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Idiosyncratic momentum factors: A path to improved risk-return trade-offs*[1]

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Abstract

The paper examines the risk and return characteristics of four distinct (idiosyncratic) momentum factors, as well as their time-varying exposures to common risk factors. The research demonstrates that applying more advanced factor models in returns residualization, such as the Fama and French five-factor model and the Stambaugh and Yuan mispricing model, enhances the risk and return profile of momentum factors, constructed as a zero-cost winners-minus-losers portfolio, and effectively reduces time-varying exposures to systematic risk factors. Idiosyncratic momentum factors exhibit lower downside risk as compared to total return momentum factors. This paper also discusses the risk-based versus behavior-based theories which aim to explain the returns of momentum either as a compensation for risk or as a result of behavioral mispricing correction and suggests that both theories are important in explaining momentum returns, but lean more towards behavioral explanations, such as underreaction effect resulting from slow dissemination of information among investors. This research supports recent findings that indicate that idiosyncratic momentum is an anomaly distinct from total return momentum.

Keywords: *asset pricing, idiosyncratic momentum, factor models, time-varying risk*

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1. Introduction

Momentum strategies involve buying recent winners and selling recent losers, as in Jegadeesh and Titman (1993), who show these strategies yield positive excess returns, challenging efficient market hypothesis. Momentum returns are debated, with risk-based explanations attributing them to compensation for risk while behavioral theories explain momentum returns with investor underreaction and overreaction to new information (Barberis et al., 1998; Harrison and Stein, 1999).

Grundy and Martin (2001) note that momentum portfolios exhibit time-varying risk exposures, which causes return volatility during periods of market distress. Blitz et al. (2011, 2020) improve momentum strategies by ranking stocks using idiosyncratic returns instead of total returns, successfully reducing exposure to systematic risk factors. This study builds on these findings by constructing idiosyncratic momentum factors using the Fama and French (1992) three-factor model, Fama and French (2015) five-factor model, and Stambaugh and Yuan (2017) mispricing model. We find that idiosyncratic momentum factors, particularly those constructed utilizing the five-factor and mispricing models, deliver better risk-adjusted returns and lower downside risk than total return momentum. Conditional regressions reveal reduced systematic exposures, leading to fewer severe drawdowns for idiosyncratic momentum factors.

This paper demonstrates the benefits of utilizing advanced asset pricing models in momentum strategy design, such as improved risk and return trade-offs and reduced downside risk. The research results align with behavioral theories, emphasizing investor underreaction caused by the gradual dissemination of information as key driver of idiosyncratic momentum returns.

The rest of this paper is organized as follows. Section 2 presents the literature review regarding momentum and reversal effects, followed by a literature review of the most common academic asset pricing models and idiosyncratic momentum and develops hypotheses. Section 3 describes the sample construction and empirical methods performed to construct and test momentum portfolios. Section 4 presents the descriptive statistics of momentum portfolios as well as the results of empirical tests, which are elaborated further in a discussion. Section 5 concludes.

2. Literature review

This section covers the most common literature in momentum, thus providing a broader perspective on the issues encountered by academics and practitioners. In this section, the theoretical framework regarding the total return momentum anomaly is exposed first, followed by the reversal effect. Afterward, the recent advances in the literature on asset pricing models are presented. This section concludes with a presentation of the literature on idiosyncratic momentum and hypotheses development.

2.1. Momentum and reversal effects

Momentum refers to the tendency of assets with strong past performance to continue outperforming, while those with weak past performance continue underperforming, challenging the efficient market hypothesis. Jegadeesh and Titman (1993) showed that a strategy that buys past winners and sells past losers yields significant abnormal returns. Subsequent studies, including Chan et al. (1996), Asness (1997), and Asness et al. (2013), found that momentum generates abnormal returns across markets, across asset classes like bonds, currencies, and commodities, and across economic environments (Rouwenhorst, 1998). Carhart (1997) highlighted momentum's critical role in mutual fund performance by showing that a four-factor model which adds momentum to Fama and French three-factors explains mutual fund returns.

Momentum returns vary significantly by market conditions. To this note, Cooper et al. (2004) found that momentum returns are stronger in rising markets when overall risk aversion tends to be lower. On similar note, Chordia and Shivakumar (2002) linked momentum returns to business cycle, citing poor performance during downturns with high volatility. An interesting observation comes from Hanauer (2014) who observed that Japan exhibits weaker momentum, a fact generally referred to as an empirical failure of momentum, linking this finding to historically highly volatile market dynamics. Momentum existence inspired both behavioral and risk-based explanations. On one hand, Daniel et al. (1998) and Barberis et al. (1998) attribute it to behavioral factors such as investor underreaction and overreaction due to systematic market inefficiency in processing information. This explanation is further emphasized by Jegadeesh and Titman (2001) and supported by Harrison and Stein (1999) who provides theoretical support. Evidence of market inefficiencies in processing information driving momentum returns is provided in Harrison et al. (2000) who found that stocks with low analyst coverage exhibit stronger momentum. One interesting explanation comes from Chui et al. (2010) who argues that individualism as a cultural factor plays a role in momentum returns and shows that countries with high levels of individualism exhibit more pronounced momentum than countries with low levels of individualism. On the other hand, risk-based explanations suggest momentum returns are a compensation for risk. Within risk-based theories, one of the most explanations is from Agarwal and Taffler (2018) who tied momentum profits to financial distress and Avramov et al. (2007) who linked momentum returns to the mispricing of credit risk. It is also found that tax-loss selling around the end of year contributes to momentum anomalies (Grinblatt and Moskowitz, 1993; Griffiths and White, 1993; D'Mello et al. 2003).

Reversal effect can be classified as either short-term or long-term reversal. It is a tendency of assets that have performed well to perform poorly in the near or distant future and vice versa. Short-term and long-term reversals are supposed to be driven by different mechanisms. From a purely behavioral perspective, short-term reversal is caused by investor overreaction to new information, which causes temporary mispricing. Jegadeesh (1991) presents evidence of short-term reversals in U.S. and U.K. stock markets. Short-term reversals influence momentum portfolio formation period, leading researchers to exclude the most recent week or month of returns when constructing momentum portfolios. As a further explanation of short-term reversals, Gutierrez and Pirinsky (2007) found that institutional investors drive short-term reversals through contrarian strategies which involve buying underperforming and selling outperforming stocks, believing recent price movements misrepresent valuations. Long-term reversals are also tied to overreaction but over extended periods, which then represents a gradual mean reversion. DeBondt and Thaler (1985) show that poorly performing stocks over three to five years often outperform later, attributing this to behavioral factors like investor overconfidence.

2.2. Asset pricing models

The cornerstone in financial economics has been the development of asset pricing (factor) models which try to describe the risk and return relationship of risky assets. Since the idea of the single factor model, which is derived from optimality conditions under portfolio theory, there has been a growing body of literature on multi-factor models, which aim to extract cross-section return premiums and thus explain the variation in stock returns.

Modern portfolio theory, introduced by Markowitz (1952) provided a new framework of investing and risk management. Markowitz emphasizes the importance of diversification as rational choice investors make and the trade-off between risk and return. Markowitz demonstrated that an investor attains the highest level of utility by selecting a combination of assets that minimizes the risk for a given level of return and vice versa. The foundation on MPT, served William Sharpe (1964) to develop the first equilibrium model of asset prices, the capital asset pricing model (CAPM) which predicts linear relationship between expected return and systematic risk. A year later, John Lintner (1965) contributed to the development of CAPM by including aspects of portfolio selection and risk asset valuation.

The CAPM of Sharpe (1964) and Lintner (1965) introduced a new framework for investment but faced criticism in the 1980s and 1990s when the empirical evidence began to emerge. Fama and French (1992) addressed this by proposing the three-factor model, adding size (SMB) and value (HML) factors to explain cross-sectional variation in returns. Fama and French (1993) demonstrated the improved explanatory power. Fama and French (2015) introduced the five-factor model, adding profitability (RMW) and investment (CMA) factors to the existing ones. RMW captures the outperformance of high-profitability stocks, and CMA captures the outperformance of conservative investment firms. While the model explains more risk dimensions, it omits momentum due to weak risk-based justification. Momentum increases the model's stochastic discount factor volatility, with concerns that it is impossible for risk to change that frequently. However, Fama and French (2018) add the momentum factor to their model.

Due to the plethora of behavioral errors investors consistently make, Stambaugh and Yuan (2017) proposed a mispricing model to improve the explanatory power by incorporating systematic mispricing. The model includes market, size, and two mispricing factors: MGMT (management-related anomalies) and PERF (performance-related anomalies). They argue that behavioral biases lead to systematic mispricing, which traditional models fail to capture. The mispricing model better explained the cross-section of stock returns than the competing models of Fama and French but without sacrificing the model's ability to capture return variance.

2.3. Idiosyncratic momentum and hypotheses development

Traditional momentum strategies focus on total returns over the formation period. Grundy and Martin (2001) showed that momentum loads positively on systematic risk factors when they experience positive premiums in the formation period and negatively when they exhibit negative premiums. This means that a momentum strategy will exhibit negative returns when systematic factor premiums exhibit opposite sign in holding period compared to formation period. This issue led Blitz et al. (2011) to construct a risk management technique which attempts to isolate stock-specific returns by removing the effects of systematic factors and form portfolios by sorting stocks on idiosyncratic (residual) returns. The study by Blitz et al. (2011) thus states there are risks involved with total return momentum which are not compensated with additional returns and that successful mitigation of those risks leads to improved momentum performance.

Building on the foundation of Blitz et al. (2011), Blitz et al. (2020) further explore the idiosyncratic momentum anomaly by extending the analysis to a set of international markets. They found that idiosyncratic momentum is well observed in international markets and conclude it is a global phenomenon. Blitz et al. (2020) state that the prominent explanations for the momentum premium, such as crash risk, investor overconfidence and overreaction cannot explain idiosyncratic momentum profits and conclude that the long-term behavior of idiosyncratic momentum provides support for the underreaction hypothesis. Chaves (2016) found that idiosyncratic momentum exists across developed and emerging economies, suggesting it is not driven by specific market conditions but rather a more fundamental aspect of investor behavior.

The persistence of idiosyncratic momentum anomaly among regions points out to a consistent pattern of mispricing giving support to behavioral explanations for its existence.

Since the paper of Blitz et al. (2011) there have been several significant developments in asset pricing models and this paper focuses on two recent models, Fama and French (2015) five-factor model and Stambaugh and Yuan (2017) mispricing model. Following the recent developments in asset pricing models, the first hypothesis of this paper is formulated as:

> *H1: Sorting stocks on idiosyncratic returns obtained by using Fama and French (2015) five-factor model and Stambaugh and Yuan (2017) mispricing model as opposed to total returns improves the risk and return relationship of momentum factors.*

Given the nature of construction of Stambaugh and Yuan (2017) mispricing model and the body of literature on behavioral explanations for momentum effect, this research is concerned with the explanatory power of mispricing model over momentum. Thus, the second hypothesis of this paper is formulated as:

> *H2*: *The mispricing model of Stambaugh and Yuan (2017) achieves greater explanatory power over momentum factor specifications compared to Fama and French (1992) three-factor model and Fama and French (2015) five-factor model.*

The success of idiosyncratic momentum depends on the level of reduction in time-varying systematic factor exposures. The reduction in dynamic factor exposures is the main goal of return residualization. Since in this paper the idiosyncratic momentum is constructed using more advanced factor models compared to Blitz et al. (2011) and Blitz et al. (2020), the third hypothesis is formulated as:

> *H3: Using more advanced factor models in obtaining idiosyncratic returns results in lower dynamic exposures of idiosyncratic momentum portfolios to systematic risk factors.*

3. Sample and methodology

This section provides an overview of the datasets used in this study and describes the cleaning procedures performed to obtain the sample for analysis. A detailed outline of empirical procedures utilized is outlined next. In this paper, four momentum factors are constructed: total return momentum factor, idiosyncratic momentum factor FF3, idiosyncratic momentum factor FF5 and idiosyncratic momentum factor M4, differing with respect to factor model used in obtaining idiosyncratic returns. For all momentum factor portfolios, this study adopts an approach of using formation period of previous twelve months with the exclusion of the most recently ended month to avoid short-term reversal effect (12-2 formation period) and holding period of one month.

3.1. Sample construction

Monthly stock data is obtained from the Center for Research in Security Prices (CRSP). Observations are collected for all common equity stocks (sharecodes 10 and 11) listed on NYSE, AMEX, and NASDAQ stock exchanges over the period from January 1965 until December 2022. The final sample covers 54 years, beginning in January 1968 and ending in December 2022. To accommodate a rolling regression window of 36 months for the estimation of alphas and betas for individual stocks, an additional three years of data have been included. Data for monthly factor-mimicking portfolios returns, as well as one-month U.S. T-Bill rate and monthly NYSE size breakpoints are obtained from Kenneth R. French data library. Data on monthly mispricing factors returns are obtained from Robert R. Stambaugh data library.

To avoid microstructure concerns, this paper excludes all observations for a single stock if the mean share price during the listed period is below \$1. This allows us to obtain continual data for each listed entity. To accommodate the rolling window regression requirement of 36 months, stocks with less than 36 months of total observations are removed from the sample. Following the work of Blitz et al. (2020), each month the stocks which are below the 20^{th} percentile of NYSE market capitalization breakpoint are excluded from the sample. By excluding small-cap stocks, it is ensured the sample contains only liquid stocks. Furthermore, the stock-month observations with missing price, return or shares outstanding data are excluded. In this way, relevant variables can be calculated without obtaining missing values. The market capitalization of each stock in each month is calculated by multiplying the end-of-month price of stock i with shares outstanding of stock i at specific month t. The final sample contains 1100 stocks at the beginning of 1968 and 2690 stocks at the end of 2022.

3.2. Total return momentum procedure

Total return momentum factor is constructed following the methodology outlined in Jegadeesh and Titman (1993), an approach which forms the basis for most cross-sectional momentum strategies. The formation period spans the prior twelve months, excluding the most recently ended month.

Specifically, the cumulative return for month t is calculated from $t - 12$ to $t - 2$. The cumulative returns are calculated for every stock-month observation using the formula:

$$Momentum_{i,t} = \left[\prod_{j=t-12}^{t-2}(1+R_{i,j})\right] - 1\,, \tag{1}$$

where $R_{i,j}$ is the monthly return of stock i in month j. The cumulative return serves as a ranking criterion when sorting stocks into portfolios. Stocks with the highest cumulative return over the formation period are placed into "winners" portfolio (P10) and stocks with the lowest cumulative return over the formation period are placed into "losers" portfolio (P1).

3.3. Idiosyncratic momentum procedure

To obtain idiosyncratic returns, this paper closely follows the procedure established by Blitz et al. (2011) and expanded upon Blitz et al. (2020). Three distinct idiosyncratic momentum factors are constructed by isolating the residual (idiosyncratic) component of stock returns utilizing different asset pricing models. The objective is to capture the portion of return not explained by systematic risk factors contained in each respective asset pricing model, a measure reflecting stock-specific events.

Firstly, idiosyncratic momentum factor (FF3) is constructed by isolating idiosyncratic returns using the Fama and French (1992) three-factor model. To isolate idiosyncratic returns the following equation is estimated for all stocks in the sample over the 36-month rolling window:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}\,MKT_t + \beta_{2,i}\,SMB_t + \beta_{3,i}\,HML_t + \varepsilon_{i,t}\,. \tag{2}$$

In the second step, idiosyncratic returns are calculated as:

$$\varepsilon_{i,t} = R_{i,t} - R_{f,t} - \widehat{\alpha_i} - \widehat{\beta_1}_{,i}\,MKT_t - \widehat{\beta_2}_{,i}\,SMB_t - \widehat{\beta_3}_{,i}\,HML_t\,, \tag{3}$$

where $R_{i,t}$ is the return of stock i at time t. $R_{f,t}$ is the risk-free rate, MKT_t, SMB_t and HML_t are the three Fama and French factors and $\beta_{1,i}$, $\beta_{2,i}$ and $\beta_{3,i}$ are the factor loadings, α_i is the stock i's intercept and $\varepsilon_{i,t}$ is the idiosyncratic (residual) return. The residuals represent the portion of stock return unexplained by systematic factors. There are certain differences in literature regarding the treatment of estimated alpha in the estimation of idiosyncratic returns. Blitz et al. (2011) exclude the alpha when estimating idiosyncratic returns and argue that alpha, since it is estimated in a 36-month window that extends further back than the formation period, is capturing long-term reversal effect. On the other hand, Gutierrez and Pirinsky (2007) and Blitz et al. (2020) include the alpha in the calculation of idiosyncratic returns. This paper aims to stay consistent with recent literature, so the alpha is included in the calculation of idiosyncratic returns.

Secondly, idiosyncratic momentum factor FF5 is constructed by isolating idiosyncratic returns using the Fama and French (2015) five-factor model. Since this model captures more risk dimensions than Fama and French (1992) three-factor model, the aim is to achieve a greater reduction in systematic risk exposures. To obtain idiosyncratic returns, the following equation is estimated over the 36-month rolling window for all stocks in the sample:

$$\begin{aligned} R_{i,t} - R_{f,t} &= \alpha_i + \beta_{1,i}\, MKT_t + \beta_{2,i}\, SMB_t + \beta_{3,i}\, HML_t + \\ &+ \beta_{4,i}\, RMW_t + \beta_{5,i}\, CMA_t + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

Idiosyncratic returns are obtained as:

$$\begin{aligned} \varepsilon_{i,t} &= R_{i,t} - R_{f,t} - \widehat{\alpha_i} - \widehat{\beta_1}_{,i}\, MKT_t - \widehat{\beta_2}_{,i}\, SMB_t - \widehat{\beta_3}_{,i}\, HML_t - \\ &- \widehat{\beta_4}_{,i}\, RMW_t - \widehat{\beta_5}_{,i}\, CMA_t, \end{aligned} \tag{5}$$

where $R_{i,t}$ is the return of stock i at time t. $R_{f,t}$ is the risk-free rate, MKT_t, SMB_t, HML_t, RMW_t and CMA_t are the three Fama and French factors and $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$, $\beta_{4,i}$ and $\beta_{5,i}$ are the factor loadings, α_i is the stock i's intercept and $\varepsilon_{i,t}$ is the idiosyncratic return.

Finally, the idiosyncratic momentum factor M4 is constructed by isolating idiosyncratic return using the Stambaugh and Yuan (2017) mispricing model. To obtain idiosyncratic returns the following equation is estimated over the 36-month rolling window for each stock in the sample:

$$\begin{aligned} R_{i,t} - R_{f,t} &= \alpha_i + \beta_{1,i}\, MKT_t + \beta_{2,i}\, SMB_t + \beta_{3,i}\, MGMT_t + \\ &+ \beta_{4,i}\, PERF_t + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

In the next step, idiosyncratic returns are obtained as:

$$\begin{aligned} \varepsilon_{i,t} &= R_{i,t} - R_{f,t} - \widehat{\alpha_i} - \widehat{\beta_1}_{,i}\, MKT_t - \widehat{\beta_2}_{,i}\, SMB_t - \widehat{\beta_3}_{,i}\, MGMT_t - \\ &- \widehat{\beta_4}_{,i}\, PERF_t, \end{aligned} \tag{7}$$

where $R_{i,t}$ is the return of stock i at time t. $R_{f,t}$ is the risk-free rate, MKT_t, SMB_t, $MGMT_t$ and $PERF_t$ are the four mispricing factors and $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$, *and* $\beta_{4,i}$ are the factor loadings, α_i is the stock i's intercept and $\varepsilon_{i,t}$ is the idiosyncratic return.

3.4. Portfolio construction

After obtaining idiosyncratic returns for all stocks in the sample, three idiosyncratic momentum factors are constructed, differing by the asset pricing model used to obtain idiosyncratic returns. Total return momentum signal used for portfolio sorting is the cumulative return over the period from $t - 12$ to $t - 2$. Idiosyncratic return momentum signal is obtained using a different approach. Instead of calculating cumulative idiosyncratic returns, the signal is obtained by simply summing the idiosyncratic returns over the formation period and then scaling them by their standard deviation. In this way, it is ensured that idiosyncratic returns are treated differently than total returns since idiosyncratic returns are prediction errors rather than actual returns. The motivation to volatility-scale idiosyncratic returns stems from the observation that idiosyncratic returns are noisy signal across stocks, so volatility scaling allows to uncover those stocks which are experiencing extreme stock-specific returns across the cross-section. Idiosyncratic return momentum signal for portfolio sorting procedure is thus calculated as:

$$IdiosyncraticMomentum_{i,t} = \frac{\sum_{j=t-12}^{t-2} \varepsilon_{i,j}}{\sqrt{\sum_{j=t-12}^{t-2}\left(\varepsilon_{i,j} - \overline{\varepsilon_i}\right)^2}}, \tag{8}$$

where $\varepsilon_{i,j}$ is the idiosyncratic return of stock i in month j and $\overline{\varepsilon_i}$ is the mean idiosyncratic return over the formation period. After obtaining four variables, using the methodology described above, where each variable represents respective momentum score, decile portfolios are constructed each month such that the highest “winners” decile (P10) contains stocks with the highest average momentum score, and the lowest “losers” decile (P1) contains stocks with the lowest average momentum score. In line with Blitz et al. (2011) and Blitz et al. (2022) as well as standard academic practice, the portfolios are equally weighted. Institutional investors in practice opt for different weighting schemes, such as value weighting or signal weighting schemes, to either satisfy capacity constraints or to magnify the potential alpha of the signal.

Momentum factors are then formed in each month by taking a long position in the top decile portfolio and a short position in the bottom decile portfolio. This represents a zero-cost investment strategy, and any returns released from such strategy are attributable to the effects of an anomaly (sorting variable). These positions are held for one month. In the following month, the ranking process is applied again, and the portfolios are reformed. The returns of the factors are calculated as the return spread between the highest decile portfolio (P10) and the lowest decile portfolio (P1). The monthly rebalancing ensures the strategy remains responsive to changes in stock rankings and recent performance.

3.5. Empirical testing procedure

Firstly, the performance of decile portfolios is evaluated using the following metrics: annualized average return, annualized standard deviation, Sharpe ratio, and factor model alphas. Additionally, in line with the methodology employed by Blitz et al. (2011), conditional models are constructed to estimate the alphas of factor portfolios and investigate the effect of returns residualization on dynamic exposures to common risk factors.

To evaluate the performance of each momentum portfolio, monthly alphas are estimated with respect to three factor models: CAPM, Fama and French (1992) three-factor and Fama and French (2015) five-factor models. In addition, t-statistics are presented to determine the statistical significance of estimated alphas. Furthermore, factor spanning tests of four momentum factors are conducted to investigate whether momentum can, and to what extent, be explained with other common factors.

As in Grundy and Martin (2001) and Blitz et al. (2011), conditional factor models are constructed for each of the three factor models employed in estimating idiosyncratic returns. Conditional models are constructed by augmenting the model with conditional variables related to each factor, where conditional variables take on the value of the respective factor premium for particular month if the average factor premium over the formation period from $t-12$ to $t-2$ was positive, and zero otherwise. The following equations outline the conditional models:

$$R_{i,t} - R_{f,t} = \alpha_i + FF3_t + FF3_t^{UP} + \varepsilon_{i,t} \tag{9}$$

$$R_{i,t} - R_{f,t} = \alpha_i + FF5_t + FF5_t^{UP} + \varepsilon_{i,t} \tag{10}$$

$$R_{i,t} - R_{f,t} = \alpha_i + M4_t + M4_t^{UP} + \varepsilon_{i,t} \tag{11}$$

Idiosyncratic momentum factor returns are regressed only on a (conditional) model which was used for obtaining the idiosyncratic returns. This approach of conditional regression allows us to analyze whether persistence in factor returns presents unnecessary risk and is this risk successfully mitigated by employing the returns residualization process.

4. Results and discussion

This section provides analysis and interpretation of results and ends with a discussion. Descriptive statistics and return analysis of momentum portfolio are presented first. Next, the results of conducted empirical tests including factor spanning tests and conditional framework regressions are presented, followed by the downside risk and performance over time. The main aim of this section is to either confirm or reject the hypotheses formulated in the Literature review section.

4.1. Portfolios descriptive statistics

Portfolios descriptive statistics start by examining the descriptive statistics of four momentum factors as well as the decile portfolios. Table 1 provides a comprehensive description of the characteristics of decile portfolio across four different momentum specifications. To investigate the drivers of momentum factors performance, both the short and long legs of the factors are examined. The analysis of intermediate portfolios (P2 – P9) offers insight into the impact of sorting variable across the broader stock universe. Additionally, the Gibbons, Ross and Shanken (GRS) F-test is performed to assess the statistical significance of alphas across the decile portfolios, allowing us to determine whether the observed momentum behavior deviates significantly from statistical norms. Table 1 also presents the p-values of the GRS test statistics.

The first section of Table 1 shows descriptive statistics for total return momentum portfolios. The return pattern across deciles is non-monotonic, with the lowest decile not yielding the lowest return. The Sharpe ratio shows some consistency but does not follow a strictly increasing trend. The *Mom* factor, defined as the return spread between winners and losers' portfolios, achieves an annualized return of 3.29% with a Sharpe ratio of 0.15. All ten portfolios, except the *Mom* factor, exhibit statistically significant alphas across three asset pricing models. In contrast, the idiosyncratic momentum factor based on the Fama and French three-factor model (*iMomFF3*) significantly improves portfolios metrics, including a Sharpe ratio increase to 0.59. The residualization procedure enhances the risk and return trade-off, concentrating high idiosyncratic return stocks in winner portfolio and low idiosyncratic return stocks in loser portfolio. *iMomFF3* alphas are more significant in higher deciles. While the *iMomFF3* factor shows significant alphas under CAPM and the Fama and French three-factor model, it loses significance under the five-factor model, which captures more relevant risk dimensions. The third section of Table 1 highlights idiosyncratic momentum portfolios based on the Fama and French five-factor model (*iMomFF5*). These portfolios display a monotonic increase in annualized returns and a decrease in volatility across deciles. The *iMomFF5* Sharpe ratio improves to 0.71, a 20% increase over *iMomFF3*. Alphas remain positive and statistically significant under CAPM and three-factor model but are less significant under the five-factor model. The pattern of alpha significance mirrors *iMomFF3*, with higher significance concentrated in higher deciles.

Table 1: Performance of decile portfolios

Mom	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	GRS_p
Return	23.18	16.97	16.38	15.51	15.66	16.29	17.02	18.27	20.80	27.15	3.29	
Volatility	29.13	21.67	19.02	17.39	16.54	16.11	16.41	16.95	18.67	23.53	21.65	
Sharpe	0.80	0.78	0.86	0.89	0.95	1.01	1.04	1.08	1.11	1.15	0.15	
α CAPM	0.58	0.31	0.33	0.31	0.34	0.39	0.43	0.51	0.64	1.71	0.02	
t-stat	(3.06)	(2.58)	(3.49)	(3.83)	(4.61)	(6.14)	(6.55)	(7.16)	(7.41)	(12.17)	(0.12)	0.00
α FF3	0.45	0.17	0.18	0.17	0.21	0.28	0.33	0.45	0.63	1.79	0.24	
t-stat	(2.68)	(1.70)	(2.50)	(2.89)	(3.88)	(6.10)	(6.94)	(8.26)	(9.17)	(16.63)	(1.06)	0.00
α FF5	0.69	0.23	0.17	0.11	0.12	0.19	0.25	0.35	0.57	1.85	0.05	
t-stat	(4.08)	(2.21)	(2.28)	(1.94)	(2.39)	(4.23)	(5.36)	(6.47)	(8.11)	(16.95)	(0.22)	0.00
iMomFF3	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	GRS_p
Return	14.46	15.18	15.25	17.19	16.79	18.06	17.93	19.39	20.16	21.99	6.66	
Volatility	20.60	19.17	18.31	18.10	17.70	17.68	17.52	17.45	17.92	18.50	11.33	
Sharpe	0.70	0.79	0.83	0.95	0.95	1.02	1.02	1.11	1.13	1.19	0.59	
α CAPM	0.14	0.22	0.25	0.39	0.37	0.47	0.46	0.57	0.61	1.46	0.21	
t-stat	(1.38)	(2.56)	(3.17)	(5.23)	(5.19)	(6.48)	(6.70)	(8.01)	(8.00)	(16.97)	(1.69)	0.00
α FF3	0.02	0.10	0.13	0.26	0.25	0.35	0.27	0.45	0.51	1.31	0.25	
t-stat	(0.32)	(1.55)	(2.31)	(5.10)	(5.01)	(7.11)	(5.99)	(9.70)	(8.98)	(19.49)	(2.01)	0.00
α FF5	0.05	0.08	0.09	0.21	0.20	0.28	0.27	0.38	0.38	0.42	1.31	
t-stat	(0.56)	(1.19)	(1.58)	(4.05)	(3.29)	(5.64)	(5.99)	(8.08)	(7.42)	(18.11)	(1.19)	0.00
iMomFF5	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	*GRS_p*
Return	13.92	14.99	16.27	16.51	16.38	17.75	18.31	19.87	19.92	22.05	7.21	
Volatility	20.12	19.05	18.47	17.89	17.97	17.68	17.47	17.69	17.93	18.29	10.23	
Sharpe	0.69	0.79	0.88	0.92	0.94	1.00	1.05	1.12	1.11	1.21	0.71	
α CAPM	0.11	0.21	0.32	0.35	0.37	0.44	0.49	0.59	0.60	1.47	0.25	
t-stat	(1.15)	(2.47)	(4.06)	(4.72)	(5.05)	(6.31)	(6.94)	(8.42)	(7.77)	(17.38)	(2.24)	0.00
α FF3	0.00	0.10	0.19	0.23	0.24	0.33	0.37	0.48	0.49	1.38	0.28	
t-stat	(0.04)	(1.46)	(3.33)	(4.36)	(4.91)	(7.02)	(8.01)	(10.48)	(8.95)	(20.3)	(2.51)	0.00
α FF5	0.00	0.07	0.16	0.17	0.18	0.26	0.3	0.41	0.43	1.32	0.22	
t-stat	(0.03)	(0.92)	(2.69)	(3.25)	(3.60)	(5.63)	(6.44)	(8.93)	(7.62)	(19.03)	(1.86)	0.00
iMomM4	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	GRS_p
Return	13.48	14.80	15.58	16.48	17.65	18.29	18.88	19.90	21.58	22.72	8.22	
Volatility	20.47	19.05	18.22	17.72	17.45	17.25	17.41	17.52	17.47	18.04	12.34	
Sharpe	0.66	0.78	0.86	0.93	1.01	1.06	1.08	1.14	1.24	1.26	0.67	
α CAPM	0.09	0.21	0.28	0.36	0.45	0.50	0.54	0.61	0.73	1.61	0.31	
t-stat	(0.80)	(2.21)	(3.93)	(4.62)	(5.96)	(6.70)	(7.30)	(7.75)	(8.93)	(17.29)	(2.13)	0.00
α FF3	-0.04	0.06	0.12	0.21	0.30	0.33	0.38	0.46	0.59	1.49	0.34	
t-stat	(-0,4)	(0.74)	(1.97)	(3.55)	(5.42)	(6.75)	(7.83)	(8.45)	(10.0)	(19.43)	(2.30)	0.00
α FF5	0.05	0.05	0.06	0.15	0.20	0.24	0.30	0.35	0.49	1.41	0.16	
t-stat	(0.43)	(0.63)	(0.96)	(2.59)	(3.74)	(4.99)	(6.14)	(6.53)	(8.42)	(18.01)	(1.11)	0.00

Source: Author's calculations

The final section of Table 1 presents idiosyncratic momentum portfolios based on the mispricing model of Stambaugh and Yuan (*iMomM4*). These portfolios show monotonic return increase and volatility decrease across deciles. P1 decile achieves a 13.48% annualized return, while P10 decile reaches 22.72%. The Sharpe ratio of 0.67 is slightly lower than *iMomFF5* of 0.71. Alphas for CAPM and three-factor model are significant at 5% level, but the five-factor model alpha is not statistically significant.

Based on evidence presented in Table 1, the first hypothesis is confirmed, and it is concluded that using idiosyncratic returns in sorting stocks to form portfolios does indeed improve the risk and return trade-off compared to total returns.

4.2. Factor spanning tests

In this subsection, factor spanning tests are conducted to evaluate whether the four momentum factors can be considered as distinct factors or if they are subsumed by traditional asset pricing models. To conduct factor spanning tests, the returns of the four momentum factors are regressed on the Fama and French (1992) three-factor and Fama and French (2015) five-factor model. Additionally, the returns are also regressed on the Stambaugh and Yuan (2017) mispricing model.

Table 2: Factor spanning tests (FF3 and FF5)

	Alpha	Mkt-Rf	SMB	HML	RMW	CMA	Adj. RSQ
Mom	0.24	-0.30	-0.03	-0.55			0.09
	(1.06)	(-5.66)	(-0.42)	(-7.09)			
	0.05	-0.23	-0.01	-0.81	0.13	0.57	0.10
	(0.22)	(-4.22)	(-0.01)	(-7.64)	(1.23)	(3.49)	
iMomFF3	0.25	-0.08	-0.04	-0.09			0.01
	(2.01)	(-2.84)	(-0.91)	(-2.32)			
	0.15	-0.05	0.00	-0.19	0.13	0.21	0.02
	(1.19)	(-1.81)	(-0.10)	(-3.42)	(2.27)	(2.33)	
iMomFF5	0.28	-0.07	-0.03	-0.07			0.01
	(2.51)	(-2.98)	(-0.79)	(-2.03)			
	0.22	-0.06	0.00	-0.13	0.10	0.12	0.02
	(1.86)	(-2.20)	(-0.10)	(-2.65)	(1.93)	(1.55)	
iMomM4	0.34	-0.11	0.03	-0.07			0.01
	(2.30)	(-3.42)	(0.81)	(-1.40)			
	0.16	-0.05	0.08	-0.26	0.20	0.42	0.04
	(1.11)	(-1.62)	(1.62)	(-3.79)	(2.98)	(3.97)	

Source: Author’s calculations

Table 2 presents the results of factor spanning tests for four momentum factors. Total return momentum (*Mom*) factor yields statistically insignificant three-factor alpha of 24 basis points per month, while the loadings on market and value factors are negative and statistically significant at 1% level. The negative loading on value factor aligns with the findings of Asness et al. (2013), who report that value and momentum exhibit a persistent negative correlation, potentially offering diversification benefits to investors. Continuing with the five-factor model, *Mom* factor generates a small, statistically insignificant alpha of 5 basis points per month, with significant negative loadings on market and value factors, and a significant positive loading on the investment factor. Compared to the three-factor model, the statistical significance of the market factor decreases slightly, while the significance of the value factor increases. The positive loading on the investment factor suggests that total return momentum factor is more exposed to firms with conservative investment policies, rather than those with aggressive ones. The idiosyncratic momentum factor (*iMomFF3*) in Table 2 generates a three-factor alpha of 25 basis points per month, which is statistically significant at the 5% level. The loadings on the market and value factors remain negative, though with lower t-statistics. Furthermore, *iMomFF3* produces a positive five-factor alpha, though statistically insignificant, of 15 basis points per month. The idiosyncratic momentum factor (*iMomFF5*) in Table 2, generates a three-factor alpha of 28 basis points per month with a statistical significance at 5% level and with similar factor loadings as the *iMomFF3* factor specification. *iMomFF5* factor produces a five-factor monthly alpha of 22 basis points, significant at 10% level, with significant negative loadings on the market and size factors, and insignificant positive loadings on the profitability and investment factors. Finally, the idiosyncratic momentum factor *iMomM4* generated a three-factor alpha of 34 basis points per month, with statistical significance at 5% level. The factor loadings for *iMomM4* behave similarly to those of *iMomFF3* and *iMomFF5*. Furthermore, *iMomM4* yields a five-factor alpha of 16 basis points per month, though this result lacks statistical significance. The factor loadings are negative for the market and value factors, while being positive for the investment and profitability factors.

Finally, the explanatory power of Stambaugh and Yuan's mispricing model over the four momentum factors is assessed and presented in Table 3. The results show that this model consistently outperforms both Fama and French three-factor and five-factor models in explaining the momentum factor returns, thereby supporting the second hypothesis of this paper. All four momentum factor alphas are negative, indicating the mispricing model fully subsumes the return premia associated with total and idiosyncratic return momentum.

Table 3: Factor spanning test (M4)

	Alpha	Mkt-Rf	SMB	MGMT	PERF	Adj. RSQ
Mom	-0.99	0.07	0.17	0.10	1.12	0.45
	(-4.67)	(1.33)	(2.43)	(1.31)	(21.65)	
iMomFF3	-0.16	0.03	0.02	0.09	0.40	0.20
	(-1.24)	(1.13)	(0.65)	(1.87)	(12.21)	
iMomFF5	-0.05	0.01	0.03	0.08	0.31	0.15
	(-0.47)	(0.51)	(0.82)	(1.74)	(10.18)	
iMomM4	-0.36	0.09	0.16	0.29	0.49	0.29
	(-2.65)	(2.66)	(3.56)	(5.70)	(14.79)	

Source: Author's calculations

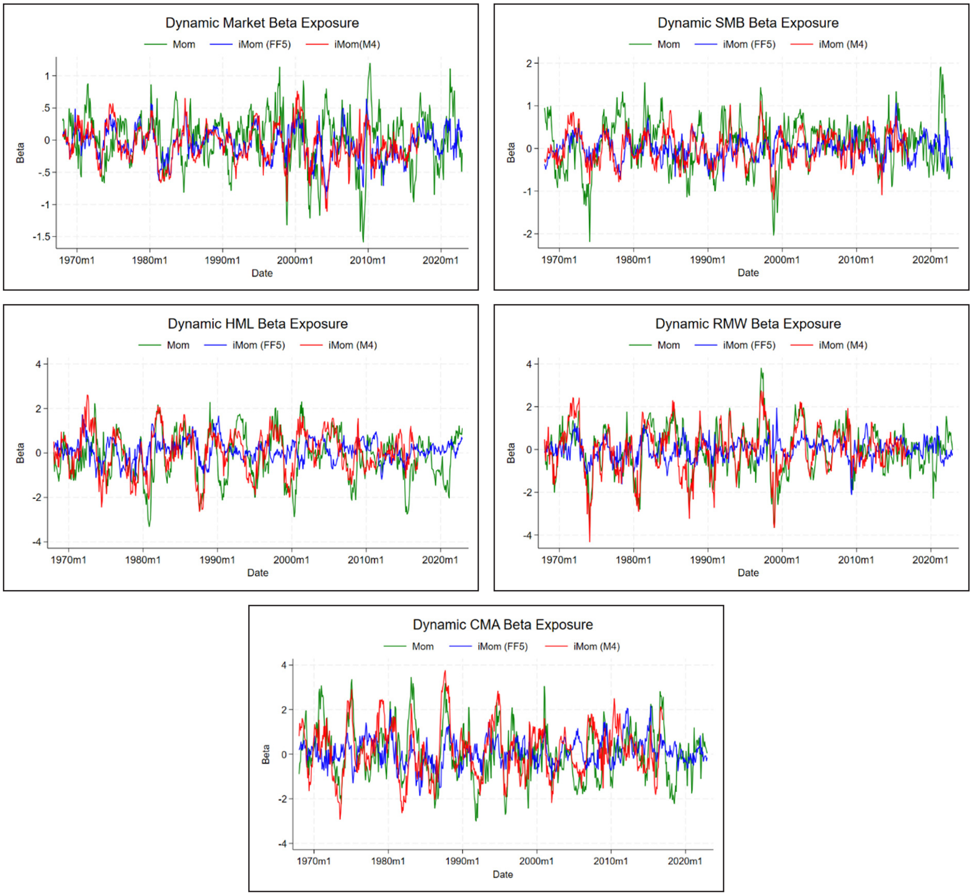
4.3. Dynamic exposures to risk factors

This section examines the time-varying behavior of factor exposures associated with momentum strategies. Traditional momentum strategies carry uncompensated risks which stem from the persistence in common factor returns. With the use of return residualization procedures, the aim is to reduce uncompensated risks. This section provides analysis of conditional factor regressions, highlighting the impact of return residualization on conditional factor exposures.

The variation in Fama and French five-factor betas is first presented graphically for three momentum factors: *Mom*, *iMomFF5* and *iMomM4*. Figure 1 illustrates the variation over time of the difference between the average beta of portfolio P10 and portfolio P1 for each of the three momentum factors. In each of the five charts in Figure 1, the net portfolio betas of *iMomFF5* and *iMomM4* factors exhibit greater stability as compared to the betas of *Mom* factor. Notably, during periods of market-wide distress, *iMomFF5* experiences a significantly lower market beta than the total Mom factor. Beyond market beta exposures, the charts also show that *iMomFF5* and *iMomM4* exhibit greater stability across other Fama and French five-factors. Specifically, *iMomFF5* demonstrates the lowest volatility in factor exposures, followed by *iMomM4*, which still shows some volatility, particularly in its exposures to value (HML), investment (CMA), and profitability (RMW) factors.

Next, a conditional regression framework is employed. As outlined in the methodology section, this paper follows the approach of Blitz et al. (2011), which incorporates conditional variables into the regression model. Using this framework, the alphas and regression coefficients are estimated for three idiosyncratic momentum factors relative to their respective conditional regression models. For comparative purposes, the same conditional models are also applied to the total return momentum factor, allowing for the analysis of how the residualization process reduces the risk of persistence in common factor returns.

Figure 1: Dynamic factor exposures



Source: Author's calculations

Table 4 presents the results of conditional regression for *iMomFF3* and *Mom* factors. The alpha for *Mom* is negative and statistically insignificant, while the alpha for *iMomFF3* is positive, amounting to 14 basis points per month, though also statistically insignificant. When comparing coefficients for the risk factors, *iMomFF3* exhibits lower coefficients across all risk factors, accompanied by lower t-statistic values. This highlights the effectiveness of the residualization procedure in reducing a substantial portion of the unrewarded dynamic factor exposure.

Table 4: Conditional up-factor model spanning test (FF3)

	Alpha	Mkt-Rf	SMB	HML	Mkt-Rf^{UP}	SMB^{UP}	HML^{UP}	Adj. RSQ
Mom	-0.15	-0.74	-0.61	-1.29	0.79	0.85	1.42	0.37
	(-0.78)	(-11.05)	(-6.03)	(-13.85)	(9.35)	(6.58)	(11.15)	
iMomFF3	0.14	-0.23	-0.16	-0.27	0.27	0.18	0.33	0.09
	(1.20)	(-5.61)	(-2.60)	(-4.58)	(5.12)	(2.25)	(4.13)	

Source: Author's calculations

In Table 5, the same analysis is presented but for the *iMomFF5* and *Mom* factors. The *iMomFF5* factor yields an alpha of 13 basis points per month, though statistically insignificant. In contrast, *Mom* factor exhibits a negative alpha of 38 basis. The coefficients for unconditional and conditional factors are significantly reduced as compared to *Mom* factor.

Table 5: Conditional up-factor model spanning test (FF5)

	Alpha	Mkt-Rf	SMB	HML	RMW	CMA	Mkt-Rf^{UP}	SMB^{UP}	HML^{UP}	RMW^{UP}	CMA^{UP}	Adj. RSQ
Mom	-0.38	-0.62	-0.54	-1.10	-0.43	-0.09	0.68	0.77	1.00	1.22	-0.50	0.43
	(-1.9)	(-9.1)	(-5.5)	(-9.2)	(-3.1)	(-0.5)	(8.27)	(6.00)	(7.09)	(6.75)	(2.48)	
iMomFF5	0.13	-0.17	-0.13	-0.21	0.05	0.10	0.18	0.19	0.21	0.14	-0.07	0.07
	(1.13)	(-4.2)	(-2.2)	(-2.9)	(0.67)	(0.95)	(3.79)	(2.50)	(2.48)	(1.32)	(-0.61)	

Source: Author's calculations

Finally, in table 6, the conditional regression framework for *iMomM4* and *Mom* factors are presented. It can be observed that both *Mom* and *iMomM4* produce negative and statistically significant alphas relative to conditional mispricing model. This is in line with the previous result of mispricing model performing better in explaining momentum returns. The coefficients, however, exhibit a similar pattern as in previous regressions.

Table 6: Conditional up-factor model spanning test (M4)

	Alpha	Mkt-Rf	SMB	MGMT	PERF	Mkt-Rf^{UP}	SMB^{UP}	MGMT^{UP}	PERF^{UP}	Adj. RSQ
Mom	-0.86	-0.30	-0.39	-0.39	0.51	0.52	0.72	0.44	0.51	0.54
	(-4.38)	(-4.02)	(-3.51)	(-2.86)	(4.21)	(6.20)	(5.39)	(3.00)	(3.91)	
iMomM4	-0.31	0.01	0.12	0.40	0.27	0.12	0.03	-0.18	0.23	0.30
	(-2.35)	(0.14)	(1.56)	(4.31)	(3.26)	(2.07)	(0.41)	(-1.84(	(2.61)	

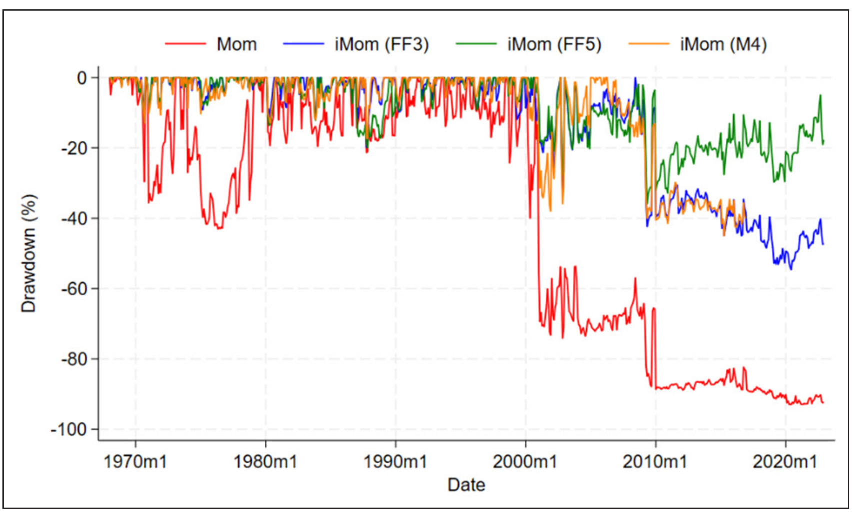
Source: Author's calculations

This section shows that using returns residualization to isolate idiosyncratic returns in momentum factor construction reduces time-varying exposures to common risk factors. The Fama and French (2015) five-factor model most effectively reduces dynamic exposures, followed by the Stambaugh and Yuan (2017) mispricing model. Our analysis shows that models with greater explanatory power, like Fama and French five-factor model, are more effective in reducing dynamic exposures than simpler models, such as the three-factor model. Evidence presented in Figure 1 and Tables 4, 5, and 6 supports the third hypothesis which states that utilizing advanced asset pricing models lowers dynamic exposures to systematic risks.

4.4. Downside risk

Momentum exhibits severe crashes triggered by market factor premia exhibiting opposite sign in holding period relative to formation period. These crashes are especially pronounced during times of market distress. This section presents the downside risk characteristics of four momentum factors constructed in this paper. The presence of severe drawdowns is associated with higher distributional momentum, which leads to higher kurtosis measures. It is one of the risks to which investors exhibit the greatest aversion to. In the context of lower partial moments, investors are concerned with the downside risk more than they are concerned with overall volatility. To assess the magnitude of downside risk and the frequency of drawdown occurrence, drawdowns of four momentum factors are presented in Figure 2.

Figure 2: Momentum drawdowns



Source: Author's calculations

From Figure 2, several insights can be drawn. It is evident that the *Mom* factor experiences the most significant and prolonged drawdowns throughout the sample period, a highly undesirable feature. In contrast, the *iMomFF5* exhibits the smallest drawdowns, followed by *iMomM4* and *iMomFF3*. This reinforces the advantages of using idiosyncratic returns when constructing momentum portfolios, as they more effectively mitigate the risks associated with dynamic factor exposures.

Furthermore, Table 7 presents the maximum percentage drawdowns incurred by four momentum factors along with the date of the drawdown and the associated market-wide theme prevailing at the time of drawdown occurrence. The *Mom* factor and *iMomFF3* experienced its biggest drawdown during Covid-19, while iMomFF5 experienced its biggest drawdown during the global financial crisis.

Table 7: Maximum drawdowns of momentum factors

	Maximum drawdown (%)	Date	Event
Mom	-92.97	June 2020	Covid-19
iMomFF3	-54.63	June 2020	Covid-19
iMomFF5	-35.88	May 2009	Financial crisis
iMomM4	-44.94	April 2015	

Source: Author's calculations

The findings presented in this section confirm the significant improvements in the risk and return relationship of momentum when employing the residualization procedure outlined by Blitz et al. (2011) and Blitz et al. (2020).

4.5. Discussion

This paper investigates the performance of idiosyncratic momentum factors constructed using three different asset pricing models. Portfolio metrics of the three idiosyncratic momentum factors are examined as well as the total return momentum factor, alongside spanning tests to check whether other anomalies, and to what extent, can explain momentum returns. Conditional framework regressions were constructed by augmenting the asset pricing regression models with conditional factors to test whether the risk of persistence in common factor returns is reduced in idiosyncratic momentum factors relative to total return momentum factor. Additionally, the downside risk associated with these factors was assessed to provide a comprehensive understanding of factor performance.

One of the key risks associated with momentum investing is its high dynamic exposure to systematic risk factors. This causes momentum strategies to exhibit severe drawdowns when the market premium shifts sign in holding period relative to formation period. This phenomenon is particularly concerning for investors who rely on momentum strategies, such as mutual funds and hedge funds, as it can lead to significant losses during market downturns. By employing a return residualization technique using advanced asset pricing model, it is shown that it is possible to effectively isolate idiosyncratic returns and achieve a more favorable risk and return trade-off, which is a crucial aspect for investors seeking to optimize their portfolios. This led to improvement in all portfolio metrics, especially Sharpe ratios, which measure the risk-adjusted return of an investment. This approach also reduced dynamic factor exposures, which are considered unrewarded risks in momentum investing. By minimizing these exposures, investors can achieve a more stable and predictable performance from their momentum strategies.

The key benefit of idiosyncratic momentum factors is reduced volatility and better return profile compared to total return momentum factor. The *iMomFF5* factor achieves the highest Sharpe ratio of 0.71, indicating a superior risk-adjusted return. In contrast, the *Mom* exhibited a Sharpe ratio of 0.15, highlighting the advantages of using idiosyncratic returns to form momentum portfolios. Furthermore, idiosyncratic momentum factors demonstrated lower downside risk, with the maximum drawdown during the global financial crisis being -35.8% for *iMomFF5* factor, compared to -57.4% *Mom* factor. This difference in drawdown magnitudes supports the findings of previous studies, especially those of Blitz et al. (2020), who argue that idiosyncratic momentum is more resilient during market downturns. This resilience is a critical consideration for investors looking to protect their portfolios from severe losses during periods of market distress.

Despite the appealing results in terms of high Sharpe ratios driven by both return enhancement and risk reduction, this paper has several limitations that should be acknowledged. First, our choice of portfolios design, which equally weights stocks and reforms itself every month, may not align with optimal institutional application, since due to constraints they face, they opt for different weighting schemes. Second, our approach to portfolios design, while common in academic setting, imposes unnecessary transaction costs which on most occasions significantly diminishes the alpha of a factor-based strategy. Additionally, this paper focuses solely on U.S. stock market, limiting the generalizability of results.

While using idiosyncratic returns in sorting stocks to form momentum portfolios offers advantages, including better return profiles, reduced volatility, and lower downside risk, it is essential to consider the limitations associated with implementation. Future research should explore the utilization of very recent academic factor models in residualizing returns, as well as the issue of minimizing transaction costs or using alternative weighting schemes. By addressing these issues, one can gain a more comprehensive understanding of the potential benefits and drawbacks of idiosyncratic momentum investing.

5. Conclusion

This paper demonstrated the benefits of sorting stocks on idiosyncratic returns as opposed to total returns when constructing momentum portfolios. By isolating idiosyncratic returns using three distinct asset pricing model, it is possible to achieve a more favorable risk and return profile compared to portfolios constructed using total returns. The findings of this paper highlight the importance of addressing the unrewarded risks in momentum investing which occur during broad market direction changes.

Given the significant academic debate about the underlying causes of momentum returns, this paper aligns with both risk-based and behavioral explanations, but however, leans more towards the behavioral explanations such as underreaction and subsequent overreaction caused by gradual dissemination of information among investors. We do not neglect risk-based explanations, because it could to some extent explain momentum returns, but fails in explaining idiosyncratic momentum returns. This could lead us to a conclusion that idiosyncratic momentum is a distinct anomaly from total return momentum, with some overlapping between them. Thus, the behavioral explanations offer a more plausible argument for the existence of idiosyncratic momentum. The underreaction to new information is often attributed to cognitive biases and limits to arbitrage, which prevents prices from adjusting immediately to new information.

This research contributes to the ongoing debate by providing empirical evidence that supports the superiority of idiosyncratic momentum strategies. By employing advanced asset pricing models like the Fama and French five-factor model and the Stambaugh and Yuan mispricing model, we were able to isolate the idiosyncratic component of stock returns more effectively. This approach not only enhanced the risk-adjusted returns but also mitigates the downside risk associated with traditional momentum strategies. The reduction in systematic risk exposure is particularly significant during periods of market-wide distress, where traditional momentum strategies tend to underperform.

Furthermore, the findings of this paper have practical implementations for portfolio management. Investors seeking to exploit momentum anomalies can benefit from focusing on idiosyncratic returns, thereby achieving better diversification and risk management. This approach aligns with the growing body of literature which emphasizes the idiosyncratic component of returns in searching for anomalous behavior.

In conclusion, this paper underscores the value of idiosyncratic momentum in enhancing the risk and return profile within a broader momentum investment style cluster. By addressing the limitations of traditional approaches to momentum portfolios design and incorporating advanced asset pricing models, this paper provides a framework for constructing more advanced momentum portfolios.

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Faktori idiosinkratskog zamaha: Put do poboljšanih kompromisa rizika i povrata

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Sažetak

Ovaj rad istražuje karakteristike rizika i povrata četiri različita (idiosinkratska) faktora zamaha, kao i njihovu vremenski promjenjivu izloženost uobičajenim faktorima rizika. Istraživanje pokazuje da primjena naprednijih faktorskih modela u rezidualizaciji povrata, poput Fama-French pet-faktorskog modela i Stambaugh-Yuanovog modela pogrešne procjene, poboljšava profil rizika i povrata faktora zamaha, konstruiranih kao portfelj „dobitnici minus gubitnici" bez troškova i učinkovito smanjuje vremenski promjenjivu izloženost sistemskim faktorima rizika. Faktori idiosinkratskog zamaha pokazuju i niži rizik nepovoljnih kretanja u usporedbi s faktorom zamaha ukupnog povrata. Rad također raspravlja o teorijama temeljenim na riziku nasuprot teorijama temeljenim na ponašanju koje nastoje objasniti povrate zamaha ili kao kompenzaciju za preuzeti rizik ili kao rezultat korekcije bihevioralne pogrešne procjene cijena. Sugerira se da su obje teorije važne u objašnjavanju povrata zamaha, ali se rad više priklanja bihevioralnim objašnjenima, poput efekta podreakcije koji proizlazi iz spore diseminacije informacija među investitorima. Ovo istraživanje podržava nedavne akademske rezultate koji ukazuju da je idiosinkratski zamah anomalija koja se razlikuje od zamaha ukupnog povrata.

Ključne riječi: *vrednovanje imovine, idiosinkratski zamah, faktorski modeli, vremenski promjenjivi rizik*

JEL klasifikacija: *G11, G12, C58*

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