models opened the way for multi-factor smart beta investment strategies to grow increasingly popular, and it is expected that these strategies will develop further. Another novel area of research is exploring the application of these multi-factor models to enhance risk-adjusted returns, while also considering the practical challenges of implementation issues and the impact of transaction costs.

2.4 Risk-adjusted performance measures

The Sharpe ratio is frequently used in both academic and practical studies (Sharpe, 1967, 1994). For instance, the majority of mutual funds measure their historical performance by Sharpe ratios. The Sharpe ratio divides the excess returns of the portfolio over the risk-free rate by a measure of its volatility to assess risk-adjusted performance. It is denoted as follows:

$$S_p = \frac{R_p - R_f}{\sigma_p} \tag{9}$$

where S_p is the Sharpe ratio of portfolio p, R_p is the return of portfolio p, R_f is the risk-free rate, and σ_p is the standard deviation of the excess returns of portfolio p.

Apart from the Sharpe ratio, the CAPM and the Fama-French six-factor model is used to quantify the abnormal and unexplained returns relative to the market and known risk factors, respectively. The CAPM is useful in calculating risk-adjusted excess returns, while the six-factor model best contributes to explaining the drivers of stock returns of multi-factor smart beta strategies.

3 Literature review

This part presents a literature review of the risk factors examined in this thesis, value, momentum, low volatility, and size. Most importantly, literature on multi-factor smart beta strategies is presented more thoroughly.

3.1 Value

The concept of value investing has been around for almost a century, and is commonly attributed to Benjamin Graham, an influential investor, economist, and professor. The first research paper specifically focusing on value investing was The Valuation of Common Stocks by Benjamin Graham and David Dodd (1934). They valued stocks based on fundamental analysis and tried to find the intrinsic value of those stocks by looking at the underlying business fundamentals, earnings, and assets. Graham and Dodd emphasized the significance of a safety margin and the importance of purchasing stocks at a substantial discount to their fundamental value. They also believed that investors overestimated the growth potential of growth stocks, resulting to them being overpriced and value stocks being underpriced. Their ideas laid the foundation for value investing as we know it today.

So, value investors aim to buy stocks that are undervalued compared to other stocks within their investment universe and subsequently sell overvalued stocks. Stattman (1980) was the first to find the best-known and most used signal of value stocks, the book-to-market ratio (B/M). He found that the ratio of a stock's book value of common equity to the market value of equity is positively associated with average returns of U.S. stocks.

Value investing has been thoroughly studied by academics and industry professionals. When Fama and French (1992, 1993) examined the U.S. stock markets from 1963 to 1990, they discovered that size and book-to-market ratio both contributed to the explanation of the cross-section of average stock returns. Because small businesses with high book-to-market ratios produced higher returns, they hypothesized that size and book-to-market could be two additional risk factors apart from the market factor.

Researchers found that the value premium existed also internationally and between different asset classes. Fama and French (1998) studied the value premium internationally, using data from twelve major countries from Europe, Australia, and the Far East. They found that the difference between the average returns of stocks with high and low book-to-market ratios is 7,68 percent annually from 1975 to 1995. So, they provided evidence of the value premium clearly existing in international markets as well, in addition to the U.S. market that was studied initially. Additionally, Hanauer et al. (2013) studied German CDAX returns between July 1996 to December 2011, and found a statistically significant negative size premium, and significant positive value and momentum premiums, indicating that these premiums exist in the German stock market that is studied in this thesis. They also found only a marginally positive or even negative correlation among the risk factors, indicating that combining these factors into multi-factor portfolios could provide superior risk-adjusted returns.

Using data from 1972 to 2011, Asness et al. (2013) provided additional evidence of value premium existing globally across four different equity markets. Interestingly, Asness et al. discovered that the value premium extends to various asset classes in addition to global individual stocks. They discovered that global equity indices, currencies, international government bonds, and commodity futures all exhibit the value anomaly. Naturally, they used different measures of value for each asset class but found that higher value signal was positively correlated with returns.

3.2 Momentum

Similar to value, momentum is a well-known investment style, which is backed by numerous pieces of reliable evidence from the academic community, and practitioners frequently use the approach. According to Asness et al. (2015), momentum is the propensity for securities, across all markets and asset classes, to display consistency in their relative performance over time. Momentum has been extensively researched in a variety of contexts since it was first documented in academia in the early 1990s among U.S. equities (Jegadeesh and Titman, 1993). The typical 12-1 momentum strategy is to look at a variety of assets' returns over the previous 12 months, ignoring the last month's performance, and buy stocks that have outperformed their peers and sell stocks that have underperformed. The resulting portfolio, which is both long and short, has low correlation to traditional markets and, when spread across numerous securities, captures the overall momentum premium while reducing unsystematic risk. While momentum traditionally uses certain market index's stocks historical price returns as signal, other fundamental signals, such as earnings momentum, changes to profit margins, and adjustments to analysts' stock forecasts can also be used (Asness et al., 2015). Strong risk-adjusted returns are consistently demonstrated across all markets and time periods, regardless of which momentum signal is used.

Jegadeesh (1990) was the first to study momentum factor in security prices. Using data from 1934 to 1987, Jegadeesh discovered that monthly stock returns had a highly significant negative first-order serial correlation. However, using longer lags, he found a significant positive serial correlation, which was strongest for twelve-month periods. This indicates that while stock prices typically drop following a month of solid returns, they are more likely to increase again if a stock has outperformed its peers over the previous 12 months. Three years later, Jegadeesh and Titman (1993) delved further into the subject of positive autocorrelation in stock returns. In their study, they test different trading strategies, and find that over holding periods of three to twelve months, strategies that buy stocks with a strong performance history and sell stocks with a poor performance history produce significant positive returns. These returns cannot be explained by market risk or by common factors that cause delayed stock price reactions. Jegadeesh and Titman (2001) later extended their 1993 study, and found that momentum continued to exist also in the 1990s. After Jegadeesh and Titman (1993), academic studies have shown strong support for their findings, using different time periods, asset classes, and momentum signals in an international context (Asness et al., 2013, 2015; Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Fama & French, 2012, 2015, 2018).

Fama and French (2012) study momentum in international stock returns using data from 1989 to 2021. They found strong momentum returns in all markets studied, especially Europe, but Japan was the only market with no significant momentum premium. Additionally, according to Fama and French's research, momentum returns are typically higher for small-capitalization companies than for large-capitalization companies. According to Asness et al. (2013), there are consistent value and momentum premiums in eight different markets and asset classes, and their returns have a robust risk factor structure. Their findings provide additional international evidence for the existence of value and momentum factors. Additionally, Hanauer et al. (2013) found a significant momentum premium in the German CDAX returns.

Asness et al. (2015) suggest risk-based and behavioral theories for the continuing existence of momentum premium. According to risk-based narratives, high-momentum stocks are riskier and as a result demand higher returns. For instance, high-momentum stocks are more susceptible to aggregate shocks because they have higher growth expectations in their earnings. In line with higher risk and thus more volatile growth, also liquidity risk can explain the returns of the momentum factor. According to Sadka (2006), a sizeable portion of momentum premium could be seen as making up for the exposure to unanticipated changes in liquidity. Behavioral theories suggest that a significant source of momentum may be the underreaction to new information in the short term due to anchoring or inattention, and the overreaction to price movements in the medium term due to feedback trading (Asness et al., 2015; Jegadeesh & Titman, 1993, 2001). This is in line with investors' herd behavior, also referred to as herding, where investors become more convinced in their own views when other investors share their views. Momentum may also be significantly influenced by the disposition effect, which is the propensity for investors to sell winners too soon and hold onto losers for too long (Grinblatt and Han, 2005).

While previous literature of momentum has provided significant average excess returns across different asset classes and markets, momentum strategies have also produced significant losses in a short amount of time on numerous occasions. According to Barroso and Santa-Clara (2015), among the three most prevalent factors (size, value, and momentum), momentum has generated the highest Sharpe ratio, but also experienced the worst crashes, which may lead investors who detest kurtosis and negative skewness to keep clear of using momentum strategy. They argue that momentum risk is significantly variable over time and can even be predicted by using a model to manage risk, leading to doubling the Sharpe ratio of momentum. Daniel and Moskowitz (2016) found similar results while studying momentum in international markets. They found that these infrequent and significant momentum crashes can happen during market recoveries after market uncertainty, when markets have declined and experienced unusually high volatility. Daniel and Moskowitz found a risk-based model, which can double the alpha and Sharpe ratio, by forecasting momentum strategies' mean and volatility. The effectiveness of this model cannot be explained by other risk factors and their findings hold up well across a variety of time periods, global equity markets, and other asset classes.

In conclusion, the literature discussed above offers compelling evidence in favor of momentum. Momentum has provided significant excess returns over time (Asness et al., 2013, 2015; Fama & French, 2012; Jegadeesh & Titman, 1993, 2001), but is still prone to periods of extremely weak returns (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016). While certain risk-managed models claim to enable investors to avoid momentum crashes, this thesis uses the traditional 12-1 momentum. That is, because it is much simpler and thus more available to investors, and this thesis focuses on multi-factor smart beta strategies, which offer additional diversification and risk management.

3.3 Low volatility

The risk-return tradeoff is a cornerstone principle in finance, signifying a positive long-term correlation between risk and return. Investors anticipate elevated returns in exchange for assuming higher levels of risk. According to the EMH (Fama, 1970), investors receive above-average returns only by taking greater risk. So, on average, risky stocks should yield high returns, while safer stocks should show lower returns. However, previous empirical studies suggest that the relationship is nearly the opposite and cannot be supported. For example, Baker et al. (2011) studied the 1000 biggest U.S. stocks by market capitalization, using data from 1968 to 2008, and found that riskier stocks (high-beta and high-volatility) have long underperformed stocks with lower risk (low-beta and low-volatility). Many other studies have provided similar findings (Ang et al., 2006; Baltussen et al., 2019; Blitz & van Vliet, 2007; Blitz et al., 2013; Frazzini & Pedersen, 2014).

Ang et al. (2006) study the total volatility risk in the cross-section of average returns. They found that securities with high volatility have lower than average returns, compared to the CAPM and Fama-French 3-factor model. They control for size, value, momentum, liquidity, and trading volume, and find that none of these factors can explain the low average returns of securities with high market risk or high level of unsystematic risk. Similarly, evidence from Blitz and van Vliet (2007) shows that stocks with low historical volatility have higher risk-adjusted returns, with annual alpha spreads of 12 percentage points between global portfolios in the low- and high-volatility deciles over the period 1986–2006. The U.S., European, and Japanese markets all experience this volatility effect on their own, and it cannot be explained by implicit loadings on traditional risk factors like value, size, and momentum despite being comparable in size to those effects. These high returns of low-risk stocks show evidence of investors taking unnecessary risk by buying risky stocks.

In their 2013 study, Blitz et al. looked at the empirical relationship between risk and return in emerging equity markets and discovered that it was either flat or negative. Similar to Ang et al. (2006) and Blitz and van Vliet (2007), their findings cannot be explained by common risk factors, such as value, momentum, or size. So, Blitz et al. (2013) provided valuable evidence of volatility effect existing in emerging markets, in addition to U.S. and other developed markets. However, they discover weak correlations between the volatilities of developed (U.S., Europe, Japan) and emerging equity markets, which challenges the idea that there is a single common risk factor explanation.

According to renowned empirical research “Betting against beta” by Frazzini and Pedersen (2014), high-beta asset portfolios have lower alpha and Sharpe ratios than low-beta asset portfolios. They discover that, in addition to the security market line being flatter than expected by the conventional CAPM for U.S. stocks, this relative flatness is also present in 18 of 19 international equity markets, treasury markets, and futures markets. They demonstrate that betting against beta (BAB) factors can be used to capture this departure from the standard CAPM. Frazzini and Pedersen’s practical implication is that investors may be able to utilize the BAB factor by using leverage on safe (low beta) securities and receiving compensation from investors who must take the other side, because of leverage constraints, to achieve optimal risk-return relationship.

In conclusion, the chapter delves into the critical concept of low volatility effect in finance, challenging the traditional risk-return tradeoff theory. Empirical studies, including those by Ang et al. (2006), Blitz and van Vliet (2007), and Blitz et al. (2013), consistently demonstrate that low-risk stocks tend to outperform their high-risk counterparts. These findings hold true across various markets, including emerging equity markets, suggesting a global phenomenon. Additionally, Frazzini and Pedersen's (2014) research on "Betting against beta" underscores the practical implications of this departure from the standard CAPM, providing insights into potential investment strategies for leveraging safe assets. Additionally, investors should not overpay for risky stocks, if they are not rewarded for the additional risk taken. Overall, the chapter sheds light on the complexities of risk and return dynamics, highlighting the need for a nuanced understanding in investment decision-making.

3.4 Size

In addition to the primary factors of value, momentum, and low volatility, a brief chapter on the size factor is included in this thesis to provide a comprehensive perspective on factor investing. To conduct a more thorough analysis of the variables affecting the performance of the smart beta multi-factor portfolio under consideration, it is helpful to comprehend how size interacts with value, momentum, and low volatility. Banz (1981) was the first to empirically study the correlation between the returns and the total market values of common stocks listed on the New York Stock Exchange (NYSE), using data from 1926 to 1975. Banz found that small stocks have better risk-adjusted returns compared to larger stocks. This is called the size premium, or small firm effect. Since the risk-adjusted returns between average-sized and larger firms are found to be similar, the size effect is not linear and occurs primarily in the very small size firms. He found that even with equal betas, small stocks had enhanced risk-adjusted returns compared to larger stocks. Given that the size effect has existed for more than forty years, Banz concluded that this is evidence of the CAPM's misspecification. Basu (1983) found similar returns of small NYSE stocks significantly outperforming larger NYSE stocks. However, he discovered that when returns are adjusted for variations in risk and E/P ratios, the size effect practically disappears. Finally, based on Banz (1981) and Basu's (1983) early studies on size, later research was encouraged to focus on whether the size effect is caused by size itself or whether size is simply an approximation for one or several real unknown factors that are related to size.

Since previous studies (Banz, 1981; Basu, 1983) showed evidence of CAPM being misspesified, and that firm size is negatively correlated with expected returns, Fama and French (1992, 1993) included size, together with value, in their famous 3-factor model. Firm size and anticipated returns were found to be negatively correlated by Fama and French. These results suggested that investing in small stocks might be able to produce returns that are higher than those predicted by the conventional CAPM.

Asness et al. (2018) highlight that the size premium has been criticized for having a poor track record historically, being underwhelming in comparison to other factors, varying greatly over time, decreasing after its discovery, and being concentrated in microcap stocks. They find that these problems with size factor disappear, when controlling for the quality of stocks. These findings apply across 24 international equity markets and 30 different industries. According to Asness et al., the revived size effect presents new tests and challenges for accepted theories of asset pricing and is comparable with value and momentum premiums in terms of economic significance. Esakia et al. (2019) continue on several studies (see eg. Basu, 1983; Asness et al. 2018) that the size premium is not strong as a stand-alone factor, but it can be meaningful when forming smart beta portfolios. Esakia et al. conclude that size is not among the weakest factors used by empirical asset-pricing literature, and it should be at least observed in multi-factor smart beta portfolios.

3.5 Multi-factor smart beta strategies

Academics and industry professionals have shifted their focus from single-factor smart beta strategies to multi-factor smart beta strategies in the last ten years. Single-factor smart beta portfolios offer concentrated risk exposure to the selected risk factor, such as momentum, size, value, or low beta. As mentioned above, these strategies provide excess returns on average, but putting excessive weight on one single risk factor can expose the portfolio to periods of very bad returns (Barroso & Santa-Clara, 2015). The multi-factor smart beta strategies diversify risk exposure to several risk factors to avoid these periods of extremely low returns. Additionally, as the correlations between the returns of the long-short portfolios are weak or even negative, indicating that investors can increase their risk-adjusted returns by combining several strategies into one portfolio, in comparison to single-factor investing.

There are generally two ways of implementing these multi-factor smart beta strategies: mixing and integrating (Bender & Wang, 2016; Fitzgibbons et al., 2017). These two approaches are referred to by different names in academia, but the underlying principles and meanings remain consistent for both approaches. The mixing approach refers to simply combining two or more single-factor portfolios into one multi-factor portfolio. The integrating approach, also referred to as the bottom-up method, includes building the portfolio from the security level, and each security's inclusion depends on how it ranks on multiple factors during the same period. So, the integrating approach offers integrated exposure to multiple factors.

Bender and Wang (2016) examine the returns of various multi-factor portfolios consisting of value, momentum, low volatility, and quality, using data spanning the years 1993 to 2015. They discover that integrating factors offers better absolute and risk-adjusted returns. For all eight factor pairs, the integrated approach yields better absolute and risk-adjusted returns compared to corresponding factor pairs constructed by the mixing approach. The results are similar when using all four factors in one portfolio, the integrated four-factor portfolio yields 12,13% annualized returns compared to the mixed portfolios 11,14%. Similarly, the Sharpe ratio is also higher (0,88 vs. 0,75). The integrated four-factor portfolio also outperforms all single-factor portfolios by absolute and risk-adjusted returns, while the mixed portfolio ranks in the middle of single-factor portfolios. They explain the enhanced performance of the integrating approach by the capture of non-linear cross-sectional diversification benefits between factors at the security level, which the mixing approach does not observe. Bender and Wang observe the most significant differences between the two multi-factor portfolio construction approaches of mixing and integrating in two multi-factor portfolios, value-momentum, and value-quality. In line with the discussions above, they explain the superior performance of integrating approach with these factors by the low correlations between value, momentum, and quality factors.

Clarke et al. (2016) explore the returns of mixing and integrating multi-factor smart beta strategies between 1968 and 2014, using data of the 1000 largest companies in the U.S. stock market. They used low beta, size, value, and momentum as their study's risk factors.

They used the Sharpe ratio as the main measure of performance and found that the mixed portfolio of these four factors captures 40% of the potential enhancing over the Sharpe ratio of the overall market index, and the integrated portfolio captures 80% of the improvement. More specifically, the equal-weighted portfolio integrating all four factors has average annualized returns of 10,26% and Sharpe ratio of 0,67, while the mixed portfolio has average returns of 7,63% and Sharpe ratio of 0,58. Their study provides strong support for the integrating approach, meaning that a greater portion of the possible risk-adjusted returns can be realized when portfolios are built form the bottom-up, and each stock includes the desired factor exposures.

Fitzgibbons et al. (2016) explore the combined use of long-only value and momentum portfolios among an international 500-stock universe between 1993 and 2015. They discover that the integrated portfolio provides higher excess returns and over two times greater alpha when compared to the market index. The excess return is 3,6% for of the integrated portfolio, and 2,5% for the mixed portfolio. Additionally, the information ratio is 0,87 for the integrated portfolio, 25 basis points higher compared to the mixed portfolio. Similarly, the integrated portfolio outperforms both stand-alone portfolios (value and momentum), while the mixed portfolio lands between them. Like Bender and Wang (2016), Fitzgibbons et al. explain the outperformance of the integrating approach by the fact that integrated portfolio contains only stocks with both wanted factors, value and momentum. At the same time, in the 50/50 mixed portfolio, momentum portfolio can contain growth stocks, and value portfolio can contain stocks with poor past relative performance, thus failing to capture both risk factors that the investor considers significant.

According to Ghayur et al. (2018) and Chow et al. (2018), the relationship between the mixing and integrating approach is more complex than the above mentioned literature suggests. Ghayur at al. used data from the Russell 1000 universe from 1979 to 2016, combining value, momentum, quality, and low volatility. At smaller tracking error and low-to-moderate factor exposure, the mixing approach performed better (30 basis points higher information ratio), mainly because of the different interactions among the factors. They found that securities with negative loadings to other factors within the mixed portfolio reduced active risk and increased active returns, leading to higher information ratio, which was the risk-adjusted performance measure used in the study. However, they found that the integrating approach performed better when targeting high levels of tracking error and factor exposure.

Chow et al. (2018) study single- and multi-factor strategies with U.S. data from 1968 to 2016 using value, momentum, profitability, investment, and low beta factors. When simply simulating the strategies, they find all factors outperforming the market, and integrating approach performing the best. The integrated portfolio has an annual return of 13,59% and volatility of 13,4%, while the mixed portfolio generated annual returns of 11,83% and volatility of 14,3%. Thus, the integrated portfolio has Sharpe ratio of 0,65, 17 basis points higher than the mixed portfolio. However, when decomposing active risk based on level of factor exposure, their findings are in line with Ghayur et al. (2018). Chow et al. also find that mixed portfolios are more cost-effective, since the trades of each factor portfolio partially cancel out each others. They also suggest that the integrated approach performs better when the sample is small, and trading costs are excluded. Finally, Chow et al. prefer the easier implemented and more transparent mixing approach, that also has lower transaction volume and fees.

Amenc et al. (2017) find additional proof that, in terms of relative performance, the mixed approach outperforms the integrated approach. They use data of 500 U.S. stocks between 1975 to 2015. They state that the integrated approach fails to control factor exposures, since securities in the integrated multi-factor portfolio also have exposure to other non-factor risks, that are not expected to generate excess returns. Amenc et al. find that the mixed approach generates superior risk-adjusted return per unit of factor exposure and include less turnover and better diversification benefits. Based on their findings, multi-factor smart beta strategies constructed by mixing single-factor portfolios, where loser stocks are excluded, generates higher absolute and risk-adjusted returns. Additionally, the integrated approach includes much more turnover, for example, when using the top quintile as basis for stock inclusion, the integrated approach's annualized one-way turnover is 87%, compared to the mixed approach's 69%. Thus, trading costs are also much higher for the integrated approach, and they conclude that the mixed approach is the more effective alternative.

Leippold and Rueegg (2018) use U.S. data between 1963 to 2016 and studied long-only smart beta strategies using five styles, value, profitability, investment, momentum, and low volatility. They suggest contradicting evidence to the above presented hypothesis of other academics that the integrated approach contributes to superior risk-adjusted returns. While previous literature utilized single hypothesis testing, and discovered statistically and economically significant excess returns, Leippold and Rueegg consider a multiple hypothesis approach, and the returns of the integrating and mixing approaches are not statistically different from one another. Leippold and Ruegg also find that the integrated approach is more exposed to the low volatility factor. Thus, the integrating approach includes lower total risk, but is also associated with lower returns, meaning that integrating different factors does not improve risk-adjusted returns.

Blitz and Vidojevic (2018) support the findings of Leippold and Rueegg (2018) that mixing and integrating approaches provide similar risk-adjusted returns if both approaches are implemented comparably, i.e., offer a similar degree of concentration and factor exposure. They use U.S. data from 1963 to 2017, trying to study the multi-factor returns at a factor-portfolio level. Blitz and Vidojevic find that the performance of an integrated approach can be matched by a mix of enhanced single-factor portfolios that offer more pronounced factor exposures. They enhance the single-factor portfolios of the mixed approach by excluding stocks with negative factor exposures to other factors considered, and stocks with expected returns below the market. So, Blitz and Vidojevic find no evidence of a factor integration premium, if the portfolio construction methods are comparable.

While most of the research on multi-factor smart beta strategies has focused on U.S. or global markets, Silvasti et al. (2021) study the combination of value, momentum, and low beta in the relatively small Nordic markets. They find that the integrating approach clearly outperforms the mixing approach, measured by excess return, CAPM alpha, and Sharpe ratio. However, they mention some drawbacks of the integrating approach, which include more trading, higher costs, and less transparency and simplicity.

Previous literature has studied the performance of multi-factor smart beta strategies quite comprehensively, but as the topic is still quite novel, there is no clear consensus on which methodologies are most efficient when implementing these strategies. However, all studies provide evidence of both multi-factor smart beta strategies beating the market index, and also generally providing better risk-adjusted returns than single-factor strategies. Academics are divided on how to implement these multi-factor smart beta strategies most efficiently. Some prefer the integrated, or bottom-up approach of building multi-factor portfolios from the security level based on scoring or ranking systems rather than the mixing approach (Bender & Wang, 2016; Clarke et al., 2016; Fitzgibbons et al., 2017; Ghayur et al., 2018). Other studies show contradicting evidence, when both approaches are implemented in a comparable way (Amenc et al., 2017; Blitz & Vidojevic, 2018; Chow et al., 2018; Leippold & Rueegg, 2018).

The literature presented above concludes that the integrated approach benefits from exposure only to the desired risk factors, while the traditional mixed approach suffers from greater diversification that leads to unwanted factor exposure (Bender & Wang, 2016; Clarke et al., 2016; Fitzgibbons et al., 2017). The integrated approach may still suffer from higher turnover and trading costs, and it is less transparent. Furthermore, if the mixed approach is enhanced, it may generate better risk-adjusted returns (Amenc et al., 2017; Blitz & Vidojevic, 2018).

4 Data and methodology

This chapter describes the data set of monthly CDAX returns, which are used to create different smart beta portfolios based on style signals. Additionally, style signals and portfolio construction methodologies are presented.

4.1 Data

The data consists of monthly CDAX returns for the 228-month period between July 2004 and June 2023. The first accounting data observations were made at the end of June 2001, and portfolios are rebalanced monthly. The data das derived from Thomson Reuters' database. The sample of CDAX returns represents the biggest German companies listed in the Prime Standard and General Standard indices. The data set is compiled with monthly prices, raw and total return indices, and quarterly book and market values of equity. In the context of Europe, risk-free rates are based on three-month EURIBOR rates rather than T-bill rates, and stock data is quoted in euros. The values for the six-factor regressions are downloaded from Kenneth French's online library. This thesis uses European factors, which are converted into euros using the month-end closing spot prices for USD/EUR rates. The data for monthly spot prices is collected from Thomson Reuters. However, since the Kenneth French factor loading are in USD even for European factors, there is a chance that the converted EUR values have an embedded foreign exchange effect due to variations in FX rates.

Financial companies aren't included in the sample, as is standard in the literature, because their high leverage levels and different use of capital are different from those of non-financial companies (Fama & French, 1992, 1993; Asness et al., 2013). The data also excludes all non-equity investment instruments, such as ETFs. In accordance with Fama et al. (1992), firms with a negative book value of equity are not included in the sample. Finally, following Asness et al. (2013) and Silvasti et al. (2021), the smallest 10% of companies are not included in the data sample due to possible liquidity restraints, and the delisting (or bankruptcy) returns are assumed to be zero.

The descriptive statistics for the stocks included in the data set are presented below in table 1. Minimum number of companies in the data sample was 211 in July 2004, while maximum was 316 in June 2023. The average number of companies was 265. The average market value of companies included in the CDAX index was 4,578 billion euros, implying that the companies analyzed could be relatively liquid. The lowest average market value was 2,295 billion euros during the global financial crisis, in the second quarter of 2009.

Table 1: Descriptive statistics

Descriptive statistics of the data set for the 228-month period between July 2004 and June 2023. Minimum, maximum and average number of companies is presented. Average market capitalization is also presented.

Minimum number of companies	211
Max number of companies	316
Average number of companies	265
Average market value (EURm)	4 578

4.2 Methodology

This chapter discusses the construction of portfolios and style signals. In accordance with Asness et al. (2013), this thesis uses the most straightforward and, to the extent that a standard exists, most common measures for style signals, which are value, momentum, and low volatility. Following Silvasti et al. (2021), portfolios are equal-weighted, and the ranked stocks are assigned into one of five quintile portfolios. Similar to Fama & French (2015, 2018), portfolios are reconstructed monthly based on updated style signals, if data is easily and publicly available. If data is limited, like book value of equity for value signal, the signal is lagged and updated annually to ensure practical implementation of these strategies. For the volatility measure, stocks with the lowest scores are assigned to the top quartile, while for the value and momentum strategies stocks with the highest factor scores are the preferred ones. Long-short portfolio is the top quintile minus the bottom quintile.

The value signal is the ratio of book value of equity to market value of equity, or book-to-market (B/M) ratio, which is commonly used (see e.g. Fama & French, 1992, 1993). Following Fama and French (2015, 2018), the value signal (B/M) is calculated and value portfolios are constructed annually at the end of June of year t, where B is the book value of equity at the end of year t-1 and M is the market value of equity at the end of year t-1. The value signal is calculated annually and lagged six months, since the book value of equity is not continuously available to investors with accurate and updated values. Companies with missing or negative book values of equity at the end of year t-1 are not included in the sample. So, the value portfolio stays the same every year from July to June, after which it is recalculated, leading to value stocks being unchanged while multi-factor portfolios are reconstructed monthly, following Fama and French (2015, 2018).

The momentum signal is the widely used 12-1 momentum signal (see e.g. Asness et al., 2013; Fama & French, 2018; Jegadeesh & Titman, 1993). So, the momentum signal is the past 12-month cumulative raw return, skipping the most recent months' return, to avoid a potential one-month reversal in monthly stock returns due to negative serial-correlation (Jegadeesh, 1990). Following Fama & French (2018), momentum signal is updated monthly instead of annually. That is, because 12-month price data is available to investors in real time as opposed to value factor, and the signal can, even in practice, be updated more frequently. Naturally, 12-month price data is needed, otherwise the stock is excluded.

The low volatility signal is 36-month rolling standard deviation of total returns of each stock, following Blitz & van Vliet (2007) and Leippold & Rueegg (2018). A 36-month period is generally considered more robust for capturing the inherent risk of an investment, since it reduces the impact of short-term market anomalies and one-off events, that could lead to biased risk estimates if the estimation periods was shorter. The rolling nature of this measure allows for a dynamic evaluation of total volatility, providing insight into the evolving risk characteristics of stocks the investment universe. Similar to the momentum signal, the low volatility signal is updated monthly. Finally, 36-month price data is needed to include each stock.

The risk-adjusted performance measures, including the Sharpe ratio and CAPM and Fama-French six-factor regressions are presented in chapter 2. Furthermore, the performances of different portfolios are measured and compared by monthly absolute returns, annualized standard deviations, worst monthly drawdowns, and maximum drawdowns. Also, the average number of stocks in each portfolio is displayed to assess whether portfolios are too thin, leading to larger investments in each stock and liquidity issues. The detailed portfolio construction methodologies for the different long-only and long-short multi-factor portfolios are presented below in chapter 5 before presenting the returns of the corresponding portfolios.

5 Results

The purpose of this section is to try to answer to the research questions introduced in chapter 1. The main research question is whether long-only and long-short smart beta strategies consisting of value, momentum and low volatility have provided statistically significant excess returns over the CAPM and six-factor model in the German CDAX returns during the research period. Additionally, the factor exposures of these multi-factor smart beta strategies are measured, to better understand which factors can explain most of the superior risk-adjusted returns.

5.1 Single-factor portfolios

This chapter shows the returns of single-factor portfolios, including value, momentum, and low volatility, aiming to provide evidence of these style premiums existing in the German stock market.

5.1.1 Value portfolios

Table 2 below presents evidence indicating a positive correlation between B/M ratios and portfolio returns. As the B/M ratio increases, monthly absolute returns, alphas, and Sharpe ratios increase correspondingly, suggesting that the German stock market exhibits a value premium. Several other studies have also documented a value premium in German stock market returns (see e.g., Fama & French, 1998; Hanauer et al., 2013), in addition to global markets (Asness et al., 2013). However, the results for the five long-only portfolios are not statistically significant, except for the lowest quintile (growth) portfolio having -0,77% monthly CAPM alpha at 1% significance level. Additionally, since the realized beta for the value portfolio (0,77) is slightly lower than that of the growth portfolio (0,89), it is notable that exposure to systematic market risk does not explain the positive relationship that exists between B/M ratios and average returns.

The long-short portfolio, which represents the spread between the highest and lowest quintiles, shows impressive and statistically significant results. The monthly absolute return is 0,89% and the monthly CAPM alpha is 0,96% at the 1% significance level. Furthermore, the market beta is negative, and annualized standard deviation is extremely low, leading to an impressive Sharpe ratio of 0,98.

The long-short portfolio also has the smallest monthly drawdown and maximum drawdown among the portfolios analyzed. As can be expected, the growth portfolio has the largest maximum drawdown of -74%, which occurred in February 2009 during the global financial crisis.

Table 2: Value

Value factor in CDAX returns, July 2004-June 2023

This table shows value-sorted portfolio returns. At the end of June of year t, stocks are ranked in ascending order on the basis of their value signal (book-to-market ratio) at the end of fiscal year t-1. The ranked stocks are assigned to one of five quintile portfolios. The long-short portfolio is the highest quantile minus the lowest quantile. All stocks are equally weighted within a portfolio, and portfolios are rebalanced annually at the end of June. Average monthly absolute returns, CAPM alphas and betas from regressions, and annualized standard deviations, and Sharpe ratios are presented. Additionally, worst monthly drawdown and maximum drawdown is presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Low	2	3	4	High	Value
Monthly return	-0,23 %	0,34 %	0,36 %	0,48 %	0,66%*	0,89%***
	(-0,61)	(-0,98)	(0,97)	(1,42)	(1,96)	(4,26)
Monthly CAPM alpha	-0,77%***	-0,19%	-0,20 %	-0,04%	0,18 %	0,96%***
	(-3,38)	(-1,09)	(-1,13)	(0,22)	(0,92)	(4,64)
CAPM Beta	0,89	0,88	0,92	0,85	0,77	-0,11
Standard deviation	20,00 %	18,42 %	19,20 %	17,65 %	17,46 %	10,88 %
Sharpe	-0,14	0,22	0,22	0,33	0,45	0,98
Worst monthly drawdown	-23,98 %	-23,21 %	-23,48 %	-19,77 %	-19,03 %	-9,71 %
Maximum Drawdown	-74,13 %	-66,52 %	-67,76 %	-59,54 %	-58,10 %	-34,78 %
N	48	47	47	47	48	96

5.1.2 Momentum portfolios

Table 3 below shows the returns of momentum portfolios. The highest quintile (winners) portfolio clearly outperforms the lowest quintile (losers) portfolio, suggesting that the momentum anomaly exists in the German stock market. The findings are in line with previous studies that have found momentum premium in European stock returns (see e.g., Asness et al., 2013, 2015; Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Fama & French, 2012, 2015, 2018). Similar to the value portfolios, results for long-only portfolios are not statistically significant, except for the loser portfolio having -1,35% monthly CAPM alpha at 1% significance level. Additionally, as the winner portfolio has lower market beta (0,74) compared to the loser portfolio (1,03), the momentum phenomenon does not seem to be driven by market exposure.

The long-short momentum portfolio has 1,63% monthly absolute return, indicating almost 20% annual absolute return, and the monthly CAPM alpha is 1,81%. Both are statistically significant at the 1% level, thus systematic risk cannot explain these abnormal returns. The market beta is -0,28, but the annualized standard deviation is just slightly lower than that of the highest quintile portfolio. However, the Sharpe ratio is 1,19, driven by significantly higher average returns.

The long-short portfolio experiences a slightly lower worst monthly drawdown and the smallest maximum drawdown compared to the highest quintile portfolio among all momentum portfolios analyzed. However, the maximum drawdown is 38% for the long-short momentum portfolio and the worst monthly drawdown is 17%, suggesting that the German stock market did not experience significant momentum crashes. Daniel and Moskowitz (2016) found momentum crashes in international equity markets, but the German avoided significant crashes between July 2004 to June 2023. The lowest quintile portfolio has a significant maximum drawdown of -93%, which notably happened in June 2023.

Table 3: Momentum

Momentum factor in CDAX returns, July 2004-June 2023

This table shows momentum-sorted portfolio returns. At the beginning of each calendar month, stocks are ranked in ascending order on the basis of their momentum signal (12-month cumulative raw return, skipping the most recent month) at the end of the previous month. The ranked stocks are assigned to one of five quintile portfolios. The long-short portfolio is the highest quantile minus the lowest quantile. All stocks are equally weighted within a portfolio, and portfolios are rebalanced every month. Average monthly absolute returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Additionally, worst monthly drawdown and maximum drawdown is presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Loser	2	3	4	Winner	Momentum
Monthly return	-0,72 %	0,05 %	0,50 %	0,80%*	0,91%*	1,63%***
	(-1,53)	(0,14)	(1,56)	(2,66)	(2,80)	(5,17)
Monthly CAPM alpha	-1,35%***	-0,49%***	0,01%	0,34%**	0,46%**	1,81%***
	(-4,27)	(-2,63)	(0,04)	(2,30)	(2,30)	(5,97)
CAPM Beta	1,03	0,90	0,81	0,75	0,74	-0,28
Standard deviation	24,83 %	19,03 %	16,88 %	15,74 %	16,97 %	16,51 %
Sharpe	-0,35	0,03	0,36	0,61	0,64	1,19
Worst monthly drawdown	-28,97 %	-26,17 %	-23,84 %	-19,35 %	-16,94 %	-17,17 %
Maximum Drawdown	-92,97 %	-71,73 %	-62,91 %	-51,39 %	-56,22 %	-37,73 %
N	52	52	52	52	52	104

5.1.3 Low volatility portfolios

Table 4 below presents the returns of low volatility portfolios. The lowest quintile portfolio shows the results for the stocks with lowest volatility, which is the desired attribute. For the long-only portfolios, the lowest and highest quintiles both have slightly over 0,5% monthly absolute return (0,55% vs. 0,53%), but the lowest quintile portfolio has half the annualized standard deviation of the highest quintile portfolio (12,02% vs. 24.06%). This gives clear evidence of the low volatility premium in the German stock market returns. Similar findings have been discovered in European context by previous literature (see e.g., Blitz and van Vliet, 2007; Blitz et al., 2013). For the long-only portfolios, only the “worst” portfolio, or the highest quintile, has highly statistically significant monthly CAPM alpha (-1,12%), as was the case for value and momentum. Additionally, as the beta is lower for the lowest quintile (0,58) and highest for the highest quintile (0,97), low volatility does not seem to be driven by market exposure either.

The long-short portfolio has highly statistically significant monthly absolute return (1,08%) and CAPM alpha (1,32%). The market beta is lowest of the three single-factor long-short portfolios (-0,39). However, as the lowest quintile includes the stocks with the lowest standard deviation (12,02%), the long-short portfolio naturally has higher standard deviation (16,91%), since it takes a short position in the most volatile stocks. The Sharpe ratio is still higher for the long-short portfolio (0,77) compared to the lowest quintile (0,55).

The worst monthly drawdowns are consistent for the portfolios, ranging between -17% to -27%. The worst monthly drawdown is smallest for the long-short portfolio (-43%) and largest for the highest portfolio which includes the most volatile companies (-89%). The maximum drawdown of the highest quintile was in May 2023. This can be attributed to the fact that during the sample period, the highest quintile portfolio reached its peak in September 2021, with the CDAX index also being at its highest. Subsequently, as inflation and interest rates increased, the most volatile stocks within the CDAX index started to decline significantly. This decline in value contributed to the overall poor performance of the highest quintile portfolio during the period examined.

Table 4: Low volatility

Low volatility factor in CDAX returns, July 2004-June 2023

This table shows low volatility -sorted portfolio returns. At the beginning of each calendar month, stocks are ranked in descending order on the basis of their low volatility signal (36-month rolling standard return of total returns) at the end of the previous month. The ranked stocks are assigned to one of five quintile portfolios. The long-short portfolio is the lowest quantile minus the highest quantile. All stocks are equally weighted within a portfolio, and portfolios are rebalanced every month. Average monhtly absolute returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Additionally, worst monthly drawdown and maximum drawdown is presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Min.	2	3	4	Max.	Low volatility
Monthly return	0,55%**	0,71%**	0,46%	0,26%	0,53%	1,08%***
	(2,38)	(2,20)	(1,25)	(0,66)	(-1,16)	(3,38)
Monthly CAPM alpha	0,20%*	0,21%	-0,11 %	-0,32%	-1,12%***	1,32%***
	(1,74)	(1,39)	(-0,60)	(-1,48)	(3,54)	(4,44)
CAPM Beta	0,58	0,82	0,93	0,96	0,97	-0,39
Standard deviation	12,02 %	16,77 %	19,22 %	20,68 %	24,06 %	16,91 %
Sharpe	0,55	0,50	0,29	0,15	-0,27	0,77
Worst monthly drawdown	-17,44 %	-21,37 %	-26,64 %	-22,01 %	-22,11 %	-17,14 %
Maximum Drawdown	-50,80 %	-64,25 %	-65,46 %	-67,84 %	-88,56 %	-43,29 %
N	53	53	53	53	53	106

The evidence for the existence of value, momentum, and low volatility premiums is strong in the German CDAX returns, as can be observed from tables 2, 3, and 4. Regarding the long-only portfolios, the results are generally not statistically significant, but the top quintile portfolios have the highest absolute returns, alphas, and Sharpe ratios. The highest quintile (winners) for momentum is the best performing long-only portfolio.

All of the long-short portfolios (value, momentum, and low volatility) have highly statistically significant absolute returns and CAPM alphas at the 1% significance level. Based on these measures, the momentum long-short portfolio performs best, while the value portfolio is the worst performing long-short portfolio. However, regarding Sharpe ratios, low volatility long-short portfolio is the worst performer, explained by the fact that it goes long on stocks with lowest volatility and short on stocks with highest volatility, increasing the volatility spread. Based on the evidence above regarding excess returns of these single-factor smart beta strategies, the first hypothesis can be accepted.

5.2 Multi-factor smart beta portfolios

This chapter is designed to respond to the main research question presented in this thesis, whether long-only and long-short multi-factor smart beta strategies, comprising of value, momentum, and low volatility, have yielded statistically significant excess returns over the CAPM and 6-factor model in the German stock market throughout the research period.

5.2.1 Long-only mixed multi-factor portfolios

This chapter presents the returns of long-only multi-factor portfolios constructed by mixing value, momentum, and low volatility. The portfolios with two factors are weighted 50/50, and the portfolio with all three strategies allocates 1/3 weight to each factor. So, for example, the value-momentum portfolio weighs 50% to the high portfolio presented above in table 2 and 50% to the winner portfolio of table 3.

Table 5 shows the returns of long-only portfolios constructed by using the mixing approach. Value-momentum has the highest monthly absolute return of 0,78%, while value-low volatility has the lowest monthly absolute return, 0,60%. The momentum-low volatility portfolio has the highest CAPM alpha (0,33%) and lowest standard deviation (13,92%). The Sharpe ratios range from 0,51 to 0,63, and momentum-low volatility has the highest value. All four strategies have market betas of approximately 0,7, indicating relatively low systematic risk. Regarding worst monthly drawdowns and maximum drawdowns, the strategies perform equally. The combined long-only portfolios perform, on average, just slightly better than the single-factor long-only portfolios, but the difference is not significant.

Table 5: Long-only multi-factor portfolios, mixing

Long-only multifactor portfolios, mixing, July 2004-June 2023

This table shows the returns for long-only smart beta portfolios constructed by mixing value, momentum, and low volatility. The portfolios with two strategies are weighted 50/50 and the portfolio with three strategies has 1/3 allocation to each strategy. Average monthly absolute returns, CAPM alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Additionally, worst monthly drawdowns and maximum drawdowns are presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Monthly return	0,78%**	0,60%**	0,72%***	0,70%**
	(2,46)	(2,21)	(2,73)	(2,50)
Monthly CAPM alpha	0,32%*	0,19%	0,33%**	0,28%*
	(1,79)	(1,38)	(2,40)	(1,94)
CAPM Beta	0,76	0,68	0,66	0,70
Standard deviation	16,62 %	14,22 %	13,92 %	14,71 %
Sharpe	0,56	0,51	0,63	0,57
Worst monthly drawdown	-16,98 %	-18,23 %	-16,19 %	-17,12 %
Maximum Drawdown	-56,33 %	-53,50 %	-52,05 %	-53,60 %
N	98	99	105	151

Table 6 shows the six-factor loadings for the long-only multi-factor portfolios. The six-factor alphas are insignificant for all four portfolios. The market betas are highly statistically significant and are slightly lower than those derived from CAPM regressions. The factor loadings for SMB are positive at the 1% significance level, for all four portfolios, indicating that the portfolios consist of small stocks. Additionally, HML, RMW, and MOM have positive and statistically significant loadings that are in line with the strategies. This is evidenced by the fact that the value-low volatility portfolio does not have a statistically significant MOM loading, while the momentum-low volatility portfolio does not have a statistically significant HML loading. Finally, R-squared is relatively high for all four strategies, ranging from 0,67 to 0,69, meaning that the independent variables explain around 68% of the variance of the dependent variable.

Table 6: Six-factor regressions, long-only multi-factor portfolios, mixing

Long-only multifactor portfolios, mixing, July 2004-June 2023

This table shows the returns for long-only smart beta portfolios constructed by mixing value, momentum, and low volatility. The portfolios with two strategies are weighted 50/50 and the portfolio with three strategies has 1/3 allocation to each strategy. The factor loadings of the 6-factor model regressions are presented. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Alpha	0,04	0,07	0,09	0,06
	(0,18)	(0,37)	(0,51)	(0,36)
MKT	0,68***	0,55***	0,61***	0,61***
	(15,26)	(14,56)	(16,73)	(16,05)
SMB	0,67***	0,52***	0,44***	0,54***
	(6,03)	(5,54)	(4,88)	(5,72)
HML	0,33**	0,32**	0,18	0,28**
	(2,30)	(2,58)	(1,57)	(2,24)
RMW	0,51**	0,41**	0,38**	0,43**
	(2,57)	(2,47)	(2,34)	(2,56)
CMA	-0,16	-0,22	-0,17	-0,18
	(-0,85)	(1,42)	(-1,10)	(-1,15)
MOM	0,15**	0,04	0,16***	0,11**
	(2,34)	(0,65)	(3,30)	(2,09)
R-squared	0,67	0,67	0,68	0,69

5.2.2 Long-short mixed multi-factor portfolios

This chapter presents the returns of long-short multi-factor portfolios constructed by mixing value, momentum, and low volatility. Similar to the long-only portfolios, the portfolios with two factors are weighted 50/50, and the portfolio with all three strategies allocates 1/3 weight to each factor. In the context of long-short portfolios, value-momentum portfolio weighs 50% to the value portfolio presented above in table 2 and 50% to the momentum portfolio of table 3.

The returns of long-short portfolios by the mixing approach are presented below in table 7. On average, the monthly absolute returns are significantly higher compared to the long-only mixed portfolios. Monthly return is highest for the momentum-low volatility portfolio, 1,36 percent, indicating an annualized return of over 16 percent. The CAPM alphas are statistically significant at the 1% significance level and range between 1,14%-1,56%, and market betas are negative. The value-momentum portfolio has lowest annualized standard deviation (10,79%) and highest Sharpe ratio (1,40), thus providing superior risk-adjusted returns.

The worst monthly drawdowns are slightly lower than those of the long-only mixed portfolios, but the maximum drawdowns are significantly lower, on average almost half of those of the long-only mixed portfolios. When comparing the combined long-short portfolios to the single-factor portfolios, the diversification benefit can be clearly observed. On average, the combined long-short portfolios perform significantly better than the single-factor long-short portfolios, measured by Sharpe ratio. However, the long-short momentum strategy performed strongly with Sharpe ratio of 1,19, which is better than value-low volatility (1,09) and momentum-low volatility (1,07).

Table 7: Long-short portfolios, mixing

Long-short multifactor portfolios, mixing, July 2004-June 2023

This table shows the returns for long-short smart beta portfolios constructed by mixing value, momentum, and low volatility. The portfolios with two strategies are weighted 50/50 and the portfolio with three strategies has 1/3 allocation to each long-short strategy. Average monthly absolute returns, CAPM alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Additionally, worst monthly drawdowns and maximum drawdowns are presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Monthly return	1,26%***	0,98%***	1,36%***	1,20%***
	(6,11)	(4,74)	(4,68)	(5,49)
Monthly CAPM alpha	1,38%***	1,14%***	1,56%***	1,36%***
	(7,03)	(5,99)	(5,84)	(6,78)
CAPM Beta	-0,20	-0,25	-0,34	-0,26
Standard deviation	10,79 %	10,84 %	15,14 %	11,42 %
Sharpe	1,40	1,09	1,07	1,26
Worst monthly drawdown	-10,96 %	-9,97 %	-16,17 %	-12,36 %
Maximum Drawdown	-19,35 %	-22,01 %	-31,51 %	-20,83 %
N	200	202	210	306

Table 8 shows the six-factor loading for the long-short multi-factor portfolios. The alphas are impressive, approximately 1%, for all portfolios at the 1% significance level. The market betas are statistically significant and slightly negative, indicating that the strategies are relatively market-neutral. All three strategies seem to be at least partially driven by the size effect expect for the value-momentum portfolio, that does not have a statistically significant SMB loading. Compared to the combined long-only portfolios, RMW has lost its ability to explain returns, and CMA is still insignificant. HML is only significant for the value-momentum portfolio at 10% significance level, but not significant for other factors. The MOM loading is highly statistically significant for all portfolios, but clearly smallest for the value-low volatility portfolio.

The R-squared ranges between 0,28 to 0,37, meaning that the six-factor model loses its power in explaining the returns for the multi-factor portfolios, when they are long-short instead of long-only as presented in table 6. The returns of mixed long-short portfolios are driven by size and momentum factors, but those factors cannot explain the majority of the variance of the strategies.

Table 8: Six-factor regressions, long-short multi-factor portfolios, mixing

Long-short multifactor portfolios, mixing, July 2004-June 2023

This table shows the returns for long-short smart beta portfolios constructed by mixing value, momentum, and low volatility. The portfolios with two strategies are weighted 50/50 and the portfolio with three strategies has 1/3 allocation to each long-short strategy. The factor loadings of the 6-factor model regressions are presented. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Alpha	0,93***	0,96***	1,01***	0,96***
	(4,82)	(4,82)	(3,89)	(4,86)
MKT	-0,08**	-0,22***	-0,15**	-0,15***
	(-2,12)	(-5,18)	(-2,59)	(-3,54)
SMB	-0,17	-0,30**	-0,42***	-0,30***
	(-1,62)	(-2,85)	(-3,04)	(-2,80)
HML	0,24*	0,20	0,01	0,15
	(1,81)	(1,46)	(0,03)	(1,09)
RMW	0,36**	0,19	0,41	0,32*
	(1,98)	(1,00)	(1,64)	(1,69)
CMA	0,28	0,09	0,27	0,21
	(1,60)	(0,53)	(1,15)	(1,19)
MOM	0,38***	0,17***	0,45***	0,33***
	(6,30)	(2,67)	(5,61)	(5,37)
R-squared	0,32	0,28	0,37	0,35

5.2.3 Long-only integrated multi-factor portfolios

This chapter presents the returns of long-only multi-factor portfolios constructed by integrating value, momentum, and low volatility. Stocks that have the best fit across several factors are selected for each portfolio in order to create a multi-factor portfolio using the integrating approach. A number of authors, including Fitzgibbons et al. (2017), Novy-Marx (2013), and Silvasti et al. (2021) have used a similar approach to portfolio construction. Simply, to be included in an integrated portfolio, a stock must exhibit a strong style signal across all considered factors. Thus, in order for a stock to be part of, for example, value-momentum portfolio, it must have a strong and positive style signal for both value and momentum factors. In contrast, in the 50/50 mixed value-momentum portfolio, momentum portfolio can contain growth stocks, and value portfolio can contain stocks with poor past relative performance, thus failing to capture both risk factors that the investor considers significant. That is, since for an investor looking to maximize their exposure to both value and momentum, this stock is not the best choice because it exhibits a strong momentum signal but a negative value signal. The portfolios will eliminate undesirable negative exposure to other considered factors by using the integrating methodology.

So, to build the integrated portfolio, stocks are arranged into quintile portfolios each month based on their factor signals. Stocks that rank in the two highest quintiles (i.e. above the 60th percentile) for both factors are selected for the integrated portfolio after sorting. For portfolio integrating all three risk factors, the stocks must have all three factors with values above the 60th percentile. The mixed portfolios included stocks with signals above the 80th percentile, but since the integrating approach requires more for stocks, the 60th percentile is used instead. That is, because the portfolio could otherwise consist of only a handful of stocks, making the portfolio harder to implement in practice. Moreover, the integrated portfolio contains stocks with a correspondingly strong value and momentum signal at the same time (signal above the 60th percentile). These same stocks would be excluded from the mixed multi-factor portfolio because their signals are insufficient to be included in either single-factor portfolio.

The returns for the different long-only portfolios created using the integrating approach are displayed in Table 9. The long-only integrated portfolios perform significantly better when compared to the long-only mixed portfolios. The monthly absolute returns range from 0,78% to 1,01%, with the portfolio integrating all three factors being the best performer by absolute returns. Similarly, the CAPM alpha is highest for the portfolio integrating all three factors (0,59%), and value-low volatility is the worst portfolio (0,35%). The market betas are similar to the mixed long-only portfolios, approximately 0,7. The annualized standard deviations are slightly higher, but higher returns make the Sharpe ratios, on average, approximately 25% higher for the integrated long-only portfolios. The momentum-low volatility portfolio has the highest Sharpe ratio of 0,82.

The worst monthly drawdowns and maximum drawdowns are also quite similar when compared to the mixed long-only portfolios. The average number of stocks in the portfolios integrating two factors is 41, meaning that the portfolios could be implemented without significant liquidity restrictions. However, the portfolio integrating all three risk factors consists only of 16 stocks on average, making the portfolio quite thin.

Table 9: Long-only multi-factor portfolios, integrating

Long-only multifactor portfolios, integrating, July 2004-June 2023

This table shows the returns for long-only smart beta portfolios constructed by integrating value, momentum, and low volatility. The portfolios require that all factor signals are above the 60th percentile breakpoint to include a stock in portfolio. Average monthly absolute returns, CAPM alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Additionally, worst monthly drawdowns and maximum drawdowns are presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Monthly return	0,94%***	0,78%***	0,98%***	*1,01%***
	(2,98)	(2,74)	(3,59)	(3,35)
Monthly CAPM alpha	0,49%***	0,35%**	0,56%***	0,59%**
	(2,68)	(2,44)	(4,11)	(3,23)
CAPM Beta	0,74	0,71	0,68	0,70
Standard deviation	16,43 %	14,87 %	14,20 %	15,78 %
Sharpe	0,68	0,63	0,82	0,77
Worst monthly drawdown	-17,02 %	-19,60 %	-17,16 %	-17,60 %
Maximum Drawdown	-55,23 %	-57,53 %	-48,66 %	-54,17 %
N	38	39	46	16

Table 10 shows the six-factor loadings for the integrated long-only portfolios. Similar to the mixed long-only portfolios, the alphas are statistically insignificant for all four portfolios. All other factor loadings are also similar to the mixed long-only portfolios. The investment factor is practically insignificant. Conversely, the other five factors are statistically highly significant at the 1% level, with the exception being the value-low volatility factor, which exhibits an insignificant momentum signal. On the other hand, momentum-low volatility portfolio has statistically significant HML loading at the 5% significance level, implying the general importance of value stocks in the portfolios. Market betas are approximately 0,6, and the SMB factor shows highest loadings on average, implying that the size effect partially drives the returns. Finally, similar to the mixed long-only portfolios, the R-squared is relatively high for all four strategies, ranging from 0,61 to 0,70, meaning that the independent variables explain, on average, 65% of the variance of the dependent variable. The average r-squared is lower than for the mixed portfolios (65% vs 68%), but the difference is not significant.

Table 10: Six-factor regressions, long-only multi-factor portfolios, integrating

Long-only multifactor portfolios, integrating, July 2004-June 2023

This table shows the returns for long-only smart beta portfolios constructed by integrating value, momentum, and low volatility. The portfolios require that all factor signals are above the 60th percentile breakpoint to include a stock in portfolio. The factor loadings of the 6-factor model regressions are presented. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Alpha	0,12	0,15	0,19	0,23
	(0,57)	(0,82)	(1,13)	(1,08)
MKT	0,67***	0,57***	0,64***	0,61***
	(14,28)	(14,32)	(17,72)	(13,33)
SMB	0,57***	0,42***	0,40***	0,46***
	(4,89)	(4,22)	(4,52)	(4,03)
HML	0,44***	0,55***	0,29**	0,54***
	(2,92)	(4,28)	(2,48)	(3,66)
RMW	0,56***	0,60***	0,59***	0,60***
	(2,71)	(3,45)	(3,75)	(2,98)
CMA	-0,01	-0,27*	-0,24	-0,27
	(-0,06)	(-1,67)	(-1,64)	(-1,41)
MOM	0,24***	0,08	0,24***	0,24***
	(3,52)	(1,37)	(4,63)	(3,61)
R-squared	0,62	0,67	0,70	0,61

5.2.4 Long-short integrated multi-factor portfolios

The results of long-short multi-factor portfolios that integrate low volatility, momentum, and value are shown in this chapter. The long parts of the portfolios are as presented in chapter 5.2.3., stocks that rank in the two highest quintiles (i.e. above the 60th percentile) for all targeted factors are selected for the integrated long portfolio. Similarly, for the short part of the portfolio, stocks that rank in the two lowest quintiles (i.e. below the 40th percentile) for all selected factors are included in the integrated short portfolio.

Table 11 below shows the returns for different long-short portfolios created using the integrating approach. The long-short portfolios perform superiously when compared to both long-only approaches and long-short mixed portfolios. The absolute monthly returns range from 1,48% to 2,00%, indicating an average annualized return of 1,84% for the four integrated long-short portfolios. The CAPM alpha is highest for the momentum-low volatility portfolio (2,22%), and alphas are statistically significant at the 1% significance level for all four portfolios. The market betas are slightly negative, similar to the long-short mixed portfolios. However, the annualized standard deviations are significantly higher than for the long-only integrated portfolios. That leads to Sharpe ratios being lower than for the mixed long-only portfolios.

The worst monthly drawdowns and maximum drawdowns are also higher compared to the long-short mixed portfolios, but lower than for the long-only portfolios constructed by using the mixing and integrating approach. The average number of stocks in the portfolios integrating two factors is 68. As seen in table 9, the average number for the corresponding long-only portfolios is 41, meaning that, on average, a greater number of stocks rank in the two highest quintiles (long) for two selected factors than in the two lowest quintiles (short) at the same time.

Table 11: Long-short multi-factor portfolios, integrating

Long-short multifactor portfolios, integrating, July 2004-June 2023

This table shows the returns for long-short smart beta portfolios constructed by integrating value, momentum, and low volatility. The portfolios require that all factor signals are above the 60th percentile breakpoint to include a stock in the long portfolio and below the 40th percentile to include the stock in the short portfolio. Average monthly absolute returns, CAPM alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Additionally, worst monthly drawdowns and maximum drawdowns are presented. N is the average number of stocks in portfolio. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Monthly return	1,89%***	1,48%***	2,00%***	1,97%***
	(4,58)	(4,07)	(4,23)	(3,44)
Monthly CAPM alpha	2,01%***	1,58%***	2,22%	2,10%***
	(4,89)	(4,36)	(4,82)	(3,65)
CAPM Beta	-0,19	-0,16	-0,36	-0,20
Standard deviation	21,55 %	19,04 %	24,77 %	30,04 %
Sharpe	1,05	0,93	0,97	0,79
Worst monthly drawdown	-22,85 %	-17,92 %	-23,84 %	-27,97 %
Maximum Drawdown	-38,30 %	-41,98 %	-50,45 %	-57,26 %
N	63	67	73	31

Table 12 below shows the six-factor loadings for the integrated long-short portfolios. The alphas are highly statistically significant at the 1% significance level for the portfolios that integrate two factors, and at the 5% significance level for the portfolio integrating all three factors. The six-factor alpha is highest for the portfolio integrating all three factors, 1,35%, and over 1,2% for other portfolios as well. Interestingly, the SMB loading is negative for all portfolios, indicating that the portfolio consists of larger stocks. Thus, it seems that these returns are not driven by the size effect, as opposed to long-short mixed portfolios and both mixed and integrated long-only portfolios. Additionally, HML, RMW, and CMA loadings are not statistically significant, and cannot explain the returns. Momentum is highly statistically significant at the 1% level for all other portfolios expect for the value-low volatility portfolio, which also has a significant momentum loading at the 5% level, but it is now as strong. Finally, the R-squared is only 0,15 on average, meaning that the six-factor model can explain only a small amount of the returns of these long-short integrated portfolios.

Table 12: Six-factor regressions, long-short multi-factor portfolios, integrating

Long-short multifactor portfolios, integrating, July 2004-June 2023

This table shows the returns for long-short smart beta portfolios constructed by integrating value, momentum, and low volatility. The portfolios require that all factor signals are above the 60th percentile breakpoint to include a stock in the long portfolio and below the 40th percentile to include the stock in the short portfolio. The factor loadings of the 6-factor model regressions are presented. T-stats are found in brackets below regression estimates. ***, **, * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Portfolio	Value-Momentum	Value-Low volatility	Momentum-Low volatility	All
Alpha	1,28***	1,22***	1,30***	1,35**
	(3,07)	(3,15)	(2,79)	(2,22)
MKT	0,03	-0,10	-0,04	0,01
	(0,28)	(-1,19)	(-0,42)	(0,11)
SMB	-0,58**	-0,56***	-0,55**	-0,81**
	(-2,59)	(-2,68)	(-2,20)	(-2,46)
HML	(0,13)	0,27	0,04	0,20
	(0,45)	(1,01)	(0,12)	(0,47)
RMW	0,68*	0,54	0,87*	0,77
	(1,72)	(1,47)	(1,97)	(1,34)
CMA	0,43	0,06	0,57	0,13
	(1,15)	(0,17)	(1,36)	(0,24)
MOM	0,56***	0,27**	0,66***	0,59***
	(4,35)	(2,19)	(4,56)	(3,11)
R-squared	0,19	0,10	0,24	0,11

To conclude, integrated long-only multi-factor portfolios generate superior absolute and risk-adjusted returns compared to any long-only single-factor or long-only mixed portfolios. Other multi-factor smart beta studies have found similar results of the superior performance of the integrated approach (see e.g., Bender & Wang, 2016; Chow et al., 2018; Clarke et al., 2016; Fitzgibbons et al., 2016). For example, when combining all studied factors, Bender & Wang (2016) found the integrating approach generating 13 basis points higher Sharpe ratio and Clarke et al. (2016) found 9 basis points better Sharpe ratio for integrated portfolios compared to corresponding mixed portfolios. This study found an even greater outperformance of the integrated approach in the German stock market, 20 basis points (0,77 vs. 0,57). The long-only value portfolio has the lowest risk-adjusted returns among the long-only portfolios, followed by the long-only low volatility portfolio. Long-only momentum portfolio yields better risk-adjusted returns compared to any mixed long-only portfolio, indicating that momentum phenomenon is strongly present in the German stock market.

Long-short portfolios yield superior absolute and risk-adjusted returns compared to long-only portfolios, with integrated long-short portfolios generating highest absolute returns, followed by long-short momentum and mixed portfolios. When considering risk-adjusted returns, long-short mixed portfolios are the top performers, followed by momentum and value portfolios. Long-short integrated portfolios have additional risk, but this risk doesn't result in proportionally increased returns, suggesting that the mixing approach may be more suitable for risk-averse investors.

The results regarding long-only smart beta portfolios align with previous research conducted in other international equity markets. Integrating portfolios generate superior returns for investors, who have leverage or short-selling constraints, compared to mixed portfolios and single-factor portfolios (Bender & Wang, 2016; Chow et al., 2018; Clarke et al., 2016; Fitzgibbons et al., 2016). However, single-factor and multi-factor portfolios should be implemented as long-short, based on both absolute and risk-adjusted returns, if the investor is able to take short positions. In the case of long-short portfolios, using one or a mix of single-factor portfolios may be sufficient, as integrating multiple factors and building portfolios from the bottom-up can include unnecessary risk that doesn't lead to increased returns.

5.3 Limitations

This thesis acknowledges certain limitations, particularly regarding transaction costs and practical implementation, which could serve as avenues for future research. These areas present opportunities for enhancing the applicability of the study's findings to real-world equity investment scenarios.

The first limitation of this thesis concerns the transaction costs associated with the multi-factor strategies. Detzel et al. (2023) explore the effectiveness of various asset pricing models in explaining the variation in returns, factoring in transaction expenses. The findings indicate that the adjustment for costs significantly changes the results of model evaluation exercises. Previous studies in model selection have favored monthly-updating factors, recognizing the advantages of regular updates but ignoring the associated transaction expenses. Compared to models with factors that update only once a year, these models have an unrealizable and misleading advantage. Models that have less frequent rebalancing typically perform better when costs are considered. The integrating approach also has higher turnover compared to the mixing approach, and transaction costs would thus be greater for integrated portfolios. Also, because some of the stocks are small-sized and may have limitations on short selling, long-short strategies should be researched conservatively.

Secondly, this thesis performs Fama & French (2018) six-factor regressions for multi-factor portfolios, to better understand the drivers of returns and exposures to known factors. The factors used are European factors obtained from Kenneth French's database which are converted into euros using the month-end closing spot prices for USD/EUR rates and are thus not optimal for the German stock market. Creating domestic factors that are denominated in euros using the German CDAX returns would enhance the relevance and applicability of the results. The Fama and French's (2018) factors are created by using the highest (lowest) decile for the long (short) parts of the portfolios, while this thesis uses the highest quintile or two highest quintiles for the long-only portfolios, and vice versa for the short parts of the long-short portfolios. However, the multi-factor regressions are still useful in comparing the portfolios studied in this thesis but are not directly comparable to other studies that construct portfolios by different rules.

6 Conclusions

Over the past decade, asset managers have globally invested trillions of dollars in smart beta funds and ETFs. The primary driving force behind examining the performance of various smart beta strategies in the understudied German stock market is the quick and widespread adoption of this investing approach. This thesis examines multi-factor portfolio construction methods, which has emerged as a topic of current academic discussion alongside the growing interest in smart beta investing, and aims to answer whether long-only and long-short smart beta strategies mixing and integrating value, momentum, and low volatility have provided statistically significant abnormal returns over the CAPM and 6-factor model in the German stock market during the research period.

The findings show that both single-factor and multi-factor portfolios consistently outperform the overall German stock market, as measured by CDAX returns. These results are in alignment with previous research, confirming the presence of value, momentum, and low volatility anomalies in the German stock market, which generate superior risk-adjusted returns. Furthermore, when comparing various long-only single-factor and long-only multi-factor portfolios, it becomes evident that integrated long-only multi-factor portfolios consistently deliver superior absolute and risk-adjusted returns. Notably, momentum appears to be a prominent factor in the German stock market, as demonstrated by the higher returns achieved by long-only momentum portfolios in comparison to mixed long-only portfolios. These conclusions regarding long-only smart beta portfolios are consistent with earlier studies conducted in other global equity markets. Integrated portfolios have demonstrated their ability to generate superior returns, particularly benefiting investors with constraints on leverage or short-selling, who are unable to construct long-short portfolios.

Long-short portfolios consistently outperform long-only portfolios both in terms of absolute returns and risk-adjusted returns. Among these, integrated long-short portfolios exhibit the highest absolute returns, followed by long-short momentum portfolio and mixed portfolios. However, when considering risk-adjusted returns, long-short mixed portfolios emerge as the top performers, followed by momentum and value portfolios. Interestingly, the additional risk associated with long-short integrated portfolios is not met with proportionately higher returns. This suggests that risk-averse investors may find the mixed approach more advantageous. Consequently, it appears that using a single-factor portfolio or a mix of several single-factor portfolios is sufficient when constructing long-short portfolios.

Regardless of implementing portfolios as long-only or long-short, it is evident from a comparison of the integrating and mixing approaches that the mixing approach has certain benefits compared to the integrating approach. Through mixing straightforward single-factor smart beta portfolios into a multi-factor portfolio, investors can effortlessly break down their risk and return exposures across the various factors. Thus, mixing makes it straightforward for investors to reweight the exposures for different risk factors. Additionally, the integrating approach includes only a relatively small number of stocks in the investment universe, which may potentially lead to liquidity issues and higher trading costs. Finally, for long-only investors, building portfolios from bottom-up to include stocks with only desired factor exposures may be the optimal approach, while long-short investors may prefer mixing multiple long-short single-factor portfolios in the German stock market.

In summary, this study's findings offer valuable insights into the risk and return attributes of various smart beta strategies. For professional asset managers with an emphasis on the German stock markets, the thesis also offers further documentation about alternative smart beta multi-factor portfolio implementation techniques. Future research could, for example, study the effects of transaction costs, costs associated with short selling and implementation issues for these strategies. Novy-Marx and Velikov's (2022) observations suggest that addressing these issues can offer practitioners valuable insights into the real-world application of these strategies, allowing them to evaluate whether portfolios that are theoretically effective are also viable in practice. Detzel et al. (2023) explore the effectiveness of various asset pricing models in explaining the variation in returns, factoring in transaction expenses. The findings indicate that the adjustment for costs significantly changes the risk-adjusted returns generated by different strategies. Thus, future research could include these costs to better compare mixed and integrated multi-factor portfolios, and to decide if long-short implementation is still more effective compared to long-only, as proposed by this thesis. Additionally, examining smart beta portfolios built with ESG screens may prove to be a useful and novel field of study in the future. Also incorporating other screens that could potentially decrease the gap between theoretical back-testing and practical implementation, for example trading volume, could offer valuable insight for future research.

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