Anette Havana

The performance of risk-managed residual momentum

Evidence from Europe

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Author:	Anette Havana
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ABSTRACT:

In this study, two enhancement methods are applied for residual momentum portfolios – constant volatility-scaling and dynamic volatility-scaling in Europe using daily stock return data from January 1992 to December 2021. Enhanced strategies' applicability to generate higher returns with lower risk is tested and compared with conventional momentum, volatility-scaled methods applied for conventional momentum, and residual return momentum.

Residual momentum delivers statistically significant alpha of 1.20-5.88 % (1.32-5.76 %) on Fama and French's (2015) five-factors, total return, constant (dynamic) volatility-scaled total return, and constant (dynamic) volatility-scaled residual return on the annual level depending on the holding period. Instead, constant (dynamic) volatility-scaled residual return delivers positive significant annualized alpha of 0.72 % (1.68 %) on Fama and French's (2015) five-factors, total return, residual return, constant (dynamic) volatility-scaled total return, only for a six-month holding period. Residual momentum, constant volatility-scaled residual momentum, and dynamic volatility-scaled residual momentum enhance conventional momentum by delivering annualized Sharpe ratios of 0.47-0.68, 0.43-0.57, and 0.39-0.51 respectively, depending on the holding period.

The benefits from the volatility-scaling for residual return momentum are not as strong as presented in the existing literature. However, both constant and dynamic volatility-scaling residual momentum strategies succeed to deliver significant positive alphas, and to improve the Sharpe ratio of conventional momentum.

KEYWORDS: Asset pricing, momentum, residual momentum, risk managing

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TIIVISTELMÄ:

Tässä tutkimuksessa käytetään kahta paranneltua menetelmää residuaali-momentum portfolioihin – jatkuva volatiliteettiskaalaus ja dynaaminen volatiliteettiskaalaus, käyttäen päivittäistä osakedataa Euroopassa tammikuusta 1992 joulukuuhun 2021 asti. Strategioiden soveltuvuutta korkeampaan tuottoon pienemmällä riskillä testataan ja verrataan tavanomaiseen momentum strategiaan, volatiliteettiskaalattuihin momentum strategioihin ja residuaali-momentum strategiaan.

Residuaali-momentum tuottaa tilastollisesti merkitsevän ylituoton vuositasolla 1.20-5.88 % (1.32-5.76 %) jatkuvalla (dynaamisella) volatiliteettiskaalauksella pitoajanjakson mukaan verrattuna viiteen FamaFrench (2015) faktoriin, tavanomaiseen momentumiin ja jatkuvaan (dynaamiseen) volatiliteettiskaalattuun residuuali-momentumiin. Vastaavasti jatkuva (dynaaminen) volatiliteettiskaalattu residuaali-momentum tuottaa tilastollisesti merkitsevän ylituoton vuositasolla ainoastaan kuuden kuukauden pitoajalla 0.72 % (1.68 %) verrattuna viiteen FamaFrench (2015) faktoriin, tavanomaiseen momentumiin, residuaalimomentumiin ja jatkuvaan (dynaamiseen) volatiliteettiskaalattuun momentumiin. Residuaali-momentum, jatkuva volatiliteettiskaalattu momentum ja dynaaminen volatiliteettiskaalattu momentum parantavat tavanomaista momentumia tuottamalla vuosittain pitoajan mukaan 0.47-0.68, 0.43-0.57 ja 0.39-0.51 Sharpen luvulla mitattuna.

Volatiliteettiskaalatun residuaali-momentumin hyödyt eivät ole niin merkittäviä kuin olemassa olevassa kirjallisuudessa esitetään. Sekä jatkuvalla että dynaamisella volatiliteettiskaalatulla residuaali-momentum strategialla onnistutaan kuitenkin tuottamaan tilastollisesti merkitseviä positiivisia ylituottoja ja parantamaan tavanomaisen momentum strategian Sharpen lukua.

AVAINSANAT: Omaisuuden hinnoittelu, momentum, residuaali-momentum, riskikorjaus

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Abbreviations

CAPM	Capital Asset Pricing Model
CMA	Conservative Minus Aggressive
DDM	Dividend Discount Model
EMH	Efficient Market Hypothesis
FF3	Fama and French Three-Factor Model
FF5	Fama and French Five-Factor Model
HML	High Minus Low
MOM	Momentum Portfolio
RMOM	Residual Momentum Portfolio
cMOM	Constant Volatility-Scaled Total Return Momentum Portfolio
dMOM	Dynamic Volatility-Scaled Total Return Momentum Portfolio
cRMOM	Constant Volatility-Scaled Residual Return Momentum Portfolio
dRMOM	Dynamic Volatility-Scaled Residual Return Momentum Portfolio
RMW	Robust Minus Weak
SMB	Small Minus Big

UMD	Up Minus Down

1 Introduction

The theory of efficient markets or the Efficient Market Hypothesis (EMH) by Fama (1970) is one of the most important theories in finance literature. The theory assumes market efficiency and prices reflecting all available information. Prices follow a random walk, so investors cannot know the prices or their development in advance. However, markets are not always efficient, and inefficiencies or anomalies are the main arguments against the efficient market hypothesis.

Momentum is a widely known anomaly in the finance literature and represents one of the main anomalies that contradict efficient market theory and the assumption of random walk. Momentum anomaly refers to the observation that stocks will continue their past price development in the short to medium-term. Thus, it is possible to predict future price developments based on past price data. The momentum anomaly was first introduced by Jegadeesh and Titman (1993). They find that stocks that have outperformed in the past continue to rise and stocks that have underperformed continue to fall in the future. Momentum strategy takes a long position in winner stocks and a short position in loser stocks. Since their research, the momentum has achieved a robust position in the financial markets by providing significant returns to investors.

Despite the success of the momentum anomaly, several problems have been documented in this strategy. After a market downturn and high volatility, momentum strategies have been found to provide negative returns. These momentum crashes usually occur after the market declines when the market begins to recover. In normal times, the winner stock portfolio outperforms the loser stock portfolio, but the opposite happens during a momentum crash. During this period, an investor who follows a momentum strategy goes long in low-beta stocks and shorts high-beta stocks. As the market begins to recover, high-beta stocks rise faster than low-beta stocks resulting in the loss of a significant amount of revenue in the short term due to negatively skewed return distribution (Daniel & Moskowitz 2016).

The challenges of momentum make the strategy less attractive to investors. Several variations have been presented to enhance the performance of conventional momentum strategy and reduce momentum crashes. One approach is residual momentum, first introduced by Blitz et al. (2011), where the stock selection process is based on the stock returns adjusted by Fama and French (1993) factors rather than the total returns, as in the conventional momentum. By ranking stocks on their residual returns helps to isolate the stock-specific component of momentum and the time-varying exposure of momentum to Fama-French factors is reduced. Residual momentum provides higher risk-adjusted results, consistency over time, and strategy is less focused on the extremes of the stocks' cross-section, yet it fails to avoid momentum crashes completely. Another approach in the finance literature is volatility-managed momentum. The reasoning for the approach is to scale the exposure to momentum risk systematically by utilizing the good predictability of momentum volatility and average returns. Predictability enables forecast momentum crashes and reduces risk before these events occur. Strong evidence for this approach is found by Barroso and Santa-Clara (2015) with constant volatility-scaling and Daniel and Moskowitz (2016) with dynamic volatility-scaling.

Despite the robust evidence for both approaches, only a few studies aim to test these approaches in tandem. Whether the residual momentum can be combined with the volatility-managing method is examined only by Chang et al. (2018), Seppä-Lassila (2020) in his master's thesis, and Hanauer and Windmüller (2023). Chang et al. (2018) test two approaches residual momentum by Blitz et al. (2011) and dynamic volatility-scaling by Daniel and Moskowitz (2016) in Japan, whereas Seppä-Lassila (2020) applies constant volatility-scaling by Barroso and Santa-Clara (2015) for residual momentum portfolios in U.S. Partly in their study, Hanauer and Windmüller (2023) examine idiosyncratic momentum (same as residual momentum) with three volatility-scaling methods in international markets. All these studies find robust results for improved performance compared to conventional momentum. This study compares two enhanced momentum strategies by combining residual momentum with two different volatility-scaling methods, constant and dynamic, in stock markets in Europe.

1.1 Purpose and the hypothesis

This study examines the performance of two enhanced momentum strategy by combining residual momentum by Blitz et al. (2011) with constant volatility-scaled momentum by Barroso and Santa-Clara (2015), and with dynamic volatility-scaled momentum by Daniel and Moskowitz (2016). The aim is to test whether constant and dynamic volatility-scaling methods are applicable for residual return momentum in Europe and if these enhanced strategies manage to generate higher average returns with lower risk using different holding periods and applying spanning regressions on Fama and French five-factor model for the strategies. The results are compared with each other and with conventional momentum, volatility-scaled methods applied for conventional momentum, and plain residual momentum to see which strategy performs best.

The reasoning behind residual momentum by Blitz et al. (2011) is to lower the overall risk of the momentum strategy by reducing the time-varying exposure to the common equity factors by using residual returns instead of total returns. The strategy provides higher risk-adjusted returns, consistency over time, and less focus on the extremes of the cross-section of stocks. Thus, the first hypothesis of the study is as follows:

H1: The residual momentum outperforms statistically significantly the conventional momentum strategy in Europe.

However, momentum crashes are not fully inhibited with residual return momentum, and therefore it implies that there might be room for improvement and testing different enhancement strategies is reasoned.

The volatility-scaling aims to benefit from the predictability of the momentum return and risk. The constant volatility-scaling by Barroso and Santa-Clara (2015) exploits the continuity of momentum volatility and the phenomenon in which after the periods of low volatility the high average momentum returns are followed. If similar predictability can be seen in residual momentum returns as in total momentum returns, the constant volatility-scaling method can be applicable for residual momentum too, and therefore the second hypothesis of the study is as follows:

H2: The constant volatility-scaling applied for residual momentum outperforms statistically significantly plain residual momentum and conventional momentum strategies in Europe.

However, Blitz et al. (2020) find later that the market beta of the residual momentum still has some time variation left depending on the market state. This mean-return predictability is not directly considered in the study of Barroso and Santa-Clara (2015) thus Daniel and Moskowitz (2016) apply the dynamic volatility-scaling method to enhance the constant method by including both expected momentum volatility and return and find the results of the option-like momentum behaviour. Since residual momentum has similarities in its volatility and return predictability to conventional momentum, the third hypothesis of this study is as follows:

H3: The dynamic volatility-scaling applied for residual momentum outperforms statistically significantly other momentum strategies presented in this study in Europe.

1.2 Contribution

Even though momentum anomaly is widely studied, it still interests researchers for investigating it and suggesting various enhancements for conventional momentum strategy to improve its performance and reduce momentum crashes. This thesis contributes to the existing literature in various ways and introduces two enhanced momentum strategies in more detail – constant volatility-scaled residual momentum and dynamic volatility-scaled residual momentum.

The only studies that examine the combination of residual momentum and volatility-scaling are made by Chang et al. (2018), Seppä-Lassila (2020), and Hanauer and Windmüller (2023). In the study of Chang et al. (2018), dynamic volatility-scaling for residual momentum is applied in Japan, whereas Seppä-Lassila (2020) combines constant volatility-scaling and residual momentum in U.S. Hanauer and Windmüller (2023) examine three volatility-scaling methods more broadly considering international markets and include idiosyncratic momentum factor (same as residual momentum) only partly in their study.

This study applies two combination strategies – constant volatility-scaled residual momentum and dynamic volatility-scaled residual momentum in Europe. The aim is to examine whether constant and dynamic volatility-scaling methods are applicable for residual return momentum in Europe by providing a comprehensive analysis of their performance and a comparison of their results to see if one strategy performs better than the other.

Although the focus is on two enhanced strategies applied, this study also provides results of the current situation on the performance of the other momentum strategies in Europe stock markets and includes the Covid-19 period as well. This study also analyzes different holding periods and whether they have an impact on the results of momentum strategies in Europe. As Hanauer and Windmüller (2023) provide results either by comparing the U.S. with non-U.S. or countries individually, Seppä-Lassila (2020) in U.S. and Chang et al. (2018) in Japan, this study focuses specifically on Europe.

1.3 Structure of the thesis

The structure of this thesis is as follows. The second chapter discusses on theoretical background by introducing the main theories and models regarding momentum anomaly. The relevant previous studies are introduced in the literature review in the chapter three which encompasses the momentum anomaly in more detail by discussing its existence and possible explanations, performance, and enhanced versions. In chapter four, data and methodologies used in this study are determined. Results are discussed and analysed in the chapter five, and finally, the conclusion summarizes and concludes the study.

2 Theoretical background

This section presents the main theoretical concepts and models regarding momentum anomaly. The first subsample discusses how efficient markets should operate in theory by introducing the most well-known theory of market efficiency - efficient market hypotheses. Different violations of market efficiency, such as anomalies, contradict the theory and its assumption of prices' random walk. Followed by the theory of market efficiency, the second subsample introduces the methods of pricing individual assets by discussing the main asset pricing models in the existing momentum literature.

2.1 Efficient market hypothesis

One of the most important theories in finance, the Efficient Market Hypothesis (EMH), was first introduced by Fama (1970). Investors assume information efficiency at the financial markets when making decisions. One of the assumptions of the Efficient Market Hypothesis is that prices follow a random walk, which indicates that prices cannot be known in advance. If all available and relevant information is incorporated into prices immediately, and investors are unaware of future information, they cannot forecast the development of prices.

Market efficiency prevails when sufficient conditions are met at the markets. Fama (1970) finds three different conditions: first, there cannot be any transaction costs when trading, second, all participants have access to all available information without costs, and finally, all participants agree on the effects of information on current and future prices. Moreover, Fama (1970) finds three forms of efficient market depending on the way prices reflect on the information: weak form, semi-strong form, and strong form.

The weak form of the efficient market hypothesis suggests that current market prices reflect all the past information (Fama, 1970). According to this assumption, all the trading strategies based on past information cannot be profitable. However, as showed in the literature this is not the case, for example, a momentum strategy that relies on past price data. In addition to momentum strategies, several other investment strategies are based on past information such as technical analysis and trend following.

The semi-strong form of the efficient market hypothesis states that market prices reflect all available public information, including the information of the weak form hypothesis. Semi-strong form assumes that all announcements of the events or new information will be incorporated immediately into prices (Fama, 1970). Since the information is adjusted into prices correctly, there should not be under-or overvalued securities at the markets and thus rational investors do not trade too much or little.

Finally, the strong form of the efficient market hypothesis assumes that prices reflect all public and private available information. Due to the availability of insider information, individual investors are not expected to gain superior trading profits (Fama, 1970). Fama (1970) states that strong from efficiency may not represent the real world rather it can be considered as a benchmark when examining the deviations from market efficiency.

Following the limitations of Fama's (1970) efficient market hypotheses, many studies have pressured theory, such as Grossmann and Stiglitz (1980), who stated that markets cannot be fully efficient and all available information is not perfectly incorporated into prices due to the cost of information. In an efficient market, there would be no incentive for investors to find superior information when it is reflected immediately into the market prices. Malkiel (2003) investigates studies related to behavioral finance, momentum investing, and fundamental ratios that contradict the efficient market theory. He questions the claims of these theories and believes in the theory of efficient markets, however, pointing out that there is a difference between market efficiency and pricing in which market misprices securities in the short run.

Anomalies, or the market inefficiencies, are the main arguments against the efficient market hypotheses, as Schwert (2002) states that anomalies either show market inefficiency or the limitations of the underlying asset-pricing model. When anomalies are discovered and released in academics, they will generally diminish or even disappear, and thus, new research findings make the market more efficient as they decrease the performance of anomalies. Schwert (2002) concludes his study by stating that anomalies are more evident than real.

The academic debate for and against the efficient market theory is extensive, making it difficult or even impossible to end up with an unambiguous conclusion. Fama (1970) states that strong form of the efficient hypotheses is not working in the real world making the hypothesis false and raising the question in his later study of efficient market hypotheses (1991) of whether the efficiency of the markets itself can be examined rather than different forms of efficiency. Fama (1991) suggests that either the market is not efficient, or the models are wrong, as discussed below in the study of Schwert (2002). Market efficiency and asset pricing models are an essential part when it comes to anomalies, followed by the efficiency of the market the next chapters discuss different pricing models.

2.2 Asset pricing models

In this section, the most common and widely used asset pricing models are introduced by focusing on the models that are generally used in the momentum literature.

2.2.1 Capital asset pricing model

The Capital Asset Pricing Model (CAPM) was first introduced by Sharpe (1964) and Lintner (1965) leading to the invention of asset pricing theory. Since then, the theory has been widely used in the finance literature becoming one of the most important theories in finance. The theory measures the relationship between systematic risk of an asset and expected return and the model is expressed as follows:

$$E(R_i) = R_f + \beta_{iM} [E(R_M) - R_f], \tag{1}$$

where $E(R_i)$ represents the expected return of an asset *i*, R_f is the risk-free interest rate, coefficient β_{iM} is the market beta of a stock *i*, and factor $E(R_M)$ is the expected market return.

The logic behind CAPM is the modern portfolio theory by Markowitz (1952) in which investors are considered as risk-averse aiming to optimize their portfolio's risk and return relationship and getting a "mean-variance-efficient" portfolio as a result. Furthermore, CAPM considers different assumptions to hold. Investors are assumed to be rational and risk-averse portfolio optimizers that can borrow and lend at the same risk-free rate without transaction costs or taxes. All investors have the same public information, are allowed to short sell, and all securities are available and public for every investor. Finally, investors have similar expectations and the same time horizon to invest (Fama & French, 2004).

Due to these simplifying assumptions and theoretical limitations, CAPM may not be able to explain with sufficient accuracy and thus it has faced a lot of criticism. Even though the model has many limitations and weaknesses, still its popularity seems to remain. Moreover, CAPM represents one of the most important factors in the other asset pricing models that have been developed later to explain factors that CAPM cannot. The next chapters introduce these modern asset pricing models in more detail.

2.2.2 Fama and French's three-factor model

Fama and French (1993) introduced the three-factor model which is an extension of the traditional capital asset pricing model (CAPM) by adding size and value factors in addition to the market factor. This model explains the average excess returns of securities, with the market risk premium from CAPM, and with size factor and book-to-market factor.

The market factor is the market risk premium or market excess return, the size-factor *(SMB, Small minus big)* contains the difference between the returns of small stocks and large stocks, and the value factor *(HML, High minus low)* is the difference between the returns of value stocks and growth stocks (Fama & French, 1993). The model is expressed as follows:

$$R_{i,t} - R_{ft} = \alpha_{it} + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}\ , \tag{2}$$

where expected excess return of the asset *i* at time t is on the left-hand side of the formula. On the right-hand side, the abnormal return of an asset *i* that the model cannot explain is expressed as α_{it}, coefficients or loadings for the market, size and book-to-market factors, are $b_i, s_i, and\ h_i$ respectively, and finally $\varepsilon_{i,t}$ is the error term with zero mean (Fama & French, 1993).

Fama and French (1993) find that market factor alone cannot explain accurately enough the average excess returns but by adding two more factors, size, and value, together they create an appropriate model. The size factor is motivated by the evidence of small stocks' tendency to outperform large stocks, whereas the book-to-market factor is based on that value stocks outperform growth stocks. Even though the three-factor model offers more accurate results compared to the traditional CAPM by explaining the returns of size and book-to-market equity portfolios, the model cannot explain the expected returns of all different securities or portfolios. Fama and French (1996) find that the three-factor model cannot explain the momentum profits, in other words, the model is unable to explain the continuation of returns on a short-term presented by Jegadeesh and Titman (1993) and Asness (1994).

2.2.3 Carhart's four-factor model

Motivated by Jegadeesh and Titman (1993) and Asness (1994) insights of momentum anomaly, and Fama and French (1996) results of three-factor model's disability to explain momentum profits, Carhart (1997) expands the three-factor model by adding momentum factor (WML, Winner minus loser) into the model to explain the mutual fund performance. The momentum factor is the difference between stocks with momentum one-year return and stocks with a one-year contrarian return. The model is expressed as follows:

$$R_{i,t} - R_{ft} = \alpha_{it} + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + p_i WML_t + \varepsilon_{i,t} \quad (3)$$

The model is similar as three-factor model, except it adds the fourth factor, $p_i WML_t$, into the examination. Loading for the momentum factor is determined as p_i, and the momentum *(WML, Winner minus loser)* is the momentum portfolio's excess return where the purpose is to go long in past winner stocks and short the past loser stocks as determined by Jegadeesh and Titman (1993). By adding the momentum factor, Carhart (1997) finds that it improves the average pricing errors that occurred in the CAPM and three-factor model.

2.2.4 Fama and French's five-factor and six-factor models

Due to the criticism of Fama and French's (1993) three-factor model about its disability to explain average excess returns of all securities and portfolios, Fama and French (2015) suggest an extension of the model by adding two more factors into the model, profitability, and investment. Fama and French's (2015) five-factor model explains better the portfolio's excess return variation, especially the anomalous returns. A profitability factor (RMW, Robust minus weak) considers the difference between robust profitability portfolio returns and weak profitability portfolio returns. An investment factor (CMA, Conservative minus aggressive) is the difference between conservative portfolio returns and aggressive portfolio returns. The formula is expressed as follows:

$$R_{i,t} - R_{ft} = \alpha_{it} + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t} , \quad (4)$$

where the components from three-factor model remain the same. The five-factor model adds two factors into the model, the profitability $r_i RMW_t$ and investment $c_i CMA_t$, where r_i and c_i represent the loadings for the factors. Both RMW_t and CMA_t provide excess returns of long-short portfolios, in which RMW_t goes long in robust profitability stock and shorts weak profitability stocks, instead CMA_t takes a long position in conservative investment stocks and short aggressive investment stocks (Fama & French, 2015).

Fama and French (2015) browse a wide range of different factors ending with the choice of profitability and investment factors. This selection is motivated by another pricing model, the dividend discount model (DDM), and the findings of Novy-Marx (2013), Titman et al. (2004). According to the findings of Novy-Marx (2013), higher expected profitability leads to higher expected returns, considering other variables constant. Moreover, Titman et al. (2004) suggest that there is a negative relationship between expected investments and expected returns. The five-factor model offers more accurate results compared to the three-factor model by explaining anomalous returns, however, its main problem is the disability to explain low average returns on small stocks when the returns are similar to firms' that make a lot of investments regardless of the low profitability.

Followed by the study of Fama and French's (2015) five-factor model, they conduct a study (2016) in which they provide evidence that the five-factor model explains anomalies that the three-factor model cannot. They construct the portfolios and examine several anomalies: market beta, net share issues, low volatility, accruals, and momentum, and regress the five-factor model against them. They find that these anomalies are the main anomalies that their previous three-factor model cannot explain. According to the results, the list of anomalies decreases when composing the regressions with the five-factor model. On the one hand, this is due to the situation where returns of many anomalies are reduced when regressing with the five-factor model, i.e., the returns become less anomalous. On the other hand, different anomaly variables have similar factor exposures in the regressions and thus indicating that they are the same phenomenon (Fama & French, 2016).

As Fama and French (1996) stated, the three-factor model cannot explain the momentum profits, Fama and French (2016) find the same phenomenon with their five-factor model (2015). They add momentum factor, MOM, as the sixth factor to the model but find that it does not add explanatory power significantly for anomalies other than momentum. According to their findings, models without momentum factor underperform in the tests but still, authors believe momentum is a rough estimate and leading a lot of momentum profits unexplained in “the six-factor model” (Fama & French, 2016).

Due to the public pressure rather than its theoretical motivation, Fama and French (2018) add a new factor into the five-factor model, momentum factor (UMD, up minus down). Generally, the momentum factor can be termed UMD, MOM, or WML. The momentum factor contains the long-short portfolio which includes the difference in excess returns by going long on best-performing stocks historically and shorting the weakest ones. The six-factor model by Fama and French (2018) is expressed as follows:

$$R_{i,t} - R_{ft} = \alpha_{it} + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + m_i UMD_t + \varepsilon_{i,t}\ , \tag{5}$$

where the components from five-factor model remain the same. The six-factor model adds the momentum $m_i UMD_t$ into the model, where m_i being the loading for the UMD_t factor. According to findings of Fama and French (2018), the six-factor model tend to outperform the CAPM and five-factor model. Moreover, the model with small stocks and cash profitability RMW_C instead of operating profitability RMW_O, appears to be the best model to examining portfolio excess returns. Despite their results, examining momentum and including it into the models as a factor, is not an unambiguous issue, and they conclude that even though momentum factor has robust performance in the tests it still lacks theoretical motivation. The next chapters discuss momentum anomaly in more detail.

3 Literature review

During the past decades, many investing strategies have challenged the efficient market hypothesis. The momentum anomaly represents the widely known anomaly in the finance literature that contradicts the theory of efficient markets. The academic debate around momentum anomaly is wide. This phenomenon has been extensively studied by researchers providing results on its existence and possible explanations, performance, and its enhanced versions. The following chapters address these issues, among others.

3.1 Momentum anomaly

Momentum anomaly is a well-known and generally accepted in the academic world that exists during different times, in many asset classes and geographical areas (Asness et al., 2013). Commonly, the momentum phenomenon refers to the observation that assets will continue their past price development in the future. In other words, this theory states that stocks that have outperformed in the past continue to rise and stocks that have underperformed continue to fall. Momentum strategy lies in the theory in which investors are betting for historical good and bad performances to continue in the future (see Jegadeesh & Titman, 1993).

The momentum anomaly was first introduced by Jegadeesh and Titman (1993) who test the mid-term momentum strategy for common US stock returns from the New York Stock Exchange (NYSE) and American Stock Exchange from 1965 to 1989. Based on the returns of the past 3 to 12 months of certain stocks (excluding the recent month), they rank them into ten deciles where the winner stocks are in the top decile and loser stocks in the bottom decile. They buy the winner stocks (top 10 % portfolio) and sell the loser stocks (bottom 10 % portfolio) and hold this portfolio for 3- to 12-month holding periods. By repeating this action every month, they will have a long position in 12 winner portfolios and a short position in 12 loser portfolios after each time point. According to their main finding, strategy in which they buy past winners and sell past losers generates significant abnormal returns, and for example, the stocks based on their past six months return yield 12.01 % per year on average when holding them for six months. After this first study of the existence of momentum anomaly, the phenomenon has motivated researchers to examine it from other perspectives as well.

In many different geographical areas, there is a momentum effect found. Followed by the study of Jegadeesh and Titman (1993) from the U.S., Rouwenhorst (1998) investigated the momentum phenomenon at the European stock market during 1978 and 1995. He finds that the winner stocks outperform loser stocks by an average of one percent per month which is consistent with the findings of Jegadeesh and Titman (1993). When Rouwenhorst's (1998) study focuses on developing countries, his later study in 1999 considers the momentum effect in emerging equity markets. The momentum effect is found in country indices by Asness et al (1997) as well as different industries by Moskowitz and Grinblatt (1999), and Grobys and Kolari (2020).

The momentum phenomenon is studied not only in different regions but also in different periods. Gutierrez and Kelley (2008) examined the existence of momentum in a short period by conducting a weekly study of a portfolio that has a long position in last week's winner stocks and a short position in last week's loser stocks. They find that this portfolio generates positive profits during the 52 weeks and the state momentum effect is the main reason for the weekly returns. In the contrast, many studies have examined the momentum effect in extended periods (e.g., Jegadeesh & Titman, 2001; Israel & Moskowitz, 2013), ending up to the same conclusion as previous studies.

In addition to equity, momentum anomaly is examined in several other asset classes. For example, Luu and Yu (2012) apply study in fixed income (e.g., bonds), whereas the studies of Erb and Harvey (2006), and Moskowitz et. al (2012) offer an examination of momentum in commodities. Finally, Menkhoff et al. (2012), and Okunev and White (2003) study momentum in currencies. All these studies find robust results of momentum effect in the specific asset class. Comprehensive research of the existence of momentum conducted by Asness, et al. (2013), examines momentum in several stock markets (US, U.K., Japan, and Europe) and several asset classes (different futures, government bonds, and currencies) and find momentum everywhere. Even though previous studies find the success of momentum in different currencies, momentum in cryptocurrencies is not much researched in the literature. Grobys and Sapkota (2019) aim to fill the gap by examining the existence of momentum anomaly in the cryptocurrency market. As previous studies find momentum despite the asset class, contrarily Grobys and Sapkota (2019) find no significant momentum effect in the cryptocurrency market.

To conclude the findings, the momentum is extensively studied and found to be profitable in many different regions, periods, and markets, with some exceptions. Many studies have shown the existence of momentum anomaly, yet there is no unanimous view of the explanations for momentum.

3.2 Explanations of momentum anomaly

Although the literature agrees on the existence of momentum, there is no consensus among academics on the causes of the momentum phenomenon. Academics have suggested that explanations can be divided into two main categories: rational and behavioural reasons (Hur & Singh, 2019).

The rational explanations assume that momentum strategy returns are due to the high risk taken. Researchers have proposed various risk-based models to explain the abnormal returns of the momentum strategy. Before the 21st century, studies by Conrad and Kaul (1998), Berk et al. (1999), and Moskowitz and Grinblatt (1999) suggested different risk-based explanations of momentum. Conrad and Kaul (1998) examine trading strategies based on series patterns in security returns by introducing two strategies – momentum and contrarian. They find that the cross-sectional variation in expected return is resulting in momentum profits, rather than the predictable time-series variations in stock returns. Instead, Berk et al. (1999) propose that the profitability of momentum is due to the positive autocorrelation of expected stock returns and the systematic risk of companies is compensated with momentum return. In the 2000s before the financial crisis, several studies applied to aim to explain the momentum effect by its risk. Johnson (2002) finds that momentum returns are linked to the company growth rates in which the past winners (losers) with positive (negative) shocks at the expected growth rate will show an immediate increase (decrease) in stock prices. Bansal et al. (2005) examine the relationship between consumption risk and momentum profits, finding that profit can be due to consumption risk included in the cash flows. The effect is also examined more recently, for example, by Li (2017), and Ruenzi and Weigert (2018). Ruenzi and Weigert (2018) propose a risk-based model in which they control the crash risk of the momentum strategy and find that the profitability reduces significantly. They apply the study in the U.S., but their findings remain robust also in international samples.

Researchers supporting the behavioural explanations propose causes divided into three categories: initial overreaction, initial underreaction, and the disposition effect. These reasons seek to explain the momentum anomaly and abnormal returns it generates. Initial overreaction means a situation where the value of security differs from its intrinsic value causing short-term momentum (see Daniel et al., 1998; Hillert et al., 2014; Adebambo and Yan, 2016). Daniel et al. (1998) proposed two reasons for overreaction and thus short-term momentum effect: overconfidence and self-attribution bias. Overconfidence is defined as an investor who overestimates the private information over public information which causes the stock price to overreact, whereas self-attribution enhances the overreaction if public information supports the private information. Increased overconfidence supports the initial overreaction leading the short-term momentum returns, whereas self-attribution corrects the overreaction in prices resulting in long-term reversals. Research by Hillert et al. (2014) examines the price overreaction by studying the effect of media on momentum anomaly in the U.S. They suggest that media coverage can further increase investor biases leading to predictability in the prices of companies in the public spotlight.

Instead of overreaction, some researchers support the idea of underreaction as an explanation for momentum (see Barberis et al.,1998; Hong & Stein, 1999), Hong et al., 2000; Da et al., 2014; Chen & Lu, 2017). Barberis et al. (1998) present a model that combines two behavioral aspects: conservatism and representativeness heuristic. Conservatism refers to the tendency of investors to believe in previous information and the slow change of beliefs as new information arrives, when representativeness heuristic investors believe that past information represents a general view in the future. These factors lead to an underreaction of the stock price and thus to a change in its intrinsic value. Hong and Stein (1999) create a gradual-information-diffusion model based on two types of investors: news watchers and momentum traders. The investment decisions of news watchers are based on the expected future values due to the access to private information, but they do not consider current or past prices. On the contrary, momentum traders take no information other than past in their investment decisions. According to their findings, gradual dissemination of information among news-watchers causes the momentum effect. Further research by Hong et al. (2000), Da et al. (2014), and Chen and Lu (2017), test the model by Hong and Stein (1999) finding supporting results.

The behavioural explanation that considers the disposition effect as the reason for momentum refers to the tendency of investors selling outperforming stocks too early and holding underperforming stocks for too long, for example, Grinblatt and Han (2005), Hur et al. (2010), and Hur and Singh (2019). Grinblatt and Han (2005) divide investors into two groups: rational and disposition investors. They propose a model in which the behavior of disposition investors causes the difference between the current price and the intrinsic value, and rational investors take long or short positions in stocks which increases the upward or downward momentum even further. Supporting evidence of disposition effect is offered by Hur et al. (2010) considering individual investors, and Hur and Singh (2019) who show disposition effect and anchoring effect together explain the momentum profits.

To conclude, the causes of the momentum phenomenon are extensive, and no single explanatory reason could be determined. Depending on the reasons, academics have tried to find ways in which the returns of the momentum phenomenon can be utilized even better by creating different improved versions of momentum.

3.3 Enhanced momentum strategies

The momentum phenomenon is widely documented in various markets and asset classes and has proved to generate abnormal returns for investors relative to the level of risk. However, during the post-crisis period in 2009, conventional momentum strategies performed poorly and faced a significant collapse (Moreira & Muir, 2017). This was one of the main reasons for researchers to find alternative strategies that improve conventional momentum performance even in times of crisis.

Although most enhancement momentum strategy researches were conducted after the financial crisis, the first version of the enhanced momentum strategy was already introduced by George and Hwang (2004). They suggest that the superior performance over conventional momentum is possible to gain when the stocks are selected based on the ratio of their current prices to the high prices during the past 52-week. Supporting evidence of the profitability of a 52-week high momentum strategy was found by Marshall and Cahan (2005), Du (2008), and Liu et al. (2011). However, more recent studies show that both conventional momentum and 52-week high momentum strategies were still outperforming during periods of high volatility, for example, Wang and Xu (2015), Min and Kim (2016), and Daniel and Moskowitz (2016).

Time-series momentum or absolute momentum is one of the well-known conventional momentum enhancement strategies introduced by Moskowitz et al. (2012). In this strategy, financial assets are selected based only on their past price performance, ignoring other assets' price performance. After this first study of time-series momentum, much research has supported their findings of the profitability of time-series momentum over conventional momentum (see, He & Li, 2015; Goyal & Jegadeesh, 2018; Lim et al., 2018). Despite the success of time-series momentum, recent studies have challenged the findings of Moskowitz et al. (2012) and for example, Huang et al. (2020) examine the phenomenon in their study finding no strong evidence of time-series momentum regardless of the asset.

Another type of momentum is residual momentum, first presented by Blitz et al. (2011). When conventional momentum strategies sort winner and loser stocks into 10 % deciles based on the total returns, residual momentum strategy uses residuals instead of totals. The strategy uses past 12-month residual returns adjusted by Fama-French factors. The strategy is based on Grundy and Martin's (2001) discovery that conventional momentum strategies show significant time-varying exposures to Fama-French factors. When a conventional momentum strategy buys the best-performing stocks and short-sells the worst-performing ones, it leads to poor momentum returns if the sign of the factor returns changes. For example, during a recession, the conventional momentum relies on low-beta stocks against high-beta stocks. As the market recovers, the problem with conventional momentum is that high-beta stocks are increasing faster than low-beta stocks. The residual momentum strategy aims to avoid this problem. Recent studies support the superiority of the residual momentum over the conventional momentum and find investor underreaction to explain its existence (Chang et al., 2018; Blitz et al., 2020).

Residual momentum seeks to correct the problem of conventional momentum, where the strategy faces large losses of returns during market recessions. Instead, some researchers suggest volatility-scaling methods to avoid these momentum crashes (Wang & Xu, 2015; Barroso & Santa-Clara, 2015; Kim et al., 2016; Daniel & Moskowitz, 2016). Barroso and Santa-Clara (2015) propose a risk-managed momentum strategy, an improvement of the conventional momentum strategy. This strategy scales the exposure to momentum risk by using the actual volatility due to its high predictability. In times of high volatility, momentum risk management reduces exposure to crashes, negative skewness, and excess kurtosis of conventional momentum. Instead of constant volatility-scaling, Daniel and Moskowitz (2016) propose an alternative approach - dynamic volatility-scaling, which is based on forecasts of mean and variance of momentum. Strategy improves the performance of conventional momentum by doubling the alpha and Sharpe ratio. They find these results to be robust in several equity markets, asset classes, and during different times.

After the famous studies of risk managing by Santa-Clara (2015) and Daniel and Moskowitz (2016), much research has exploited the methods and findings in their studies (cf. Chang et al., 2018; Grobys et al., 2018; Gao et al., 2022; Hanauer & Windmüller, 2023). Chang et al. (2018) apply their study of dynamic volatility-scaling by Daniel and Moskowitz (2016) to both conventional momentum and residual momentum strategies in Japan. They provide supporting evidence of the success of dynamic volatility scaling. Grobys et al. (2018) include both volatility-scaling methods in their analysis of industry momentum. According to their findings, there are no optionality effects found from either conventional industry momentum or risk-managed industry momentum strategies, and therefore their betas are not time-varying. Despite the different subsamples, momentum strategies, or estimators for volatility, their supporting findings for risk management remain robust.

Recently, the study of Gao et al. (2022) extends the findings of Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Barroso et al. (2020) by applying a Partial Moment Momentum trading strategy in which they use past partial moments for scaling and when the upper (lower) partial moments are predicted to be large, they load long (short) positions. They find that their method provides improved risk-adjusted performance compared to conventional momentum and volatility-managed momentum strategies. Hanauer and Windmüller (2023) provide an analysis of three enhanced momentum strategies by including constant semi-volatility-scaled momentum in the analysis which is first introduced by Wang and Yan (2021). They find enhanced strategies to improve the performance of conventional momentum. A lot of research has been done on these two famous methods and thus discussed studies only represent a small part of the existing literature.

In addition to mentioned enhancement strategies, several studies aim to improve conventional momentum by testing different strategies in tandem, such as mean reversion and momentum (Serban, 2010), value and momentum (Asness et al., 2013), cross-sectional and time-series momentum (Lim et al., 2018), risk-managing and time-series momentum (Singh et al., 2022), idiosyncratic momentum (similar as residual momentum) and volatility-scaling (Chang et al., 2018; Hanauer & Windmüller, 2023). The study of Chang et al. (2018) examines residual momentum by Blitz et al. (2011) with the combination of dynamic volatility-scaling by Daniel and Moskowitz (2016) in Japan. The study of Hanauer and Windmüller (2023) test idiosyncratic momentum and three volatility-scaling methods partly in their study in international markets (U.S. vs. non-U.S. samples). Both studies find robust results of higher average returns, Fama and French three-factor alphas, and Sharpe ratios. Moreover, less researched, and other versions of momentum in the existing literature are for example, alpha momentum proposed by Hühn and Scholz (2018), absolute strength momentum by Gulen and Petkova (2018), and Antonacci's (2014) analysis of dual momentum.

In the existing literature, various alternative strategies aim to improve conventional momentum performance even in times of crisis. However, not all versions work and there are always limitations that should consider. Volatility-managing and possible limitations and criticisms are discussed in the next chapter.

3.4 Volatility-managing and limitations

Existing literature finds the success of volatility-managing for various strategies however the method also faces criticisms and limitations. Strong evidence of the success of volatility-managed momentum strategies is shown in the literature, additionally, many studies find an improved performance by applying volatility-managing for other well-known trading strategies. For example, Ang (2014), and Moreira and Muir (2019) combine market with volatility-managing, Daniel et al. (2017) and Maurer et al. (2018) propose volatility-managed currency strategies, betting-against-beta is applied by Barroso and Maio (2017), and the recent study of Eisdorfer and Misirli (2020) examines financial distress with volatility-managing. The famous study of Moreira and Muir (2017) applies a volatility-scaled portfolio strategy and finds its success across a wide range of asset pricing factors in spanning regressions. They show that the performance of these portfolios is not explained by the risk of the business cycle, leverage constraints, risk parity factors, transaction costs, or volatility measurement methods.

Despite the success of volatility management, some studies find contradicting results. One limitation relates to the volatility-timing and the look-ahead bias. It occurs when it is assumed that a positive regression alpha expands the investor's mean-variance frontier, and then the investor should know the full-sample factors such as volatility and mean return in advance, which is not possible. As the study of Moreira and Muir (2017) finds the success of volatility management, Liu et al. (2019) challenge these results by finding evidence of look-ahead bias. The study of Moreira and Muir (2017) uses the full-sample volatility for the portfolio weight-scaling, and even correcting the look-ahead bias, Liu et al. (2019) find volatility-scaled market portfolios outperform and face large drawdowns which make it difficult to apply the strategy.

To continue the analysis of the look-ahead bias, Cederburg et al. (2020) apply an extensive analysis by examining 103 equity strategies and the performance of volatility-managed portfolios in real time. They show that volatility managing does not always improve the performance of portfolios compared to the corresponding portfolios without managing. In spanning regressions, they find similar results as Moreira and Muir (2017), however, these regressions are not applicable in real-time, and therefore these portfolios outperform when applying out-of-sample tests compared to the investments in the unmanaged portfolios. Despite their finding that the performance of equity anomalies cannot be generally improved by volatility managing, only a few strategies challenge this. In their study, momentum represents one of the strategies that can generate higher Sharpe ratios and returns with real-time volatility management and succeeds in both in-sample and out-of-sample volatility-scaling regression tests. Similar results are provided by Barroso and Detzel (2021) who examine whether limits-to-arbitrage explains the success of volatility-managed portfolios finding that the momentum factor becomes profitable even after transaction costs and when it is scaled by its realized volatility.

Related to the timing, another limitation is the problem of data mining which occurs when investors time their investing in anomalies (Novy-Marx, 2014). This pattern is suggested for example in studies of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) who apply a volatility-scaling for the momentum strategy. Data mining is also closely related to the phenomenon of anomalies disappearing after the discovery due to market inefficiency and mispricing (McLean & Pontiff, 2016).

4 Data and methodology

The data and portfolio construction methodology are described in this chapter. In the first subchapter, the data is explained in more detail, whereas the second subchapter discusses the construction of momentum strategies and their volatility-scaling methods.

4.1 Data

The data sample consists of all common publicly traded stocks listed on the stock markets in Europe. Consistent with the studies of Fama and French (2012), and Tikkanen and Äijö (2018), the dataset of this study includes companies from the following countries in Europe: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The dataset comprises the daily adjusted closing prices for all stocks during the period from January 1992 to the end of December 2021, which are collected from the Thompson Reuters DataStream. The period represents the time when European stock markets have mostly been active, and due to the limitations of the Thompson Reuters DataStream, the data is available only from the beginning of 1992 for all the countries in this study. However, the period is long enough to implement a momentum study.

In addition to the daily price data, dataset includes accounting-based data for market capitalization and firm-based data for equity type, exchange, listing currency, sector, and symbol for all stocks, which are from the Thompson Reuters DataStream. The data for the common factors (excess market return, size, value, profitability, investment) and the United States one-month T-bill rate as a risk-free rate are extracted from Kenneth French's website[1]. To compare the results, all data is in U.S. dollars and thus the view of the study is an American investor.

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

To better apply momentum strategies in practice, all illiquid stocks are removed from the sample (see Chaves et al., 2012; Moskowitz et al., 2012; Asness et al., 2013). This is applied by dividing the stocks into five groups based on their market capitalization and then subdividing each group into five (momentum) quantiles based on the stock's cumulative return. The first group comprises 90 % of the total market capitalization and is the best representative of the markets therefore this group is only used in this study. The highest (lowest) momentum quantile comprises the top (bottom) 20 % of the first group's stocks. The momentum portfolios are formed based on the past cumulative return and skipping the most recent month (12 – 1 month) and repeating the action each month for a different holding period (from 1 to 12 months).

4.1.1 Static and dynamic screens

Many static and dynamic screens were made for the data in this study. Static screens are based on the DataStream filters. To be included into the dataset, the type of the security must be equity (Ince & Porter, 2006), and only the primary quotations of the security are considered (Fong, et al., 2017). Followed by Griffin et al. (2010), the security must be listed in the respective domestic country. Securities that contain non-common stock affiliation in their name field (i.e., NAME) are removed from the sample (see Ince & Porter, 2006; Griffin et al., 2010). Moreover, the dataset excludes closed-end funds, deposit receipts, duplicates, debt, expired securities, foreign securities, illiquid securities, preferred securities, REITs, unit trusts, and warrants. These are excluded by searching harmful keywords from the names of all securities of all countries (see Ince & Porter, 2006; Hanauer & Windmüller, 2023).

In addition to statis screens, there are several dynamic screens made in the data. To avoid survivorship bias, stocks that are delisted during the holding period are included into the sample. After the delisting, the return is assumed to be zero and the associated market capitalizations are removed from the sample (see Ince and Porter, 2006; Hanauer & Windmuller, 2023). In the case of unadjusted prices (higher than 1 million), respective returns and market capitalizations are removed from the sample (Schmidt et al., 2017; Hanauer & Windmuller, 2023). Daily (monthly) returns and associated market capitalizations are removed from the sample if there are return spikes, i.e., daily (monthly) returns are more than 200 % (990 %). Return spikes are removed from the sample because of the concern of data error and to be consistent with the studies of Griffin et al. (2010), Schmidt et al. (2017), and Hanauer and Windmuller (2023). Finally, Table 1 shows the country-specific descriptive statistics of the sample for the accounting-based data after various screens made in the dataset.

Table 1. The descriptive statistics.

The table presents the descriptive statistics for the 16 countries of the Thompson Reuters DataStream sample. The first column shows the country. The column two presents the total number of companies in each country. The columns three, four, and five show the minimum, the maximum, and the average number of companies in each country per month. The column six states the average mean size per country per month, and finally the last column shows the average total size per country per month. The size is defined as market capitalization in million U.S. dollars. The requirement for the companies is to have non-missing values in both return and market capitalization in certain month. The sample period is from 1992:01 to 2021:12.

Country	Total no. firms	Min no. firms	Max no. firms	Avg. no. firms	Mean size	Avg. total size
Austria	59	10	30	20	3803	68162
Belgium	81	20	39	30	6956	207933
Denmark	82	14	39	28	6553	184386
Finland	92	3	43	30	6130	183074
France	444	114	168	135	10747	1455350
Germany	414	99	161	115	9710	1113205
Greece	102	4	74	16	2991	47434
Ireland	36	5	20	12	6543	77438
Italy	225	31	89	66	6909	452923
Netherlands	133	24	56	42	10019	417074
Norway	141	8	51	28	5413	149578
Portugal	38	4	20	12	4290	49722
Spain	161	33	78	53	9166	489106
Sweden	239	2	111	68	5476	371544
Switzerland	220	30	114	80	12252	981690
United Kingdom	914	1	298	246	8869	2185996

4.2 Methodology

This subsample introduces the methodology used in this study by discussing the construction of conventional momentum and residual momentum portfolios and applied volatility-scaling methods.

4.2.1 Construction of momentum portfolios

The purpose is to form both conventional momentum portfolio with total returns and residual momentum with residual returns and later compare these results. Both momentum portfolios are formed each month based on the past 12 months cumulative returns (excluding the most recent month) in which the 20 % of the highest (lowest) returns are determined in the top (bottom) decile and repeating the action each month for a different holding period. Consistent with the previous momentum literature, the stocks will be weighted equally in each decile portfolio (see Fama & French, 1992; Carhart, 1997; Blitz et al, 2011; Chang et al., 2018). For example, Chang et al. (2018) use equal weighting in their study, but also test value weighting and find that their results remain robust. Furthermore, following the methods of Jegadeesh and Titman (1993, 2001), the deciles will be composed separately for monthly, quarterly, semi-annual, and yearly holding periods.

The formation of a residual return momentum portfolio is consistent with the methods of Blitz et al.'s (2011) study. Their analysis follows the common momentum strategies by first forming portfolios based on past returns and then applying factor regression analyses of the (overlapping) portfolio returns obtained on common risk factors. The analysis begins with the allocation of stocks to different portfolios depending on past returns over 12 months by excluding the most recent month. The exclusion of the most recent month from the analysis is based on the aim to separate the intermediate-term momentum effect from the short-term reversal effect (see Jegadeesh, 1990 & Lehmann, 1990). The estimated residual returns for the stocks are determined each month by utilizing the following Fama and French (1992) three-factor model:

$$R_{i,t} - R_{ft} = \alpha_{it} + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \,, \tag{6}$$

where on the left-hand side of the formula R_{it} is the return on stock i at time t, and R_{ft} represents the risk-free rate in month t. On the right-hand side, α_{it}, is the abnormal return of an asset i that the model cannot explain, the coefficients or loadings for the market, size, and book-to-market factors, are $b_i, s_i, and\ h_i$ respectively, and finally $\varepsilon_{i,t}$ is the residual return of a stock i in a month t (Fama & French, 1993). In the regression analysis, the aim is to conduct a three-year estimation window (from t – 36 to t – 1) when estimating Eq. (8) at the beginning of each month t. The period enables to obtain enough return observations and thus the estimates for stock exposures to the market, size, and value are accurate (Chang et al., 2018).

The regression analysis is conducted by utilizing monthly returns which are compounded from daily stock returns including only the stocks that have a complete return history during the 36-month estimation window. Blitz et al. (2011) test both Fama-French three- and five-factor models and show in their later study (2020) that the five-factor model improves residual returns only marginally, and thus adding two factors more are only making the model more complex without a significant difference in results.

The alpha is removed from the calculation process of residual returns due to its tendency to distort the expected stock returns. For example, if the asset pricing model that should be used in this calculation is something else rather than the Fama-Fama three-factor model, the alpha would seek to capture the difference. Additionally, considering the alpha in the residual returns would cause the residuals to affect both the intermediate-term momentum effect and the long-term reversal effect when using the previous estimation window of 36 months. Based on these reasons, the residual return is only measured by epsilon which is the cumulative past return over 12 months (excluding the most recent month) (Blitz et al., 2011; Chang et al., 2018).

4.2.2 Volatility-scaling for momentum portfolios

Risk-managing methods are applied to the portfolios after the formation of momentum portfolios. The purpose is to apply constant volatility-scaling by Barroso and Santa-Clara (2015) and dynamic volatility-scaling by Daniel and Moskowitz (2016) for both the conventional momentum and residual momentum portfolios for the later comparison of the results.

Volatility-scaling aims to manage realized volatility of a strategy. Momentum strategies have shown that realized volatility has a positive correlation with future volatility and a negative correlation with future returns, with realized volatility being significant compared to other factors (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Moreira & Muir, 2017). This study examines the potential capacity of volatility-scaling methods to improve the Sharpe ratio through two identified ways – volatility smoothing and volatility timing. Smoothing is related to the lowered ex-post volatility, whereas timing captures the negative correlation between volatility and returns by improving the returns.

However, the positive autocorrelation is not captured directly by volatility-scaling in the monthly momentum strategy and thus the controlling of the realized return can be done to be able to capture it. Considering these aspects at the strategy level, the estimations of returns and volatilities enable the creation of scaling weights such that the Sharpe ratio of momentum strategy will be improved. Being a zero-investment and self-financing strategy, momentum returns can be scaled without constraints weighting the long and short legs that vary over time.

The constant volatility-scaled momentum strategy by Barroso and Santa-Clara (2015) adjusts the exposures of a strategy to have a constant risk over time by using an estimate of a momentum risk. The weight of a momentum portfolio with a constant volatility-scaling in a month t is as follows:

$$\omega_{cMOM,t} = \frac{\sigma_{target}}{\hat{\sigma}_t}, \tag{7}$$

where $cMOM$ refers to a total return momentum (the weight is calculated for the residual return momentum, $cRMOM$ as well). The level of a constant volatility target,

σ_{target} , is adjusted such that the full sample volatility of total (residual) return momentum and the volatility of volatility-scaled momentum (total and residual) are identical. The forecasted expected volatility is referred as $\hat{\sigma}_t = E_{t-1}[\sigma_t]$, and as it is not constant the weight for the constant volatility-scaling momentum varies over time. Consistent with the method of Barroso and Santa-Clara (2015), the monthly volatility forecast is calculated from the past daily momentum returns in the previous six months (126 days) in month t as follows:

$$\hat{\sigma}^2_{MOM,t} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t}}{126}, \tag{8}$$

where $R^2_{MOM,d-j,t}$ is referred as the summed squared realized daily momentum return over the previous six months. Finally, the return in a month t, $R_{MOMc,t}$, is calculated by scaling the momentum return with the inverse of the realized volatility as follows:

$$R_{cMOM,t} = R_{MOM,t} \cdot \omega_{cMOM,t}, \tag{9}$$

Dynamic volatility-scaled momentum by Daniel and Moskowitz (2016) aims to improve the constant volatility-scaled momentum strategy by including the expected return in the analysis in addition to the expected volatility. The weight of a momentum portfolio with a dynamic volatility-scaling in a month t is as follows:

$$\omega_{dMOM,t} = \left(\frac{1}{2\lambda}\right) \frac{\hat{\mu}_t}{\hat{\sigma}^2_t}, \tag{10}$$

where, $\hat{\mu}_t = E_{t-1}[\mu_t]$ represents the conditional expected return whereas the conditional variance of the momentum strategy in expressed as $\hat{\sigma}^2_t = E_{t-1}[\sigma^2_t]$. Finally, λ represents the time-invariant scalar that sets the volatility of the strategy the same as the out-of-sample volatility of the total return momentum or residual return momentum strategy. Similar as in constant volatility-scaling, the weight is calculated for the residual return momentum $dRMOM$ as well.

The estimation of μ_{t-1} and σ_{t-1}^2 is conducted by applying out-of-sample approach consistent with the study of Daniel and Moskowitz (2016). In their study, they test both in-sample and out-of-sample approaches ending up with the same results yet stating the in-sample method suffers from a look-ahead bias. The conditional expected return, μ_{t-1}, is estimated with the following regression:

$$R_{MOM,t} = \gamma_0 + \gamma_{int} \cdot I_{Bear,t-1} \cdot \sigma_{RMRF,t-1}^2 + \varepsilon_t, \tag{11}$$

where $I_{Bear,t-1}$ represents the bear market indicator which takes value one if the cumulative market return during the past 24 months (excluding the most recent month) is negative and value zero otherwise. The variance of the daily market return form the past 126 days (excluding the most recent month) is referred as $\sigma_{RMRF,t-1}^2$. The intercept of the regression is referred as γ_0 and γ_{int} represents the regression coefficient on the interaction term of the independent variables. The proxy of the conditional expected return ($\hat{\mu}_t$) is estimated by defining the fitted values from the regression. The regression Eq. (13) is updated monthly and uses an out-of-sample method rather than an in-sample. The estimation of the conditional variance σ_{t-1}^2 is conducted by applying the same approach as used in the constant volatility-scaling strategy in Eq. (10) with a 126-day window for $\hat{\sigma}_t^2$. Finally, the return in a month *t*, $R_{dMOM,t}$, is calculated by scaling the momentum return with the dynamic weight as follows:

$$R_{dMOM,t} = R_{MOM,t} \cdot \omega_{dMOM,t}\,, \tag{12}$$

5 Results

The results of the conventional momentum performance with a comparison of enhanced momentum strategies are presented in this chapter. First, the descriptive statistics of different momentum strategies in the long run compared to Fama-French risk factors are presented. This is followed by the reasoning behind the volatility-scaling methods and finally, the results of the performance of the various momentum strategies are compared.

Previous studies show the strong performance of momentum strategies, but that may no longer be the case anymore. Similarly, with the results of Hanauer and Windmüller (2023), momentum premium in Europe is not that strong in recent decades. Table 2 shows that the market generates mean average excess return of 7.05 %, whereas the returns for total return and residual return momentum strategies are 5.66 % and 5.79 % respectively. Moreover, the Sharpe ratio for markets is higher than for total return momentum but lower than what total residual momentum generates. Consistent with the previous studies, residual momentum manages to generate better Sharpe ratio than conventional momentum and slightly higher mean excess return in this study (see Blitz et al., 2011; Chang et al., 2018; Blitz et al., 2020).

To conclude, these results are referring to the possible weaking of the momentum phenomenon in recent decades (Jegadeesh & Titman, 2011). Secondly, since this study is applied for the large cap stocks only, it would imply that momentum premium is not as strong for large stocks than other stocks (Fama & French, 2012). Lastly, as this study uses stocks in Europe this would suggest the weaker momentum premium in Europe compared to U.S.

Table 2. The descriptive statistics of the strategies.

The table reports the performances of conventional momentum (MOM) and residual momentum (RMOM) strategies with the comparison of Fama and French risk factors: market (RMRF), size (SMB), value (HML), profitability (RMW), and investment (CMA). All the strategies have a formation period of 12 months (excluding the most recent month) and a one-month holding period. The reported statistics are mean average excess return, maximum and minimum return, standard deviation, skewness, kurtosis, and finally Sharpe ratio. Mean average excess return, standard deviation, and Sharpe ratio are annualized and in percent, and others are given in monthly figures. The sample period is from 1995:06 to 2021:09.

Portfolio	Mean	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	Sharpe ratio
RMRF	7.05	16.62	-22.02	17.47	-0.57	4.77	0.40
SMB	1.77	8.83	-7.33	7.41	-0.16	4.13	0.24
HML	2.59	11.16	-11.30	9.37	0.21	5.89	0.28
RMW	4.16	6.40	-5.00	5.66	-0.28	3.84	0.73
CMA	0.62	8.77	-7.30	6.64	0.38	5.98	0.09
MOM	5.66	26.29	-17.94	18.59	-0.19	3.96	0.30
RMOM	5.79	17.82	-6.99	12.36	-0.01	1.58	0.47

5.1 Momentum risk

The underlying reason for using the volatility-scaling is to benefit from the predictability of the momentum return and risk. This study applies the volatility-scaling methods by Barroso and Santa-Clara (2015) for a constant approach and Daniel and Moskowitz (2016) for a dynamic approach. The motivation behind the constant volatility-scaling by Barroso and Santa-Clara (2015) is to exploit the continuity of momentum volatility and the phenomenon in which after the periods of low volatility the high average momentum returns are followed. Instead, the residual return momentum aims to lower the overall risk of the strategy by reducing the time-varying exposure to the common equity factors. If there can be seen similar predictability in residual momentum returns as in total momentum returns, the constant volatility-scaling method can apply to residual momentum too. The persistency of volatility in total and residual momentum is shown by regressing the momentum strategies realized monthly volatility by their own lagged value as follows:

$$RV_t = \alpha + \rho RV_{t-1} + \varepsilon_t \tag{13}$$

The equation (15) illustrates the estimation of an autoregressive model of order 1 (AR(1)), in which RV_t presents the realized volatility of the momentum daily returns in a month t. The lagged realized variance is expressed as RV_{t-1} and the intercept, the coefficient, and the error term of the regression are referred as α, ρ, ε_t.

The regression results are reported in the Table 3, in which the persistency of volatility is measured, and the capacity to explain the realized volatility by its lag. R-square shows that the volatility is explained by its lagged value in both momentum strategies, yet better explained in total return momentum. These findings show that volatility-scaling is applicable for both momentum strategies.

Table 3. The autoregressive process AR(1) of 1-month momentum volatilities.

The table reports the coefficients, t-statistics, and R-square from the autoregressive process AR(1). The regression is applied by taking one-month lagged monthly volatilities from both total return momentum and residual return momentum returns. In the AR(1) regression, the non-overlapping volatility of each month are regressed on its own lagged value and a constant. The preiod for formation and holding are 12 and one month, respectively. The regression is applied to the sample in Europe from 1995:06 to 2021:09.

Portfolio	α (t-statistic)	ρ (t-statistic)	R-square
Total return momentum	0.00013	0.53	0.28
	(4.91)	(11.16)	
Residual return momentum	0.00016	0.41	0.17
	(6.51)	(8.07)	

A recent study by Blitz et al. (2020) finds the applicability of volatility-scaling to residual momentum by showing that there still is some time variation in the market beta of residual momentum which depends on the market state (bull/bear). This mean-return predictability method has shown improvements for conventional momentum during momentum crashes. This method is not directly applied to the volatility-scaling approach by Barroso and Santa-Clara (2015), instead, it underlines the motivation behind the dynamic volatility-scaling process by Daniel and Moskowitz (2016).

Daniel and Moskowitz (2016) enhance the constant volatility-scaling method by considering both expected momentum volatility and return in the analysis. They find that the state of the market affects the market beta of the momentum strategy. They motivate the dynamic volatility-scaling approach by demonstrating the option-like behaviour of momentum strategy during the bear market state. First, they find that the momentum portfolio has a negative correlation with the realized market return during bear markets. If this ex-post beta is used when constructing the hedge portfolio during bear markets, the results are biased when the portfolio generates higher beta and thus higher returns than if ex-ante beta were used. Second, they find that the momentum return is lower during bear markets when the ex-ante market risk is not correctly estimated. These results support their finding of the option-like momentum behaviour. As Blitz et al. (2020) have demonstrated the time-variations in the market beta of residual momentum, the dynamic volatility-scaling method may be applied to residual momentum returns.

Table 4 reports the results of the four monthly time-series regressions regarding the issues mentioned above for both total return and residual return momentum strategies. The return of a momentum in a month t, $R_{MOM,t}$, represents the dependent variable in all regressions. The independent variables of the regression are formed from the following factors:

1. $R_{m,t}$, represents excess market return in month *t.*

2. $I_{B,t-1}$, represents bear market indicator that equals one if the cumulative market return from the past 24 months is negative, and zero otherwise.
3. $I_{U,t}$, represents bull market indicator that equals one if the excess market return is greater than zero in a month t, and zero otherwise.

Regression 1 estimates the expected momentum return by applying the market model regression as follows:

$$R_{MOM,t} = \alpha_0 + \beta_0 R_{m,t} + \varepsilon_t, \tag{14}$$

The estimated market beta is negative, -0.504 (-0.168), and the intercept is positive and statistically significant, 0.501 (0.491), for the total (residual) momentum strategy. These results are consistent with the previous studies.

Regression 2 develops regression 1 by adding a bear market indicator, I_B, to the CAPM model as follows:

$$R_{MOM,t} = \left(\alpha_0 + \alpha_B I_{B,t-1}\right) + \left(\beta_0 + \beta_B I_{B,t-1}\right) R_{m,t} + \varepsilon_t \tag{15}$$

By adding the bear market indicator into the model, equation (17) aims to catch the differences in market beta during bear market states in addition to the expected return. Consistent with the literature, there can be seen a difference in the market beta during the bear market state (see Grundy & Martin, 2001; Daniel & Moskowitz, 2016). In this study, it is lower (and statistically significant) for both total and residual momentum strategies, with -0.493 and -0.212 respectively.

Regression 3 enhances regression 2 further by adding a bull market indicator to the model to examine the differences between up- and down-market betas. The regression is expressed as follows:

$$R_{MOM,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + \left(\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U})\right) R_{m,t} + \varepsilon_t \tag{16}$$

Consistent with the results of Daniel and Moskowitz (2016), $\beta_{B,U}$ results in -0.003 for total return momentum which implies poor performance after a bear market state. However, the result is not as strong economically or statistically as Daniel and Moskowitz (2016) show. Furthermore, this effect is not seen in the residual momentum strategy which is partly explained by the usage of residual returns instead of total returns which lowers the time-variation in the market beta. During the bear markets, the estimates of betas result -0.732 ($= \beta_0 + \beta_B$) with a negative market return and -0.759 ($= \beta_0 + \beta_B + \beta_{B,U}$) with a positive market return for total return momentum, whereas the same issue is not found from residual return momentum. Moreover, the option-like behaviour effect is not as strong as in the study of Daniel and Moskowitz (2016).

Table 4. The performance of market timing regressions.

The table reports the results of four different (R1, R2, R3, R4) monthly time-series regressions in Europe from 1995:06 to 2021:09. Panel A (B) presents the results with a dependent variable of return on the total (residual) return momentum portfolio. First column presents the regression coefficients, the second column presents the independent variables, and the remaining columns present the regression results. The independent variables are from top to bottom: a constant; bear market indicator, which equals one if the past cumulative market return is negative; the excess market return, a bull market indicator, which equals one if the market return is positive. The alpha coefficients are reported in percent and in monthly figures.

Coefficient	Variable	Estimated coefficients (t-statistics)			
		R1	R2	R3	R4
Panel A: MOM					
α_0	1	0.501	0.495	0.495	0.494
		(22.06)	(18.92)	(18.88)	(20.29)
α_B	$I_{B,t-1}$		-0.011	-0.010	
			(-0.22)	(-0.14)	
β_0	$R_{m,t}$	-0.504	-0.252	-0.252	-0.251
		(22.06)	(-3.33)	(-3.33)	(-3.33)
β_B	$I_{B,t-1} \cdot R_{m,t}$		-0.493	-0.491	-0.481
			(-4.67)	(-3.24)	(-3.59)
$\beta_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot R_{m,t}$			-0.003	-0.027
				(-0.01)	(-0.17)
Panel B: MOMR					
α_0	1	0.491	0.486	0.486	0.483
		(29.87)	(25.05)	(25.03)	(26.79)
α_B	$I_{B,t-1}$		0.005	-0.022	
			(0.14)	(-0.41)	
β_0	$R_{m,t}$	-0.168	-0.059	-0.059	-0.057
		(-4.26)	(-1.05)	(-1.05)	(-1.02)
β_B	$I_{B,t-1} \cdot R_{m,t}$		-0.212	-0.268	-0.246
			(-2.71)	(-2.39)	(-2.49)
$\beta_{B,U}$	$I_{B,t-1} \cdot I_{U,t} \cdot R_{m,t}$			0.122	0.069
				(0.69)	(0.57)

5.2 Momentum return

In this section, the various momentum strategies are discussed and compared. First, the results of the performance statistics for all the momentum strategies are presented. Secondly, the spanning regressions are applied for the momentum strategies to see the possible benefits from the mean-variance optimization by using enhancement methods. Finally, the figure shows the cumulative performance of the momentum strategies.

The performance statistics for the winner-minus-loser decile portfolios are discussed and the results are presented in tables 5 and 6. In Table 5, the results are reported for the total return, constant volatility-scaled total return, and dynamic volatility-scaled total return momentum strategies. In Table 6, the results for the residual return, constant volatility-scaled residual return, and dynamic volatility-scaled residual return momentum strategies are presented. To enhance the interpretation and comparison of the results, the full-sample momentum strategies have the same volatility as the volatility-scaled momentum strategies. Before analyzing the results, it is necessary to underline the conceptual differences since the momentum strategies are constructed in different ways. The residual and total return momentum portfolios are formed separately, and both have different stocks. The volatility-scaling methods are applied afterward for both total and residual return momentum strategies resulting in separate strategies. An initial formation period of J = M12 and different holding periods of K = M1, M3, M6, and M12 are used in all the analyses.

The general phenomenon can be seen in all strategies in which the momentum performance decreases as the holding period increases (see Blitz et al., 2011). Consistent with the existing literature, there can be seen improvements in the enhanced strategies compared to the total return momentum, but the results are not as strong as previous studies suggest (see Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016; Chang et al., 2018; Hanauer & Windmüller, 2023). When comparing the mean excess returns of total momentum and residual momentum in Tables 5 and 6, there is not a strong difference between results which slightly contradicts the existing literature (see Blitz et al., 2011; Chang et al., 2018). In the holding periods of one to three months, residual momentum generates higher returns compared to total momentum, however, for longer holding periods of six to 12 months, the mean excess returns are higher for total momentum than residual momentum. However, the volatility of the residual momentum is only two-thirds of the total return momentum for shorter holding periods of one to six months, and almost three-thirds for 12 months. The result of the lower volatility for the residual momentum strategy is consistent with the previous studies (see Blitz et al., 2011; Chang et al., 2018; Blitz et al., 2020).

To analyze the results of momentum strategies with total returns in Table 5, the constant volatility-scaling generates better mean excess returns compared to conventional momentum with a holding period from one to 6 month and outperforms the dynamic volatility-scaling strategy since it manages to generate better results than total return momentum with only a holding period of 1 and 3 months. As studies of Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Hanauer and Windmüller (2023) find strong improvements for conventional momentum by applying volatility-scaling, this study provides somewhat mixed results as the returns with volatility-scaling are not better for all holding periods.

When interpreting the results of momentum strategies with residual returns in Table 6, plain residual momentum provides higher mean excess returns than volatility-scaled strategies for all holding periods. To compare volatility-scaled residual momentum strategies with each other, constant volatility-scaling generates higher mean excess returns than dynamic volatility-scaling strategy despite the holding period. The results that scaled residual momentum strategies perform worse than unscaled residual momentum strategy challenges the findings of Chang et al. (2018) as they find improvements with volatility-scaling in Japan.

Almost every enhancement strategy improves the Sharpe ratios for the total return momentum which is consistent with the previous studies (cf. Chang et al., 2018; Hanauer

& Windmüller, 2023). Similarly, to the results of Chang et al. (2018), in this study, the residual return momentum, constant volatility-scaling, and dynamic volatility-scaling strategies for the residual return momentum enhance the total return momentum for all holding periods of 0.30-0.50 (range from worst to best) for 0.47-0.68, 0.43-0.57, and 0.39-0.51 respectively. In contrast, the improvements using volatility-scaling in a conventional momentum strategy are not as significant as Hanauer and Windmüller (2023) suggest, as the constant volatility-scaling total return strategy generates better Sharpe ratios of 0.33-0.39 with a holding period of one to six months, whereas dynamic volatility-scaling total return strategy manages to provide a slightly higher Sharpe ratio of 0.31 with only a holding period of one month. To conclude the key points of Sharpe ratios, the residual return momentum strategy provides Sharpe ratios that are approximately 1.5 times higher than the total return momentum, considering only holding periods from one to six months. When looking at the holding period of one month, the Sharpe ratio of residual return momentum differs from constant volatility-scaling by 9.30 %, and from dynamic volatility-scaling by 20.51 % in percentage terms.

Other benefits from the enhancement strategies are related to skewness and kurtosis. When considering only a one-month holding period, the skewness changes for total return momentum from -0.19 to 0.63 with constant volatility-scaling and to 1.05 with dynamic volatility-scaling, and for residual momentum from 0.00 to 0.50 with constant volatility-scaling and to 0.82 with dynamic volatility-scaling. Consistent with the results of Chang et al. (2018), residual momentum managed to lower the skewness of conventional momentum. In addition, dynamic volatility-scaling improves skewness better than the constant method and even offers positive skewness with both total and residual momentum returns. Chang et al. (2018) show that kurtosis of conventional momentum is reduced by applying the residualization process of Blitz et al. (2011). In this study, the changes in kurtosis are for total return momentum from 3.96 to 1.19 with constant volatility-scaling and to 5.81 with dynamic volatility-scaling and for residual momentum from 1.59 to 0.64 with constant volatility-scaling and to 2.00 with dynamic volatility-scaling. When dynamic volatility-scaling succeeded in improving skewness, the constant volatility-scaling provides the best benefits in kurtosis.

To conclude the results, all the enhanced strategies manage to improve conventional momentum by some criterion. However, none of the improved strategies are significantly better than the other when taking into account all aspects. When considering the holding period of one-month, plain residual momentum provides highest mean excess return, and Sharpe ratio with a lower volatility than conventional momentum, but dynamic volatility-scaled residual momentum outperforms in skewness whereas constant volatility-scaled residual momentum provides best results in kurtosis.

Table 5. The summary statistics of total return momentum strategies.

The table reports summary statistics for the total return momentum, constant volatility-scaled total return momentum, and dynamic volatility-scaled total return momentum in Europe. The reported statistics are mean excess monthly returns, standard deviation, skewness, kurtosis, maximum and minimum monthly return, and Sharpe ratio. To calculate the volatility-scaled momentum returns, the method by Barroso and Santa-Clara (2015) is used for constant volatility-scaling and the method by Daniel and Moskowitz (2016) is used for dynamic volatility-scaling. All the momentum strategies have a 12-month formation period (excluding the most recent month) for different holding periods. Mean excess return, standard deviation, and Sharpe ratio are annualized and in percent, and others are given in monthly figures. The sample period is from 1995:06 to 2021:09.

	Total return momentum				Constant vol-scaled total return momentum				Dynamic vol-scaled total return momentum			
Holding period	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Mean	5.66	5.66	5.66	5.27	6.20	6.15	5.83	4.82	5.75	5.67	5.39	4.44
Standard Deviation	18.59	17.17	15.10	10.57	18.59	17.17	15.10	10.57	18.59	17.17	15.10	10.57
Skewness	-0.19	0.06	0.55	0.64	0.63	0.69	0.85	0.83	1.05	1.26	1.61	1.97
Kurtosis	3.96	3.26	2.95	1.83	1.19	1.43	1.65	1.49	5.81	7.18	8.35	9.79
Maximum	26.29	24.55	23.97	16.45	29.58	29.07	26.99	19.41	41.04	39.84	36.83	26.00
Minimum	-17.94	-14.18	-10.14	-3.52	-10.35	-7.67	-3.17	-2.81	-11.40	-9.45	-4.53	-2.26
Sharpe ratio	0.30	0.33	0.37	0.50	0.33	0.36	0.39	0.46	0.31	0.33	0.36	0.42

Table 6. The summary statistics of residual return momentum strategies.

The table reports summary statistics for the total return momentum, constant volatility-scaled total return momentum, and dynamic volatility-scaled total return momentum in Europe. The reported statistics are mean excess monthly returns, standard deviation, skewness, kurtosis, maximum and minimum monthly return, and Sharpe ratio. The residualization process of Blitz et al. (2011) is used to form the residual momentum returns. To calculate the volatility-scaled momentum returns, the method by Barroso and Santa-Clara (2015) is used for constant volatility-scaling and the method by Daniel and Moskowitz (2016) is used for dynamic volatility-scaling. All the momentum strategies have a 12-month formation period (excluding the most recent month) for different holding periods. Mean excess return, standard deviation, and Sharpe ratio are annualized and in percent, and others are given in monthly figures. The sample period is from 1995:06 to 2021:09.

	Residual return momentum				Constant vol-scaled residual return momentum				Dynamic vol-scaled residual return momentum			
Holding period	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Mean	5.77	5.68	5.59	5.14	5.24	4.99	4.85	4.32	4.86	4.64	4.38	3.82
Standard Deviation	12.32	11.19	9.87	7.53	12.32	11.19	9.87	7.53	12.32	11.19	9.87	7.53
Skewness	0.00	0.26	0.57	0.51	0.50	0.61	0.73	0.85	0.82	1.10	1.46	1.25
Kurtosis	1.59	1.24	1.72	2.43	0.64	0.56	0.98	1.60	2.00	2.69	5.00	2.59
Maximum	17.82	18.13	18.81	15.07	16.83	16.22	15.53	14.16	19.35	19.05	21.24	14.07
Minimum	-6.99	-4.42	-2.46	-3.35	-3.91	-2.68	-1.90	-1.27	-4.36	-2.81	-1.46	-0.95
Sharpe ratio	0.47	0.51	0.57	0.68	0.43	0.45	0.49	0.57	0.39	0.41	0.44	0.51

The spanning regressions are applied for the momentum strategies to see the possible benefits from the mean-variance optimization by using enhancement methods. The regressions are conducted for the momentum strategies on the five-factor model by Fama and French (2015) as follows:

$$R_{i,t} - R_{ft} = \alpha_{it} + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t \quad (17)$$
$$+ m_i MOM_t + v_i cMOM_t + x_i RMOM_t + \varepsilon_{i,t} ,$$

where $v_i cMOM_t$ represents constant volatility-scaled momentum, and $h_i RMOM_t$ residual momentum. However, the regression is conducted by using different combinations including also dynamic volatility-scaled momentum, and volatility-scaled residual momentum strategies. The results from the spanning regressions for momentum returns on the Fama-French five-factor model (2015) and various momentum strategies are reported in Tables 7 and 8, while the intercepts (alphas) for the constant volatility-scaling are reported in Table 7, and for the dynamic volatility-scaling in Table 8.

Following the trend from the mean excess returns, the Fama-French five-factor intercepts for all strategies are economically and statistically positive, and in this study, all the strategies have succeeded to maintain this statistical significance considering all holding periods (months from one to 12). Some previous studies find that the momentum performance decreases for longer holding periods (i.e., 12 months) (see Blitz et al., 2011), and the same effect is seen in the alphas of plain total return and residual return momentum strategies. Instead, this study shows that for volatility-scaled strategies the effect goes in the opposite direction, i.e., alpha is higher the longer the holding period. There is not a significant difference between alphas of total return and residual return momentum strategies as they deliver alphas of 0.44-0.47 and 0.43-0.48 respectively (range from worst to best). Constant volatility-scaling strategies do not manage to deliver better alphas than plain momentum strategies, instead dynamic volatility-scaling delivers alpha of 0-38-0.48 for scaling applied for total returns and alpha of 0.40-0.50 for scaling applied for residual returns. To conclude, a strategy that applies dynamic volatility-scaling for residual returns slightly outperforms other strategies which is consistent with the results of Chang et al. (2018), yet their results are more significant.

When considering total return momentum in addition to FF5-intercepts, all the enhancement strategies still maintain their performance for all holding periods resulting economically and statistically significant results, consistent with the results of Hanauer and Windmüller (2023). Plain residual return momentum delivers the strongest alpha of 0.15-0.46, whereas the second-best performing strategy is dynamic volatility-scaled residual momentum with alpha of 0.20-0.22. Other strategies deliver almost similar alphas ranging from 0.08 to 0.14.

To estimating residual momentum and volatility-scaled (constant and dynamic) residual momentum further, the returns of the enhanced strategies are regressed on the FF5-factors as well as each enhanced strategy separately. The residual return and the volatility-scaled residual return strategies generate abnormal returns on the FF5-factors and each enhanced strategy separately, all except dynamic volatility-scaled residual return strategy with 12-month holding period. When testing the residual return and the volatility-scaled residual return strategies on FF5-factors with three momentum strategies, residual return manages to provide economically and statistically significant results with 0.10-0.49 with constant volatility-scaling and 0.11-0.48 with dynamic volatility-scaling.

Constant and dynamic volatility-scaling residual momentum strategies deliver significant positive results of 0.06 and 0.14 respectively, interestingly only for six-month holding period, in addition dynamic method maintain to deliver significant results also for shorter holding periods from one to three months, but only negative returns and with the significancy level of 10 %. The effect that six-month holding period outperforms other periods in many regressions remains to be examined further. The benefits from the volatility-scaling for residual return momentum is not that strong, which is partly explained that the time-variation in the market beta is reduced so much that scaling no longer produces the same advantages. However, the enhanced momentum strategies still manage to deliver significant positive alphas even included other enhanced momentum strategies into the same regression.

Table 7. The performance of spanning regressions of constant volatility-scaled momentum strategies.

The table reports the intercepts (alphas) from the spanning regressions in Europe from 1995:06 to 2021:09. Different momentum strategies represent the dependent variables, whereas the independent variables are the factors of Fama and French's (2015) 5-factor model (FF5), and the various momentum strategies: total return momentum (MOM), constant volatility-scaled total return momentum (cMOM), residual return momentum (RMOM), and constant volatility-scaled residual return momentum (cRMOM). With the formation period 12 months (excluding the most recent month) for different holding periods, the residualization process by Blitz et al. (2011) is used to form the residual momentum returns, and the method by Barroso and Santa-Clara (2015) for constant volatility-scaling. The t-statistic (in the parentheses) is Newey-West (1987) corrected for autocorrelation and heteroscedasticity.

	Total return momentum				Constant vol-scaled total return momentum				Residual return momentum				Constant vol-scaled residual return momentum			
Holding period	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
FF5	0.47	0.47	0.47	0.44	0.21	0.21	0.22	0.25	0.48	0.47	0.47	0.43	0.22	0.21	0.23	0.26
	(20.45)	(20.99)	(21.55)	(26.98)	(14.01)	(14.76)	(15.87)	(18.67)	(29.22)	(31.07)	(33.35)	(36.23)	(18.64)	(19.26)	(23.32)	(27.13)
FF5 + MOM					0.08	0.09	0.09	0.08	0.17	0.17	0.46	0.15	0.11	0.11	0.11	0.12
					(5.76)	(5.59)	(4.73)	(4.04)	(7.84)	(7.69)	(17.97)	(6.77)	(8.28)	(7.64)	(7.21)	(7.60)
FF5 + cMOM									0.31	0.30	0.49	0.30	0.06	0.05	0.07	0.08
									(10.88)	(10.53)	(24.00)	(11.52)	(7.50)	(6.16)	(6.91)	(6.25)
FF5 + RMOM													0.05	0.06	0.25	0.07
													(3.97)	(3.62)	(13.34)	(3.42)
FF5 + cRMOM									0.22	0.23	0.50	0.21				
									(8.19)	(8.95)	(19.86)	(8.32)				
FF5 + MOM + cMOM + RMOM													0.00	0.00	0.06	0.00
													(0.28)	(-0.40)	(4.87)	(0.29)
FF5 + MOM + cMOM+ cRMOM									0.12	0.13	0.49	0.10				
									(6.91)	(7.04)	(17.86)	(6.33)				

Table 8. The performance of spanning regressions of dynamic volatility-scaled momentum strategies.

The table reports the intercepts (alphas) from the spanning regressions in Europe from 1995:06 to 2021:09. Different momentum strategies represent the dependent variables, whereas the independent variables are the factors of Fama and French's (2015) 5-factor model (FF5), and the various momentum strategies: total return momentum (MOM), dynamic volatility-scaled total return momentum (dMOM), residual return momentum (RMOM), and dynamic volatility-scaled residual return momentum (dRMOM). With the formation period of 12 months (excluding the most recent month) for different holding periods, the residualization process by Blitz et al. (2011) is used to form the residual return momentum returns, and the method Daniel and Moskowitz (2016) for dynamic volatility-scaling. The t-statistic (in the parentheses) is Newey-West (1987) corrected for autocorrelation and heteroscedasticity.

	Total return momentum				Dynamic vol-scaled total return momentum				Residual return momentum				Dynamic vol-scaled residual return momentum			
Holding period	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
FF5	0.47	0.47	0.47	0.44	0.38	0.39	0.42	0.48	0.48	0.47	0.47	0.43	0.41	0.40	0.44	0.50
	(20.45)	(20.99)	(21.55)	(26.98)	(13.97)	(14.35)	(14.83)	(17.17)	(29.22)	(31.07)	(33.35)	(36.23)	(18.77)	(19.57)	(20.75)	(20.72)
FF5 + MOM					0.13	0.14	0.13	0.11	0.17	0.17	0.46	0.15	0.20	0.20	0.21	0.22
					(5.12)	(4.86)	(3.93)	(2.62)	(7.84)	(7.69)	(17.97)	(6.77)	(7.31)	(6.82)	(5.89)	(5.28)
FF5 + dMOM									0.30	0.29	0.48	0.30	0.13	0.12	0.13	0.17
									(10.44)	(9.91)	(24.83)	(11.31)	(5.88)	(4.99)	(4.31)	(4.84)
FF5 + RMOM													0.08	0.08	0.48	0.07
													(3.08)	(2.86)	(12.92)	(1.43)
FF5 + dRMOM									0.23	0.25	0.50	0.24				
									(7.90)	(8.74)	(22.24)	(9.62)				
FF5 + MOM + dMOM + RMOM													-0.02	-0.03	0.14	-0.03
													(-1.70)	(-1.96)	(3.95)	(-1.57)
FF5 + MOM + dMOM+ dRMOM									0.12	0.13	0.48	0.11				
									(7.27)	(7.27)	(19.55)	(6.99)				

To further illustrate the improvements relatively among volatility-scaled momentum strategies, Table 9 applies spanning regressions for all the four enhanced momentum strategies on Fama and French's (2015) five-factors, enhanced strategies, and conventional momentum. The regression uses 12-month holding period with different holding periods from one to 12 months. First four rows show the regression results of each enhanced momentum strategy on the FF5-factors and one enhanced strategy separately. The rest of the rows add conventional momentum into the regression. The aim is to test whether enhanced strategies manage to deliver statistically significant positive alphas even when adding other enhanced strategy as benchmark asset in the same model as proposed in the study of Hanauer and Windmüller (2023).

The regression results show that a quite many alphas are statistically significant and positive, yet the strategies with residual returns provide higher alphas than strategies with total returns on average. Consistent with Hanauer and Windmüller (2023), when adding conventional momentum as benchmark asset into the regression with five-factors and enhanced momentum strategy, the alphas are lower.

Considering first constant volatility-scaled total return momentum strategy, the results show that some alphas are quite low and even negative. Regressed with FF5-factors and dynamic total return momentum, alphas are positive and significant ranging from 0.01-0.04, and when adding conventional momentum to the regression, results remain same. These results are similar as the findings of Hanauer and Windmüller (2023). When regressing with FF5-factors and dynamic residual momentum, results are from 0.05 to 0.11, however, by adding conventional momentum, results decrease being 0.02-0.04. When regressing with FF5-factors, and constant residual momentum or the combination in which conventional momentum is included, alphas are low or even negative and non-significant, which implies that these strategies are already incorporated in the strategy of constant volatility-scaled total return momentum.

When analysing dynamic volatility-scaled total return momentum strategy, similar results are reported as there are low and even negative alphas. Testing FF5-factors with constant volatility-scaled total return momentum as benchmark asset, alphas are ranging from 0.02 to 0.04, but by adding momentum into the regression, alphas turn to negative and insignificant which is the same outcome as find in the study of Hanauer and Windmüller (2023). By regressing with FF5-factors and constant residual return momentum or the combination with the conventional momentum, results are negative or insignificant. Instead, by regressing the strategy with dynamic residual momentum, the strategy delivers its highest positive and significant alphas for six- and 12-month holding periods by 0.05-0.09 which indicates that the dynamic residual momentum is not included into the dynamic volatility total momentum strategy, or at least not completely.

Constant volatility-scaled residual momentum manages to deliver positive significant alphas despite the benchmark assets and with all holding periods. The highest alphas are with 12-month holding periods ranging from 0.06-0.11. However, when analyzing the highest alphas in the regression, the strategy that managed to deliver them is the dynamic residual return momentum on average. The results imply that this strategy is not incorporated into other strategies. However, despite the high values, the strategy yields quite low but still positive and even insignificant results when regressing with FF5-factor and constant residual momentum or the combination in which conventional momentum is added. If the assumption is that the residual return momentum and conventional momentum have similarities, this result is expected as the same situation suggested by Hanauer and Windmüller (2023) is with the regression of dynamic volatility-scaled total return momentum on FF5-factors, constant volatility-scaled total return momentum strategy, and conventional momentum.

In conclusion, the results of this spanning regression are mixed. On the one hand low or insignificant and even negative alphas indicate that enhanced strategies are already incorporated into some other enhanced strategy, but on the other hand some strategies provide statistically high and positive alphas implying possible benefits in terms of investment opportunities. Hanauer and Windmüller (2023) cannot find any strategy to outperform other in their regression analysis, however, the results of Table 9 show the success of dynamic residual momentum which is consistent with the main conclusions of Chang et al. (2018), although they do not apply exactly this kind of regression.

Table 9. The performance of spanning regressions of volatility-scaled momentum strategies.

The table reports the intercepts (alphas) from the spanning regressions in Europe from 1995:06 to 2021:09. Volatility-scaled momentum strategies represent the dependent variables, whereas the independent variables are the factors of Fama and French's (2015) 5-factor model FF5, and the various momentum strategies: total return momentum MOM, constant (dynamic) volatility-scaled total return momentum cMOM (dMOM), residual return momentum (RMOM), and constant (dynamic) volatility-scaled residual return momentum cRMOM (dRMOM). The formation period is 12 months (excluding the most recent month), whereas holding periods vary from one to 12 months. The residualization process by Blitz et al. (2011) is used to form the residual momentum returns. Volatility-scaling is applied by Barroso and Santa-Clara (2015) for constant, and by Daniel and Moskowitz (2016) for dynamic method. The t-statistic (in the parentheses) is Newey-West (1987) corrected for autocorrelation and heteroscedasticity.

	Constant vol-scaled total return momentum				Constant vol-scaled residual return momentum				Dynamic vol-scaled total return momentum				Dynamic vol-scaled residual return momentum			
Holding period	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
FF5 + cMOM					0.06	0.05	0.07	0.08	0.02	0.02	0.03	0.04	0.17	0.15	0.19	0.25
					(7.50)	(6.16)	(6.91)	(6.25)	(2.19)	(2.11)	(1.96)	(1.94)	(5.89)	(5.14)	(5.04)	(4.69)
FF5 + dMOM	0.01	0.01	0.02	0.04	0.07	0.06	0.08	0.11					0.13	0.12	0.13	0.17
	(2.04)	(2.34)	(2.21)	(2.49)	(7.25)	(6.12)	(6.80)	(6.16)					(5.88)	(4.99)	(4.31)	(4.84)
FF5 + cRMOM	-0.00	0.01	-0.01	0.00					0.00	0.02	-0.01	0.03	0.02	0.02	0.03	0.05
	(-0.42)	(0.54)	(-1.21)	(0.04)					(0.19)	(1.22)	(-0.62)	(0.99)	(1.33)	(1.26)	(1.26)	(2.08)
FF5 + dRMOM	0.05	0.06	0.07	0.11	0.03	0.03	0.05	0.08	0.05	0.07	0.05	0.09				
	(2.76)	(2.91)	(3.34)	(4.36)	(3.59)	(3.31)	(3.51)	(3.73)	(1.75)	(1.97)	(2.14)	(2.42)				
FF5 + MOM + cMOM					0.05	0.04	0.05	0.07	-0.00	-0.00	-0.00	-0.02	0.12	0.11	0.14	0.17
					(6.27)	(4.91)	(5.44)	(5.63)	(-0.48)	(-0.33)	(-0.38)	(-0.81)	(4.63)	(3.89)	(3.80)	(3.81)
FF5 + MOM + dMOM	0.02	0.02	0.02	0.04	0.06	0.06	0.07	0.09					0.11	0.10	0.12	0.15
	(2.84)	(2.98)	(2.72)	(2.87)	(6.85)	(5.83)	(6.44)	(6.92)					(4.96)	(4.21)	(3.92)	(4.38)
FF5 + MOM + cRMOM	-0.01	-0.01	-0.02	-0.03					-0.03	-0.02	-0.05	-0.06	0.01	0.01	0.02	0.02
	(-1.43)	(-0.67)	(-2.07)	(-1.98)					(-1.83)	(-1.05)	(-2.59)	(-2.19)	(0.91)	(0.88)	(0.82)	(0.98)
FF5 + MOM + dRMOM	0.02	0.03	0.03	0.04	0.02	0.02	0.04	0.06	0.01	0.01	-0.01	-0.02				
	(2.00)	(2.20)	(2.14)	(2.34)	(3.74)	(3.35)	(3.66)	(3.68)	(0.27)	(0.52)	(-0.36)	(-0.82)				

To demonstrate the features of the different momentum strategies, their cumulative returns with a 12-month formation period (excluding the most recent month) and the holding period of one month from 1995:06 to 2021:09 in Europe are plotted in Figure 1. For making the momentum returns more comparable, all the momentum strategies have the same full-sample volatility as the total return momentum in this figure. At the end of the period, all the enhanced momentum strategies are managed to deliver higher cumulative returns than the conventional momentum strategy, except dynamic volatility-scaling total return momentum that performs at the same level.

To interpret cumulative performance in more detail, strategies that use residual returns instead of total returns perform better which is consistent with the existing literature (cf. Blitz et al., 2011; Chang et al., 2018; Blitz et al., 2020; Hanauer & Windmüller, 2023). In Figure 1, residual return momentum generates the highest returns in this certain period with a full-sample volatility of total return momentum. Residual return momentum strategy is followed by the both volatility-scaling approaches that deliver slightly lower returns but are still higher than the strategies with total returns. These results slightly contradict the findings of Chang et al. (2018) in Japan that dynamic volatility-scaling enhances the returns of plain residual momentum further.

The cumulative performance regarding enhanced momentum strategies with total returns is not as strong as suggested in studies of Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Hanauer and Windmüller (2023). The study of Hanauer and Windmüller (2023) provides the most recent situation, and they find that both constant and dynamic volatility-scaling approaches improve the performance of conventional momentum significantly in the non-U.S. sample. The differences may be explained by the fact that only large cap stocks are used in this study and the sample comprises merely Europe.

At the beginning of the period, there are no significant differences between strategies, yet constant volatility-scaled residual momentum appears to perform slightly better than other strategies. In the early 2000s, strategies are performing still quite close to each other, especially total return momentum, total return momentum with constant volatility scaling, and residual momentum with dynamic volatility scaling. However, after the year of 2009, there is a gap between strategies applying residual returns versus total returns.

In 2009, almost all the enhanced momentum strategies (except dynamic volatility-scaling applied for total returns) succeeded in reducing momentum crashes. Still, there can be seen a little drop, especially in strategies with total returns instead of residual returns when the stock markets faced significant crashes. Interestingly, a similar decline is not shown during COVID-19 in early 2020, when there was turmoil in the markets in which the stock markets crashed but recovered quickly. To analyze this effect, one explanation could be the symmetric behaviour of legs (long and short) during the bear and bull market, which has not happened in the previous crashes, yet the reasoning behind this behaviour remains unsolved.

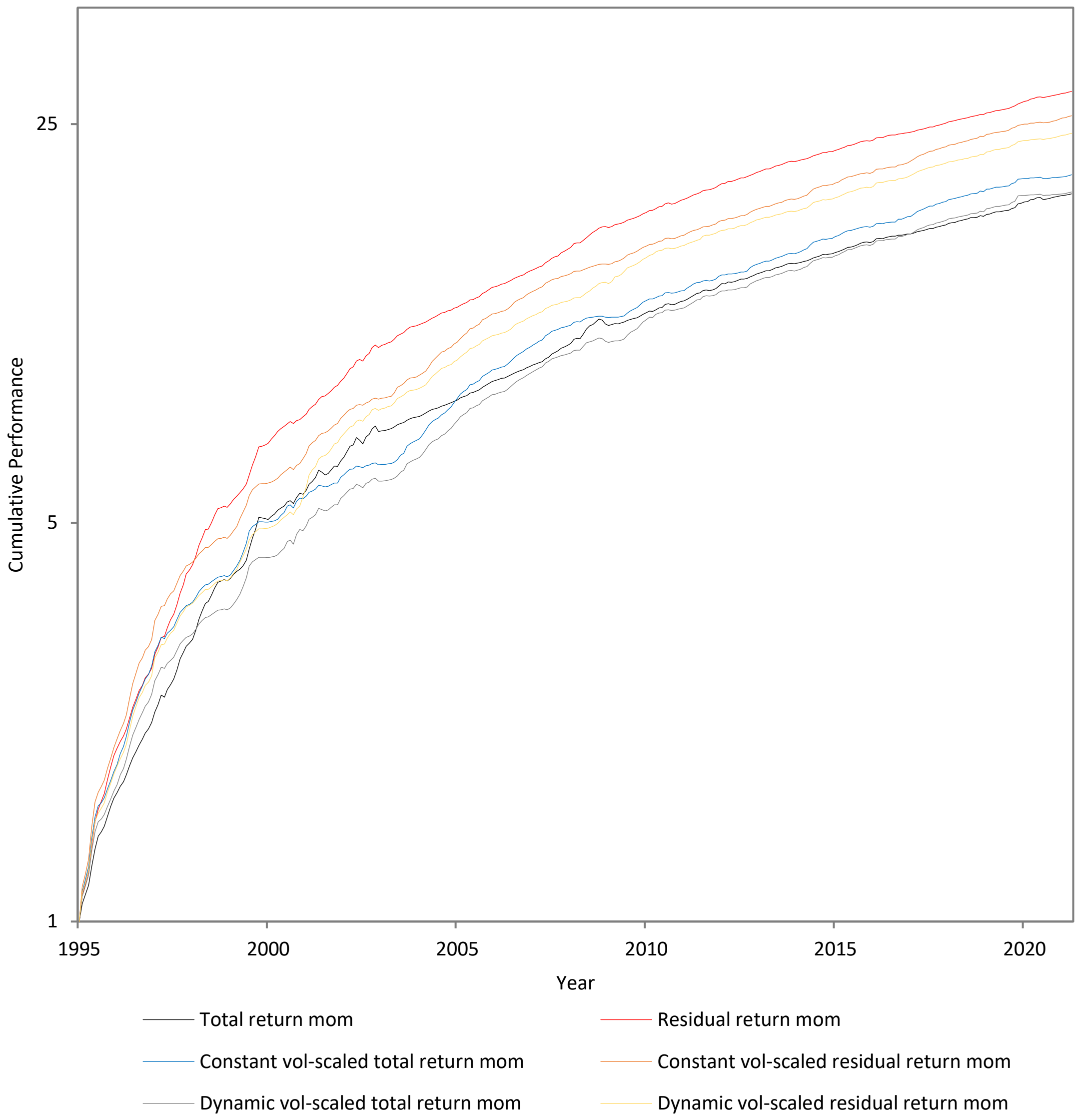

Figure 1. The performance of cumulative returns of momentum strategies.

The graph plots the cumulative returns from total return, volatility-scaled (constant and dynamic) total return, residual return, and volatility-scaled (constant and dynamic) residual return momentum strategies in Europe. The residualization process of Blitz et al. (2011) is used to form the residual momentum returns. To calculate the volatility-scaled momentum returns, the method by Barroso and Santa-Clara (2015) is used for constant volatility-scaling and the method by Daniel and Moskowitz (2016) is used for dynamic volatility-scaling. All the momentum strategies have 12-month formation period (excluding the most recent month) for holding period of one-month. To be able to compare the momentum returns, all the strategies have the same full-sample volatility as total return momentum in this figure. The sample period is from 1995:06 to 2021:09.

6 Conclusion

Momentum is widely known asset pricing anomaly in financial literature. Investing in past winners and short-selling past losers provides significant average returns which is not explained by common risk factors. Despite the attractive performance of momentum, strategy suffers from a high tail risk. During these momentum crashes that usually occur in rebounding from bear markets, momentum strategy has been shown to provide negative returns. Some studies have suggested enhancement methods to improve the performance of conventional momentum and reduce momentum crashes. This study compares two enhanced momentum strategies by combining residual momentum with two different volatility-scaling methods – constant and dynamic. The aim is to test their applicability to generate higher returns with lower risk and compare their results with each other and the results with conventional momentum, volatility-scaled methods applied for conventional momentum, and plain residual momentum.

Using daily stock returns in Europe from 1992 to 2021, this study shows that the momentum premium does not appear as strong as presented in previous studies which may be referring to the possible weakening of the momentum phenomenon in recent decades. Moreover, this study applies methods only for large-cap stocks and in Europe, therefore it would imply momentum premia being lower for large-cap stocks in Europe. However, consistent with the existing literature enhanced strategies improve the performance of conventional momentum.

This study finds that residual momentum generates slightly higher returns compared to conventional momentum but with only two-thirds of the volatility of conventional momentum. Moreover, strategies that apply residual returns outperform momentum strategies that apply total returns, plain residual momentum being slightly the best-performing strategy measured by the Sharpe ratio. One explanation for the better performance of residual momentum strategies could be the reduction in time-variation of the market's beta, which however decreases to the point where volatility-scaling does not provide significant benefits. Using residuals instead of totals the skewness is also improved, and both volatility-scaling methods manage to provide even positive skewness. In addition, by combining residual momentum and constant (dynamic) volatility-scaling kurtosis is decreased (remains the same) compared to the plain residual momentum strategy.

By applying spanning regression for residual momentum on FF5-factors and the respective momentum strategies, it generates economical and statistically significant annual alpha of 1.20-5.88 % with constant volatility-scaling and 1.32-5.76 % with dynamic volatility-scaling. Regressing constant (dynamic) volatility-scaled residual momentum on FF5-factors and other momentum strategies, the results are positively significant only for a six-month holding period with an annual alpha of 0.72 % (1.68 %). These results support the finding that the benefits from the volatility-scaling for residual return momentum are not that strong, which is partly explained by the reduced time-variation in the market beta so that scaling no longer produces the same advantages. However, both constant and dynamic volatility-scaled residual momentum strategies provide significant positive alphas in spanning regression results.

To compare the volatility-scaled momentum strategies to each other further, spanning regressions for each enhanced strategy on FF5-factors and other enhanced strategies separately are applied. In generally, all volatility-scaled momentum strategies indicate possible benefits in terms of investment opportunities, however, the implications are not equally strong for all strategies. Strategies that apply residual returns instead of total returns perform better, however, the strategy that applies dynamic volatility-scaling for residual returns provides the best benefits by generating highest alphas.

One of the limitations of the study is associated with the look-ahead bias that appears when the data that have not been available during the study is used in the analysis. If the assumption is that a positive regression alpha expands the investor's mean-variance frontier, then the investor should know the full-sample factors such as volatility and mean return in advance, which is not possible. In the case of time-varying moments, regression alphas will not provide immediate benefit to the mean-variance investor. By using the out-of-sample also in other methods (except the dynamic volatility-scaling) to allocate returns dynamically in real time, it would provide more accurate and the real picture of the feasibility of volatility-scaled residual momentum. Another limitation underlines the lack of transaction cost analysis. An estimation of the actual transaction costs would have shown the actual profitability as well as the relative profitability between the different momentum strategies.

For further research on this topic, it would be ideal to combine and compare other versions on enhanced momentum strategies to see the differences behind the momentum profits. Other widenings would be to consider different periods such as different formation periods in addition to various holding periods to see possible differences in the results, and different subperiods to see if there is any distinction between the strategies in different market states. Related to the market conditions, one could study and compare different crash periods, especially to examine the reasoning behind the long-short behaviour during Covid-19. Further, the performance of these strategies could have studied in other asset classes such as futures, currencies, or cryptocurrencies. Finally, this topic could be further studies by examining the performance of enhanced strategies in different geographical areas such as emerging markets or countries individually.

Despite the success of the momentum strategies, there can be seen a weaking of the momentum phenomenon in recent decades. It remains to be seen whether momentum will still be able to improve its performance in Europe in the future, or will some new enhanced strategy be developed, with which the momentum will reach its previous superiority.

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