# ON THE PERFORMANCE AND PRACTICAL IMPLEMENTATION OF FACTOR MOMENTUM


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ABSTRACT

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Assuming a practical point of view, factor momentum is best exploited as a long-short strategy when applied to a small set of popular stylized factors. This thesis assumes long-short factor portfolios to proxy for style ETFs and considers some of the issues regarding practical implementation of factors. The best performing monthly rebalanced long-short factor momentum strategy that relies on the one-month momentum indicator, referred to as the Winner-Loser (1-1) strategy, outperforms all other strategies on a pre-cost and post-cost basis. A return-based style analysis reveals that the monthly rebalanced Winner-Loser strategies are significantly tilted towards size, value, and momentum. Moreover, the CMA factor contributes more to the returns of the mimicking portfolios on shorter formation periods, whereas the UMD factor contributes more to the returns of the mimicking portfolios on longer formation periods. A mean-variance efficiency analysis indicates that the best performing Winner-Loser (1-1) strategy improves the performance of the ex-post tangency portfolio both before and after considering costs from implementation. Factor momentum has also avoided large market drawdowns. The return decomposition on market states reveals that the relationship between factor momentum returns over and above the market return and the market return is negative during bullish and bearish states, although the linear effects is in several instances sharply different and stronger during bearish states. Many factor momentum strategies also exhibit corresponding negative bullish state quadratic effects. Since the average return of the market has been positive (negative) during bullish (bearish) states, the return dependency analysis indicates that factor momentum has performed well during bearish states but has underperformed during bullish states with respect to the market portfolio, on average.

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Huomioiden useampia seikkoja liittyen strategioiden käytännön hyödynnettävyyteen, ’Factor momentum’ -ilmiötä onnistuu parhaiten hyödyntämään kuukausittain uudelleen painotettu strategia, joka ostaa ja myy faktoreita yhden kuukauden toteutuneiden tuottojen perusteella. Tutkimustulos perustuu sekä brutto että nettopohjaisiin suoriutumisvertailuihin. Tutkimuksessa oletetaan, että pieni määrä teoreettisia faktoreita mittaa suosittujen tyyli ETF rahastojen suoriutumista, joiden valitsemisessa on huomioitu useampia rajoitteita, tuoden suoriutumistarkastelun ja ilmiön hyödynnettävyyden astetta lähemmäksi käytäntöä. Tuottopohjaisen tyylianalyysin pohjalta parhaiten suoriutuvien strategioiden tuotto liittyy merkitsevästi koko-, arvo-, ja momentum-tyyleihin. Lisäksi kuukausittain uudelleenmuodostettujen lyhyemmältä ajalta toteutuneita tuottoja hyödyntävien strategioiden tuotot liittyvät voimakkaasti CMA faktoriin, kun taas vastaavien pidemmältä ajalta toteutuneita tuottoja hyödyntävien strategioiden tuotot liittyvät voimakkaammin UMD faktoriin. Lisäksi parhaiten suoriutuva strategia parantaa tangenttiportfolion suoriutumista sekä ennen että jälkeen strategien soveltamiseen liittyvien kustannusten huomioimisen. Tutkitut strategiat ovat myös välttäneet markkinalaskuja. Strategioiden markkinatuoton ylittävien tuottojen ja markkinaportfolion tuoton välillä on negatiivinen lineaarinen riippuvuussuhde sekä härkämarkkinoiden että karhumarkkinoiden aikaan. Lineaarinen suhde on myös tilastollisesti merkitsevästi voimakkaampi laskumarkkinoiden aikana. Lisäksi osalla strategioista on vastaava negatiivinen kvadraattinen riippuvuussuhde markkinaportfolion kanssa härkämarkkinatilassa. Koska markkinaportfolion tuotto on ollut keskimäärin positiivinen härkämarkkinoiden aikaan ja negatiivinen karhumarkkinoiden aikaan, niin lineaarinen riippuvuussuhde osoittaa, että strategiat ovat pärjänneet keskimäärin epäsuotuisammin härkämarkkinoiden aikaan ja puolestaan suotuisammin karhumarkkinoiden aikaan suhteessa markkinaportfolioon.

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Helsinki, 06.03.2023
Dani Porkka

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# 1 Introduction

The classic price-momentum strategy is described in the seminal research of Jegadeesh and Titman (1993) as buying winners and selling losers based on the recent cross-sectional performance of stocks.[1] Recently, literature has extended the concept of momentum to asset pricing factors as factors exhibit significant return persistency beside factor momentum strategies generating high theoretical returns (see for example Avramov, Cheng, Schreiber & Shemer 2017; Zaremba & Shemer 2018; Gupta & Kelly 2019; Ehsani & Linnainmaa 2022a). However, prior studies on factor momentum employ large sets of long-short factors that do not consider issues in practical implementation and the possible nonexistence of investable financial vehicles that track the performance of less popular anomalies. Long-short portfolios are also far from zero-cost investing due to ignoring the effect of, e.g., short selling constraints, higher risk of short positions, and margin requirements, among other implementation issues (Shleifer & Vishny 1997; Stambaugh, Yu & Yuan 2015). Hence, factor investing is often implemented long-only to avoid problems stemming from short selling (Blitz 2023). A large factor set also exposes the results to the risk of obscure factors driving the significance of the results.[2] This thesis contributes to existing literature by studying factor momentum from a practical viewpoint that considers some of these issues.

Stock-level momentum exhibits a tendency to sometimes crash after the market rebounds following multiyear market drawdowns and high market volatility (Daniel & Moskowitz 2016).[3] Therefore, literature has introduced various managed or alternative momentum strategies that aim to avoid momentum crashes (Grundy & Martin 2001; Barroso & Santa-Clara 2015; Daniel & Moskowitz 2016; Geczy & Samonov 2016; Dierkes & Krupski 2022). However, factor momentum differs from stock-level momentum as Gupta and Kelly (2019)

[1] The return-momentum effect counts as one of the most robust and pervasive of published stock market anomalies (Fama & French 2008; Asness, Frazzini, Israel & Moskowitz 2014; Hou, Xue, & Zhang 2020).
[2] A good, albeit a less intuitive example, of this is including the betting against beta (BAB) factor of Frazzini and Pedersen (2014) in the sample that generates exceptionally high returns from overweighting short positions in microcaps due to its unconventional construction (Novy-Marx & Velikov 2022).
[3] The UMD factor trading diversified size-sorted portfolios based on t-12 to t-2 months of prior performance returned -52.05% over two months in 1932 and -42.51% over three months in 2009. The UMD factor data is available at the website of Kenneth R. French:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

show that it completely avoided the momentum crash of 2009, generating 15-16% of profits over the crash period, thereby motivating further research towards factor momentum profits.

Prior to the discovery of factor momentum, a wide range of risk-based explanations has sprouted around the source of stock-level momentum risk and profitability over the recent decades, reaching back to the work of Jegadeesh and Titman (1993, 2001), Chan, Jegadeesh, and Lakonishok (1996), and Fama and French (1996). Momentum profitability is proposed to be explained by variation in systematic risk by Conrad and Kaul (1998), industry effects by Moskowitz and Grinblatt (1999), factor-level versus stock-specific momentum by Grundy and Martin (2001), macro-economic factors by Chordia and Shivakumar (2002), Griffin, Ji, and Martin (2003), Liu and Zhang (2008), and market states by Cooper, Gutierrez, and Hameed (2004), Siganos and Chelley-Steeley (2006), Stivers and Sun (2010, 2013), and Geczy and Samonov (2016). Prior literature finds that stock-level momentum is separate from industry momentum, is not explained by variation in expected returns, is weakly related to macroeconomic variables, and concludes that return states of the market have considerable power in explaining momentum risk and profits.

The results of this thesis also relate to the debate on whether momentum profits are ‘paper returns' that are not attainable by investors. Lesmond, Schill, and Zhou (2004) argue that stock-level momentum strategies are difficult to exploit after transaction costs, whereas Korajczyk and Sadka (2004) conclude that momentum is profitable only when traded on a small scale. In a broader anomaly spectrum, Novy-Marx and Velikov (2016) show that most standard construction long-short factors with turnover exceeding 50% are not profitable net of transaction costs. Moreover, an investor trading financial vehicles such as exchange traded funds (i.e., ETFs) or mutual funds to gain access to anomalous factor profits may also face disappointment. Zaremba and Andreau (2018) report transaction costs to wipeout profits of 120 country-level ETFs targeting equity anomalies, whereas Patton and Weller (2020) find typical mutual funds to earn no returns to momentum after considering the effect of transaction costs.[4]

[4] The net profitability of anomalies may be improved by following cost-mitigation strategies (Novy-Marx & Velikov 2016; Frazzini, Israel & Moskowitz 2018; Zaremba & Andreau 2018). Implementation costs may also be different depending on the investor type, albeit the advantage of lower transaction costs of large institutional investors can be offset by the larger price impacts of higher volume trades (Asness et al. 2014; Patton & Weller 2020).

## 1.1 Contributions and research questions

The high theoretical returns of factor momentum strategies naturally call for a study on its performance after considering several issues related to practical implementation. Hence, the main contribution of this thesis is to study time series factor momentum performance from a practical viewpoint. For this purpose, a set of eight different stylized factors are employed that are frequently targeted by investors, capturing size, value, quality, momentum, and low risk (Blitz 2021).[5] The publicly available theoretical factors that follow the factor construction of Fama and French (1993) are considered as proxies for real-world investment vehicles, such as stylized factor ETFs. Motivated by the practical viewpoint to factor investing, the raw, reward-to-risk, and risk-adjusted performance of long-short factor momentum strategies are compared against corresponding long-only strategies. Furthermore, the strategies are benchmarked against state-of-the-art factor models of Fama and French (2018) and Hou, Mo, Xue, and Zhang (2021). A return-based style analysis following Sharpe (1992) is applied to study ex-post style-exposures of the strategies, in addition to an ex-post mean-variance efficiency analysis that studies whether factor momentum is assigned positive weights in estimating the tangency portfolio. A post-cost analysis is conducted to estimate the robustness and real-world performance of the strategies. Finally, factor momentum returns are decomposed on market states, in line with a risk-based view on the source of momentum profits. The following research questions are interesting to academics as well as practitioners and summarize the research targets of this thesis.[6]

1) How long-short and long-only time series factor momentum strategies perform on pre-cost and post-cost bases using a handful of popular factors?
2) Can factor momentum generate abnormal returns when adjusted for the returns of state-of-the-art factor models?
3) Does factor momentum have tilts towards certain styles?
4) How are returns from factor momentum related to the return state of the market?

[5] A small sample is also motivated by the recent advancements in research concerning dimension reduction of pricing factors, which suggests that the quantity of cross-sectional return patterns could be explained by a small number of uncorrelated factors (Fama & French 1996; Hou et al. 2015, 2020; Hou, Mo, Xue & Zhang 2019; Feng, Giglio & Xiu 2020).

[6] From an asset pricing perspective, it is interesting to test whether factor momentum relates to market return, performs differently in bullish and bearish market return states, and loads to common risk factors that attempt to capture its cross-sectional return patterns. On the other hand, investors are interested in the style allocation of factor momentum, how factor momentum performs in bullish and bearish states, how can factor momentum generate alpha over other common investment factors or increase the Sharpe ratio of the efficient portfolio augmented with other risk factors, and ultimately is factor momentum profitable net of implementation costs.

The main results can be summarized as follows. In line with full sample results on autocorrelation in factor returns, the Winners outperform the Losers, thus implying that most of the profits from the Winner-Loser strategies stem from the long leg. The long legs also outperform an equally weighted factor portfolio on a raw return basis, thus accentuating the importance of timing in generating higher returns. In line with existing literature, the performance of the Winner-Loser (1-1) strategy is remarkable even when using a small set of factors as the strategy outperforms all other strategies in pre-cost and post-cost comparisons. By contrast, the returns from the long-only factor momentum strategies underperform against the Winner-Loser strategies, thereby suggesting that factor momentum is best exploited as a long-short strategy. Based on the risk-adjustment regressions, factor momentum exhibits varying exposures to different factors across different formation and holding period combinations. The return-style analysis reveals that the monthly rebalanced Winner-Loser strategies are significantly tilted towards size, value, and momentum. Moreover, the CMA (UMD) factor is assigned more weight in the mimicking portfolios of shorter (longer) formation-period strategies and less weight in the mimicking portfolios of longer (shorter) formation-period strategies. An ex-post mean-variance efficiency analysis also reveals that the best performing Winner-Loser (1-1) strategy is assigned positive tangency portfolio weights before and after considering the effect of transaction costs on the strategy's performance. Finally, factor momentum has also avoided large market drawdowns. The conditional CAPM betas indicate that factor momentum partially hedges against market returns in bearish states and is market neutral in in bullish states. A negative linear relationship exists between market return and the returns of factor momentum strategies over and above the market return, which is sharply different in bearish states. Since the average market return is positive (negative) in bullish (bearish) states, the results on return dependency  indicates that the factor momentum strategies exhibit inferior (superior) performance compared to the market in bullish (bearish) states, on average.

## 1.2 Limitations and structure

There are two significant limitations that may affect the validity of the results. First, selecting factors for the sample presents a challenge as the quantity of published factors is large while many of these factors are at risk of being false discoveries due to the lack of reliable significance testing frameworks and the risk of data mining (Harvey, Liu, & Zhu 2016;

Harvey & Liu 2021). Moreover, Hou, Xue, and Zhang (2020) argue that most published anomalies do not uphold to current standards for empirical finance after mitigating the effects of microcaps using NYSE breakpoints and value-weighted returns. Also, McLean and Pontiff (2016) observe that factor returns are lower post-publication and exhibit inferior performance in the past decades relative to historical factor performance. Consequently, it is popular in literature to select well-known factors, different stylized factors, or factors that survive high-dimensional robustness testing (see for example Avramov et al. 2017; Zaremba & Shemer 2018; Gupta & Kelly 2019; Blitz 2021; Ehsani & Linnainmaa 2022a).

Second, there are several definitions of market state or up-market and down-market definitions in prior literature.[7] Since, there does not exist a single correct way to define return states of the market, the validity of the results is to some degree dependent on the how market states are defined. The goal of this study is to decompose performance and assess the relationship of factor momentum with respect to market return in market return states. For this purpose, this thesis defines states of the market using a peak-to-trough approach similarly to Stivers and Sun (2013) to divide the sample into bull and bear states based on the U.S. market turning points using ±20% and ±15% thresholds. Considering the purpose of the return decomposition, the benefit of the chosen method is its simplicity and property to divide the sample into bull and bear states when the average excess return of the market portfolio has been positive and negative, respectively. By contrast, the same does not hold for the ex-ante market state definitions employed in prior literature.

The rest of the thesis is structured as follows. Section 2 discusses the theoretical background, Section 3 describes the data and methodology, Section 4 presents the results, and finally Section 5 presents the conclusions of this thesis.

[7] Grundy and Martin (2001) define market states by calculating the trailing equally weighted total return of the CRSP index above or below one standard deviation around the full sample mean return with a six-month rolling window. Cooper et al. (2004) utilize the sign of the 36-month trailing value-weighted total return of the CRSP index to divide the sample into UP and DOWN states; they also replicate the results using 12-months and 24-months of prior returns. In the context of the London stock exchange (i.e., FTSE-All share), Siganos and Chelley-Steeley (2006) use one, three, six, and 12-months of prior market performance following each period to define the bull and bear state of the market. Stivers and Sun (2013) utilize a peak-to-trough ex post value-weighted total return in excess of ±15% to divide the sample into up-state and down-state based on market turning points. Daniel and Moskowitz (2016) use the prior two-year value-weighted return of all CRSP stocks to define bull and bear market states, whereas Geczy and Samonov (2016) use a trailing 11-month return skipping the prior reversal month t-1 in defining bull and bear states and match it to the momentum formation period of their 11-months prior return sorted momentum strategy.

# 2 Theoretical background

Avramov et al. (2017) document persistence in anomaly payoffs and report strongly positive cross-sectional autocorrelation across different time horizons from one month to five years for 15 well-documented U.S. anomalies for the 1976-2013 period; they find the one-month autocorrelation to be the strongest. Zaremba and Shemer (2018) report positive autocorrelation in factor returns across time horizons ranging from one to 60 months for low risk, value, size, momentum, and quality factors within and across 24 developed countries; they observe the autocorrelation to be the strongest for the 12-month formation period for both within and across countries. Gupta and Kelly (2019) find a large set of factor returns to be strongly persistent and report positive first order autoregression test results for 59 (49 significant) of 65 U.S. factors and 51 (30 significant) of 62 international equity factors. Haddad et al. (2020) show the largest principal components of a large set of factors to robustly capture the time-varying stochastic discount factor and find the principal components to be strongly predictable in capturing common variation in risk premia. Ehsani and Linnainmaa (2022a) find economically large predictability in factor premiums for 15 U.S. and seven global equity factors over the 1963-2019 period for the U.S. factors and over the 1990-2019 period for the global factors. Moreover, they regress factor returns conditional on a factor's own 12-month performance and find average returns of individual factors to show persistency. Using a pooled regression, they show that the conditional average return of the average anomaly is statistically persistent after a year of positive returns, whereas following a year of underperformance the average return is close to zero and statistically insignificant. Hence, they conclude factors are more likely to exhibit stronger autocorrelation following a year of positive performance in comparison to a year of underperformance.

## 2.1 Performance of prior return factor timing strategies

Avramov et al. (2017) form one-month formation- and holding-period strategies that longs (shorts) the long legs (short legs) of the anomaly winner (loser) portfolios. They find the strategies to return positive alpha after controlling for the returns of the three-factor model of Fama and French (1993) over the 1976-2013 period in the U.S. market. However, they note that a strategy sorting on lagged one-month anomaly returns and market states or investor sentiment outperforms the strategy sorting only on lagged one-month anomaly returns. Moreover, they conclude that the strategy employing investor sentiment and lagged anomaly returns has uniformly performed the best in full and subsample periods.[8] Using U.S. and international equity factor returns starting from 1963 and ending in 2017, Gupta and Kelly (2019) report that factor momentum generates positive alpha after controlling for the average of factor returns or the five-factor model of Fama and French (2015). Furthermore, they report the one-month formation and holding-period strategies to return the largest alpha, which diminishes considerably at longer formation periods up to five years. Ehsani and Linnainmaa (2022a) show that annually updated factor momentum portfolios, long (short) on individual factors or 10 highest eigen value principal components of factors, generate positive alpha against the five-factor and six-factor models of Fama and French (2015, 2018).

Contrary to standard factor timing allocating portfolio weights on prior factor portfolio returns and viewing factors as bundles of stocks, the integrated long-only approach of Leippold and Rueegg (2021) views stocks as bundles of factors utilizing normalized factor scores of stocks to predict factor score weights and form long-only factor portfolios. In constructing factor timing strategies, Leippold and Rueegg (2021) employ factors utilized in the Fama and French (2015) five-factor model and include the momentum factor of Carhart (1997) using a sample period of 1963-2018 for U.S. data and a sample period of 1998-2018 for developed and emerging market data. The long-only factor timing strategies of Leippold and Rueegg (2021) with and without the inclusion of the interaction effects between factors exhibit significantly positive monthly alpha in the U.S. over the 1963-2018 period against three static benchmark factor models; the Fama and French (1993, 2015, 2018) three-factor model, five-factor model, and the five-factor model augmented with the momentum factor of Carhart (1997). However, the subperiod analysis reveals a reduction in the significance of the alpha using U.S. market and developed market data with a sample period of 1998-2018.

[8] Also, Ehsani and Linnainmaa (2022a) hypothesize factor momentum may stem from mispricing as they show the model of Kozak, Nagel, and Santosh (2018) with sentiment investors to generate factor momentum during sustained sentiment.

Haddad et al. (2020) extract the largest principal components from a sample of 50 long-short factors and apply the book-to-market ratio to each principal component. Using the valuation ratios of the principal components, they forecast individual anomaly returns and form factor timing portfolios.[9] They compare four variations of timing and report all the strategies to have positive out-of-sample Sharpe ratios, to expand the investment opportunity set based on the information ratio using a static factor investing strategy as a benchmark, and to increase the expected utility of a mean-variance investor based on the full sample spanning from January 1974 to December 2017.[10] Hence, they conclude that there is value in factor timing from both investment and asset pricing perspective.

## 2.2 Factor momentum explains other momentum strategies

Arnott et al. (2019) find that short-term cross-sectional factor momentum subsumes industry momentum. Zaremba and Shemer (2018) report the momentum in factors to be largely explained by stock-level momentum. Gupta and Kelly (2019) show factor momentum to explain the stock-level price momentum of Jegadeesh and Titman (1993) and industry momentum of Moskowitz and Grinblatt (1999). However, they find that factor momentum does not explain short-term reversal implying that both the short-term reversal factor and time series factor momentum capture unique return patterns in expected returns. Ehsani and Linnainmaa (2022a) argue long-short factor momentum strategies that utilize one year of past returns of individual factors or 10 highest eigen value factor principal components to contain more information than various other cross-sectional stock-level momentum specifications.[11] They show the Fama and French (2015) five-factor model augmented with

[9] The methodology of Haddad et al. (2020) rests on the assumption of no near arbitrage and the use of a stochastic discount factor implies that a conditional factor model holds for each anomaly portfolio. The no near arbitrage imposes restrictions on the variation of the implied stochastic discount factor. Consequently, the small principal components cannot meaningfully contribute to the return predictability and the large principal component portfolios can then be used to forecast both cross-sectional and time-series variation in expected factor returns.

[10] The description of the four timing strategies of Haddad et al. (2020) are the following: factor timing uses principal components to forecast factor weights, market timing sets the forecast of the market return to its unconditional mean, anomaly timing forecasts the market by its unconditional mean and the anomalies are given dynamic weights, and the pure anomaly timing sets the weight of the market to zero and weights anomalies based on the deviation of their forecasts from their unconditional average.

[11] Ehsani and Linnainmaa (2022a) compare the following alternative momentum specifications: the stock-level momentum of Jegadeesh and Titman (1993), Industry-adjusted momentum of Cohen and Polk (1998), industry momentum of Moskowitz and Grinblatt (1999), intermediate momentum of Novy-Marx (2012), and the Sharpe ratio momentum of Rachev, Jašić, Stoyanov, and Fabozzi (2007).

factor momentum to span the returns of a corresponding multifactor model augmented with an alternative momentum specification. By contrast, they report that none of the multifactor models augmented with alternative momentum specifications span the returns of the multifactor model that includes factor momentum. Additionally, the authors report momentum-neutral factor momentum strategies to outperform factor momentum strategies investing in standard construction factors.

## 2.3 Transaction costs

Lesmond, Schill, and Zhou (2004) use observed trading behavior as an indirect proxy for trading costs and find that momentum is not exploitable, whereas Korajczyk and Sadka (2004) conclude momentum to be profitable only on a small scale when considering the price impact of momentum. Novy-Marx and Velikov (2016) show that most standard construction long-short anomalies with turnover higher than 50% are unprofitable after considering transaction costs. Zaremba and Andreau (2018) replicate 120 equity anomalies using country-level ETFs and show transaction costs to eliminate the gross profitability of almost all the replicated strategies. Patton and Weller (2020) find typical mutual funds to earn no returns to momentum after transaction costs. Asness (2016) criticizes factor timing strategies to suffer from problems in practical implementation and argue most timing strategies to exhibit inferior returns compared to passive strategies even before considering the effect of the higher turnover from timing. Ilmanen et al. (2021) report various timing strategies to fare poorly gross and net of transaction costs as timing considerably increases the turnover of factor investing strategies.

By contrast, Gupta and Kelly (2019) report factor momentum strategies to survive transaction costs of 10 basis points per unit of turnover based on the estimates of Frazzini, Israel, and Moskowitz (2018). Also, Leippold and Rueegg (2021) report that over the 1963-2018 period, the multi-factor alpha and Sharpe ratio difference against the market portfolio of the long-only one-month formation strategy with interaction effects is positive and significant in the U.S. market net of up to 15 basis points per unit of turnover. However, a subperiod analysis reveals both the alpha and Sharpe of the timing strategies are largely insignificant net of only five basis points of costs per unit of turnover in the U.S., developed, and emerging markets during the 1998-2018 period.

Additionally, the net profitability of anomalies may be improved by following cost-mitigation strategies such as discarding high-cost securities, using infrequent rebalancing, and implementing capitalization-based weighting (Novy-Marx & Velikov 2016; Frazzini, et al. 2018; Zaremba & Andreau 2018). Implementation costs may also be different depending on the investor type as Asness et al. (2014) note that momentum profits are achievable for a large institutional investor as costs faced by a large institutional investor are considerably lower than estimated costs of the average investor. However, Patton and Weller (2020) point that the advantage of lower transaction costs of large institutional investors can be offset by the larger price impacts of higher volume trades, thus leaving smaller funds an edge to earn higher factor premia over larger funds.

## 2.4 Momentum profits

Time variation in the market betas of prior return sorted portfolios is first shown by Kothari and Shanken (1992) who argue prior return strategies to have time-varying exposures to systematic risk factors; prior winners are most likely stocks with positive factor realizations, and vice versa.[12] Grundy and Martin (2001) report momentum to exhibit time-varying market beta and loadings to the Fama and French (1993) three-factor model, even though Fama and French (1996) show that the three-factor model fails to explain momentum profits. However, Jegadeesh and Titman (1993) find that momentum profitability is not explained by systematic risk alone nor by a lead-lag effect from delayed price reactions to information related to a common factor as in Lo and MacKinlay (1990) for contrarian profits. The profitability of medium-horizon momentum strategies is conjectured by Conrad and Kaul (1998) to result from dispersion in cross-sectional mean returns and momentum's average profitability to stem from the variability in cross-sectional average returns; high realized returns of momentum portfolios emanate from stocks with high average returns, and vice versa. Moskowitz and Grinblatt (1999) report industry momentum, which buys stocks from past winning industries and shorts stocks from past losing industries to explain a large part of the profitability of stock-level momentum strategies. However, Grundy and Martin (2001) conclude that cross-sectional variability or industry risk premium do not explain the

[12] Also, Grundy and Martin (2001) show the sign and size of momentum's investment period factor loadings to reflect the magnitude of factor realizations of individual winner and loser stocks over the formation period.

profitability of momentum, the industry momentum being separate from stock-level momentum. By using an extensive sample starting from 1801 and ending in 2012, Geczy and Samonov (2016) also confirm industry momentum is separate from stock-level momentum.

### 2.4.1 Macroeconomic risk factors

Chordia and Shivakumar (2002) propose macroeconomic variables to explain momentum and find the results supporting the Conrad and Kaul (1998) hypothesis of variation in expected returns to explain momentum profits. However, Griffin et al. (2003) and Cooper et al. (2004) conclude that macroeconomic models, including the model of Chordia and Shivakumar (2002), are not effective in explaining the profitability of momentum. Furthermore, Blitz, Huij, and Martens (2011) show that the variation of momentum profits in business cycles, documented by Chordia and Shivakumar (2002), is largely attributed to the time-varying exposures to the Fama and French (1993) factors. By contrast, Liu and Zhang (2008) find the growth rate of industrial production to be a priced macroeconomic risk factor in momentum strategies, explaining more than half of momentum profits. However, Geczy and Samonov (2016) test common macroeconomic variables, including the growth of industrial production, and report that no individual macroeconomic variable explains momentum profitability in line with the results of Cooper et al. (2004). Conversely, they note market states to have the largest economic impact on explaining the source of momentum profits.

### 2.4.2 Market states

Jegadeesh and Titman (1993) observe the average beta of past losers to be higher than the average beta of past winners and the zero-cost portfolio average beta to be negative. Grundy and Martin (2001) find that the momentum portfolio has a strong exposure to high beta stocks following positive market return and a strong exposure to negative beta stocks following negative market return. Cooper at al. (2004) report the lagged return of the market to be effective in explaining momentum profitability and forecasting momentum profits out-of-sample. Furthermore, they report momentum returns to be higher following up markets in comparison to following down markets, whereas Siganos and Chelley-Steeley (2006) find momentum to be stronger after lagging negative market returns and stronger at longer durations of bearish states. Asem and Tian (2010) and Stivers and Sun (2013) show momentum payoffs to be higher within market states and lower during state transitions. Daniel and Moskowitz (2016) observe the momentum loser portfolio to exhibit option-like payoffs as the losers exhibit a high premium causing momentum to crash after the market rebounds because the strategy is short on the loser portfolio loaded with high beta stocks. Geczy and Samonov (2016) link the market beta exposure of momentum to the duration of a market state; the longer a market state lasts, the more the market exposure contributes to the risk and return of momentum.

### 2.4.3 Risk-managed momentum

Grundy and Martin (2001) discuss improving the raw momentum strategy by hedging market and size risk by calculating hedge ratios using realized future (ex post) betas, which are not implementable by investors in practice. However, Daniel and Moskowitz (2016) show hedge ratios calculated based on future realized market betas to result in a strong upward bias in the performance of the ex post hedged momentum strategy.[13] They report an unbiased hedging strategy using implementable ex-ante market betas to prove ineffective in improving the performance of the raw momentum strategy to the extent that the ex-ante hedged momentum strategy underperforms against raw momentum. Barroso and Santa-Clara (2015) decompose momentum volatility to market and momentum-specific components and argue hedging based on market betas to fail since a considerable part of momentum's risk is not linked to the market risk component but rather linked to the momentum-specific risk component. Also, Martens and van Oord (2014) warn that hedging with betas could lead to systematic biases stemming from over- and underestimation, which in turn may result in less effective hedging.

Following the work of Grundy and Martin (2001), various implementable momentum strategies have been introduced in literature that outperform the raw momentum strategy.

[13] The upward bias is caused by the hedge taking on more market exposure when the future market return is high, which stems from the more negative realized market beta of momentum that is used to calculate hedge ratios when the realized market return is positive (Daniel & Moskowitz 2016).

Bliz, Huij, and Martens (2011) sort stocks based on residual returns from the Fama and French (1993) three-factor model instead of stock returns. Martens and van Oord (2014) hedge the Fama and French three-factor model (1993) exposures of the momentum portfolio. Barroso and Santa-Clara (2015) scale the momentum portfolio by its trailing volatility. Daniel and Moskowitz (2016) dynamically scale the momentum portfolio by its forecasted return and variance (i.e., unconditional Sharpe ratio). Geczy and Samonov (2016) hedge the market beta of momentum based on market state duration to form a dynamic momentum beta strategy, which accounts for the dynamic variation in the market beta of momentum. Dierkes and Krupski (2022) construct an ex-ante crash risk indicator that isolates momentum crashes from bull market periods by scaling momentum using trailing variance during ex-ante momentum bull markets and reversing the weights of the momentum portfolio (i.e., the strategy sells winners and buys losers) during ex-ante momentum crash states.

Using a U.S. sample, Barroso and Santa-Clara (2015) show the scaled constant volatility strategy to outperform raw momentum between January 1927 and December 2011. Daniel and Moskowitz (2016) report the dynamic momentum strategy to outperform raw momentum and the constant volatility strategy of Barroso and Santa-Clara (2015) using a U.S. sample spanning from January 1927 to March 2013. Geczy and Samonov (2016) report the dynamic momentum strategy of Daniel and Moskowitz (2016) to perform best in the pre-1927 period and the dynamic momentum beta strategy to perform best in the post-1927 period. However, the authors note they employ a crude estimate of trailing volatility calculated from monthly returns due to the unavailability of daily return data for the pre-1927 period. For the 1928-2022 period as well as in subsample periods, Dierkes and Krupski (2022) report the strategy employing the crash risk indicator to outperform the constant volatility strategy of Barroso and Santa-Clara (2015) and the dynamic momentum strategy of Daniel and Moskowitz (2016) before and after transaction costs. However, they do not benchmark their strategy against the dynamic beta strategy of Geczy and Samonov (2016).

### 2.4.4 Volatility scaling

Moreira and Muir (2017) show that scaling based on the inverse of the variance and volatility of factors predicts conditional Sharpe ratios of common U.S. equity factors and improves performance compared to unmanaged factors. Also, stock-level momentum strategies can be improved by scaling momentum portfolio weights based on ex-ante volatility, variance, or forecasted Sharpe ratio of the momentum portfolio (Barroso & Santa-Clara 2015; Daniel & Moskowitz 2016; Dierkes & Krupski 2022). Recently, Gupta and Kelly (2019) applied volatility scaling in determining the portfolio weights of factor momentum strategies by scaling each factor's weight by the inverse of each factor's prior three-year or 10-year volatility depending on the formation period.[14]

Contradictory evidence on the effectiveness of volatility scaling is presented by Liu, Tang, and Zhou (2019) who find the volatility timing strategy of Moreira and Muir (2017) to be unimplementable and subject to look ahead bias. Using a U.S. sample, they show the volatility timing strategies of Moreira and Muir (2017), Barroso and Santa-Clara (2015), Kan and Zhou (2007), and Ferson and Siegel (2001) applied to the market portfolio (without look ahead bias) fail to beat the market between August 1936 and December 2017. Also, Cederburg, O'Doherty, Wang, and Yan (2020) observe volatility scaled strategies to lose to their unmanaged counterparts. Barroso and Detzel (2021) conclude volatility-managed non-market factors to be unprofitable after transaction costs with limited potential to investors even after employing cost mitigation strategies. They show the volatility managed market factor to only provide superior performance, unexplained by transaction costs, over the unmanaged market factor during periods of high sentiment.

[14] Volatility scaling assumes a relationship between lagged and current volatility by lowering (increasing) risk exposure during times of high (low) past volatility contrary to conventional theory on risk and expected return (Moreira & Muir 2017).

# 3 Data and methodology

The publicly available and replicable factor data is downloaded from Kenneth R. French's data library, the data library of AQR, and website of ROBECO.[15] The factors reported in Panel A in Table 1 capture size, value, quality, momentum, and low risk. The sample covers monthly U.S. equity factor data from July 1963 to December 2021. All factor returns are based on the factor construction of Fama and French (1993), where size (market capitalization) and a stock characteristic are used to construct value-weighted and double-sorted 2 x 3 portfolios that are used in forming the long-short factors.[16] The double-sorting on size using NYSE breakpoints and the use of value-weighted returns reduces the risk of the factor returns to be driven by microcaps (Hou et al. 2020). Furthermore, controlling for microcaps is important from a practical viewpoint as returns from anomalies in microcaps are difficult to obtain by investors because trading microcaps involves trading frictions and high transaction costs (Novy-Marx & Velikov 2016).

The SMB factor of Fama and French (2015) captures size by measuring the difference in returns between big and small stocks using diversified portfolios. The HML factor of Fama and French (2015) and the HML devil factor of Asness and Frazzini (2013) capture value by measuring the difference in returns between high and low valuation stocks using book-to-market ratio with the HML devil factor using timelier market equity values. The CMA factor of Fama and French (2015) is also assumed to capture value by measuring the difference in returns between high and low investment stocks based on growth in total assets.[17] Quality is captured by the RMW and QMJ factors. The former of the two quality factors measures the return difference between robust and weak profitability firms, whereas the latter measures the difference between high-quality and low-quality stocks with quality defined using various definitions of profitability, growth, and safety (Fama & French 2015; Asness, Frazzini & Pedersen 2019). The UMD factor captures momentum by measuring the

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[15] The data is available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, https://www.aqr.com/insights/datasets, and https://www.robeco.com/en/insights/2019/01/data-sets-volatility-sorted-portfolios.html

[16] Even though the Fama and French (1993) factor construction attempts to control for size in portfolio construction, the methodology assigns weight to small and microcap stocks and does not fully remove the possibility of microcaps inflating factor returns (Blitz 2023).

[17] Following Blitz (2021), the CMA factor can be considered to capture value as Fama and French (2015) find it to subsume their classic HML factor.

difference in returns between prior winner and loser portfolios formed based on prior (2-12) months of returns (Fama & French 2018).

Table 1: Factor description and summary statistics

This table reports the abbreviation, the original study, and monthly raw return summary statistics, and return distribution statistics of the selected U.S. equity factors. The ex post annualized Sharpe ratios are calculated by compounding geometric average returns as in Equation 3 to avoid mis-ranking issues. The sample spans from July 1963 to December 2021. The higher moments of the return distributions are calculated as in Equations 5 and 6. The significance of the average returns deviating from zero are tested using the one-sample t-test. The asterisk **, (*) marks the significances at the 1% (5%) risk level.

| Factor | Abbreviation | | Original study | |
|---|---|---|---|---|
| Panel A: Equity factors and original factor research | | | | |
| Size | SMB | | Banz (1981) | |
| Value | HML | | Rosenberg, Reid & Lanstein (1985) | |
| HML Devil | $HML_D$ | | Asness & Frazzini (2013) | |
| Investment | CMA | | Titman, Wei & Xie (2004) | |
| Profitability | RMW | | Novy-Marx (2013) | |
| Quality minus junk | QMJ | | Asness, Frazzini & Pedersen (2019) | |
| Momentum | UMD | | Jegadeesh & Titman (1993) | |
| Low volatility | VOL | | van Vliet & Blitz (2007) | |
| Factor | $\bar{r}$ (%) | SD (%) | $t(\bar{r})$ | SR |
| Panel B: Summary statistics | | | | |
| SMB | 0.23* | 3.03 | 1.99 | 0.21 |
| HML | 0.27* | 2.90 | 2.49 | 0.28 |
| $HML_D$ | 0.27* | 3.51 | 2.02 | 0.21 |
| CMA | 0.27** | 1.98 | 3.58 | 0.44 |
| RMW | 0.28** | 2.21 | 3.30 | 0.40 |
| QMJ | 0.38** | 2.29 | 4.36 | 0.54 |
| UMD | 0.62** | 4.20 | 3.93 | 0.45 |
| VOL | 0.51** | 3.41 | 3.96 | 0.47 |
| Factor | Min (%) | Max (%) | Skewness | Kurtosis |
| Panel C: Return distribution statistics | | | | |
| SMB | -15.39 | 18.38 | 0.34 | 3.11 |
| HML | -14.02 | 12.48 | 0.00 | 2.26 |
| $HML_D$ | -17.99 | 26.86 | 0.77 | 7.58 |
| CMA | -6.78 | 9.06 | 0.32 | 1.31 |
| RMW | -18.76 | 13.38 | -0.29 | 11.71 |
| QMJ | -9.10 | 12.41 | 0.17 | 2.81 |
| UMD | -34.30 | 18.20 | -1.27 | 9.78 |
| VOL | -26.32 | 13.00 | -1.00 | 8.82 |

Finally, low risk is captured by the VOL factor of Blitz and Vliet (2007) that consists of return differences between low-risk and high-risk portfolios formed on 36-month trailing volatility. The VOL factor is chosen over the BAB factor of Frazzini and Pedersen (2014) as Novy-Marx and Velikov (2022) criticize the BAB factor's non-standard construction causing a major part of the BAB premium to stem from overweighting short positions in microcaps.

Panel B in Table 1 reveals large variation in the return characteristics between the factors even though all factors have positive average returns statistically different from zero at the 5% significance level.[18] Panel C of Table 1 shows that most factors exhibit mildly positively skewness and mild to moderate kurtosis, whereas the RMW, VOL, and UMD factors exhibit negative skewness and high kurtosis. More than half of the factors have a higher Sharpe ratio than the market factor (MKT-rf), which has an annualized Sharpe ratio of around 0.38 over the same period. The UMD and VOL factors have the highest average monthly returns of 0.62% and 0.51% with the highest and third highest monthly volatility of 4.20% and 3.41%, respectively. The QMJ factor generates the third highest monthly average return of 0.38% coupled with the third lowest monthly volatility of 2.29%. Consequently, the QMJ factor has the highest annualized Sharpe ratio of 0.54, followed by the VOL factor (0.47), and the UMD factor (0.45). By contrast, the SMB factor exhibits the lowest monthly average return of 0.23% with a monthly volatility of 3.03% resulting in an annualized Sharpe ratio of 0.21.

## 3.1 Autocorrelation in factor returns

All factor returns are regressed conditional on each factors own prior average return following Ehsani and Linnainmaa (2022a). Almost half of the intercepts ($\hat{\alpha}_1$) in Table 2 are negative following one, three, six, and 12-months of negative returns even though all unconditional average returns of the factors in Panel B of Table 1 are positive. The significantly positive differential intercepts ($\hat{\alpha}_2$) indicate that most of the factor returns are highly persistent following periods of prior positive average returns. By contrast, the intercepts are insignificant except for the UMD factor following 12-months of negative returns, which generates a significant conditional average return of 0.58% that is 0.53% higher ($\hat{\alpha}_1 - \hat{\alpha}_2$) than its conditional average return following 12-months of positive performance.

[18] The full sample mean is significantly positive for all factor despite the concerns of McLean and Pontiff (2016) and Arnott, Harvey, Kalesnik, and Linnainmaa (2019) on the recent poor performance of factors.

Table 2: Factor returns conditional on a factor's own prior return

This table reports univariate regressions following Ehsani and Linnainmaa (2022a), where the dependent variable is a factor's monthly (%) return, and the independent variable $D_{i,k}$ is an indicator variable that takes the value of one if the factor's average return over the prior $k$ months is positive and zero otherwise. For each factor, the following regressions are estimated: $R_{i,t} = \alpha_{1,i} + \alpha_{2,i}D_{i,k} + \varepsilon$, where the intercept $\alpha_{1,i}$ measures the average return following a period of negative prior return, the differential intercept $\alpha_{2,i}$ measures the difference in average returns after positive prior average returns, and $\varepsilon$ is an error term. The dependent variable covers the period from June 1964 to December 2021 in all regressions to make a valid comparison between the different indicator variables. The coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The asterisk **, (*) marks the significances at 1%, (5%) risk levels.

| | Conditional on prior 1-month return | | | | Conditional on prior 3-month return | | | |
|---|---|---|---|---|---|---|---|---|
| | Intercept | | Differential intercept | | Intercept | | Differential intercept | |
| Factor | $\hat{\alpha}_1$ | t($\widehat{\alpha_1}$) | $\hat{\alpha}_2$ | t($\hat{\alpha}_2$) | $\hat{\alpha}_1$ | t($\hat{\alpha}_1$) | $\hat{\alpha}_2$ | t($\hat{\alpha}_2$) |
| SMB | -0.10 | (-0.56) | 0.64** | (2.68) | 0.00 | (-0.02) | 0.47* | (2.09) |
| HML | -0.13 | (-0.70) | 0.73** | (3.31) | -0.09 | (-0.50) | 0.63** | (2.79) |
| $HML_D$ | -0.28 | (-1.44) | 1.07** | (3.90) | -0.09 | (-0.43) | 0.67** | (2.60) |
| CMA | 0.02 | (0.15) | 0.48** | (3.00) | 0.03 | (0.34) | 0.43** | (2.83) |
| RMW | -0.12 | (-0.81) | 0.71** | (4.11) | 0.09 | (0.57) | 0.32 | (1.85) |
| QMJ | 0.01 | (0.08) | 0.67** | (3.98) | 0.18 | (1.29) | 0.33 | (1.86) |
| UMD | 0.38 | (1.39) | 0.38 | (1.12) | 0.41 | (1.24) | 0.31 | (0.83) |
| VOL | -0.07 | (-0.31) | 0.97** | (3.70) | -0.02 | (-0.06) | 0.86** | (2.89) |

| | Conditional on prior 6-month return | | | | Conditional on prior 12-month return | | | |
|---|---|---|---|---|---|---|---|---|
| | Intercept | | Differential intercept | | Intercept | | Differential intercept | |
| Factor | $\hat{\alpha}_1$ | t($\hat{\alpha}_1$) | $\hat{\alpha}_2$ | t($\hat{\alpha}_2$) | $\hat{\alpha}_1$ | t($\hat{\alpha}_1$) | $\hat{\alpha}_2$ | t($\hat{\alpha}_2$) |
| SMB | 0.02 | (0.11) | 0.39 | (1.64) | -0.11 | (-0.62) | 0.60* | (2.52) |
| HML | -0.09 | (-0.49) | 0.59** | (2.59) | -0.03 | (-0.13) | 0.48 | (1.82) |
| $HML_D$ | -0.16 | (-0.75) | 0.76** | (2.90) | -0.17 | (-0.66) | 0.74** | (2.78) |
| CMA | 0.10 | (0.99) | 0.28 | (1.85) | 0.11 | (0.90) | 0.26 | (1.61) |
| RMW | 0.10 | (0.62) | 0.28 | (1.44) | 0.04 | (0.22) | 0.35 | (1.66) |
| QMJ | 0.03 | (0.22) | 0.55** | (3.14) | 0.12 | (0.87) | 0.39* | (2.16) |
| UMD | 0.46 | (1.71) | 0.22 | (0.73) | 0.58* | (2.07) | 0.05 | (0.17) |
| VOL | -0.14 | (-0.46) | 0.95** | (2.76) | -0.31 | (-0.86) | 1.13** | (2.95) |

In line with Ehsani and Linnainmaa (2022a), the significant differential intercepts indicate that the average returns of most factors are significantly higher following periods of positive prior average returns than following periods of negative prior average returns. The return continuation of the factors appears to be the strongest following a month of prior positive return in line with Avramov et al. (2017) and Gupta and Kelly (2019). The t-statistics of all factors except the UMD factor are at their highest and significantly positive at the 1% level conditional on a factor's own prior one-month return. Moreover, Appendix 1 reports return-to-return regressions following the example of Ehsani and Linnainmaa (2022a) that reveal factors to exhibit significant autocorrelation as the slope ($\hat{\beta}$) coefficients of prior average returns of factors are significant using various prior return periods. However, the slope coefficients of the one-month prior return specification exhibit the highest statistical significance from the reported results in line with Table 2.

## 3.2 Portfolio construction

This thesis focuses on time series factor momentum strategies as both Gupta and Kelly (2019) and Ehsani and Linnainmaa (2022b) find time series factor momentum to subsume cross-sectional factor momentum. Following prior momentum literature, long-short momentum strategies are referred to as Winner-Loser strategies as they are long past winner factors and short past loser factors. The long and short legs of the Winner-Loser strategies are referred to as Winners and Losers, respectively. The portfolio construction of the factor momentum strategies follows the example of Gupta and Kelly (2019, 17-18) without employing any ex-ante volatility scaling in defining the portfolio weights. Volatility scaling in portfolio construction is omitted to simplify the analysis even though Gupta and Kelly (2019) scale factor returns by the inverse of each factor's trailing volatility and normalize portfolio weights with z-value caps.[19]

The strategy dynamically weights monthly returns of the $i$th factor according to its performance over the past $j$ months, where $j$ denotes the formation period of one, three, six, or 12-months. The strategies long and short factors based on the factors' positive and

[19] Capping z-scores sets weight limits for factors with high absolute z-scores (i.e., low trailing volatility and high absolute return) limiting potential losses, but also limiting potential gains.

negative prior return. The Winner and Loser portfolio weights are rescaled to have a unit leverage of 1$ long and 1$ short, respectively, where the sum of the weights of both portfolios equals one. Equations 1 and 2 describe the Winner and Loser strategy factor portfolio formation:

$$Winner_{j,t} = \frac{\sum_i 1_{\{w_{i,j,t}>0\}} f_{i,j,t+1}}{\sum_i 1_{\{w_{i,j,t}>0\}} w_{i,j,t}} \ , \tag{1}$$

$$Loser_{j,t} = \frac{\sum_i 1_{\{w_{i,j,t}\leq 0\}} f_{i,j,t+1}}{\sum_i 1_{\{w_{i,j,t}\leq 0\}} w_{i,j,t}} \ , \tag{2}$$

where $w_{i,j,t}$ is the compound return of factor $i$ over the formation period $j$, and $f_{i,j,t+1}$ is the return of factor $i$ following the formation period $j$. The Winner-Loser (long-short) strategy buys the Winner and sells short the Loser strategy. Holding periods of one, three, six, and 12 months are investigated for all four formation periods; the portfolio weights of longer holding-period strategies are allowed to roll forward before rebalancing the portfolio. The formation (F) and holding (H) period strategy combinations are marked by F-H or (F-H) in the empiric section.

To analyze the viability of time series factor momentum being employed as a long-only strategy, long-only Winner-rf strategies are analyzed that trade the factor momentum Winner portfolio financed by borrowing at the risk-free rate. From a practical viewpoint, a long-only strategy is closer to a more realistic implementation of factor momentum due to several issues associated with short selling, e.g., the existence of short selling constraints, risk of unlimited losses from short positions, and risk of closing positions before payoff due to margin calls (Shleifer & Vishny 1997; Stambaugh, et al. 2015). Another step is also taken to bring the analysis further closer to reality by assuming that the employed factors act as proxies for style ETFs that are systematically constructed to capture returns associated with different stock characteristics. This way, the Winner-Loser strategies can be thought to buy ETFs and finance the positions by selling short ETFs, whereas the Winner-rf strategies only buy ETFs at the cost of borrowing at the risk-free rate.

## 3.3 Reward-to-variability

The strategies are compared using the annualized reward-to-risk ratio introduced by Sharpe (1966). As the interest is in ranking the strategies' ex post performance using a reward-to-risk measure, the annualized Sharpe ratios are calculated by compounding the geometric average returns of the strategies.[20] The Sharpe ratio is refined following Israelsen (2005) by raising the measure of dispersion in the denominator to the power of $\left(\frac{ER}{|ER|}\right)$ to avoid mis-ranking issues stemming from negative excess returns, where $\overline{ER}$ is the geometric average of the monthly excess return of a portfolio. The following formula is utilized to calculate the annualized Sharpe Ratio (SR):

$$SR = \frac{(1+\overline{ER})^{12}-1}{\sigma^{(ER/|ER|)}\sqrt{12}}, \tag{3}$$

where $\overline{ER}$ is the geometric average of the monthly excess return of a portfolio, and $\sigma$ is the corresponding monthly standard deviation of a portfolio.

The statistical significance of the Sharpe ratios is assessed with the robust Sharpe ratio difference test of Ledoit and Wolf (2008) by using the market factor (MKT-rf) as the benchmark. The test of Ledoit and Wolf (2008) is based on a studentized time series bootstrap confidence interval to draw inference on the difference of two Sharpe ratios. The test employs the circular block bootstrap of Politis and Romano (1992) in resampling that considers the effect of possible autocorrelation in returns and accounts for the skewness and kurtosis of the return distributions.[21]

The skewness and kurtosis adjusted Sharpe ratio (SKASR) of Pätäri (2011) is used to consider the effects of possible distributional asymmetries of the return distributions on the value of the standard Sharpe ratio described in Equation 3. To include information from

[20] Unlike with arithmetic returns, compounding geometric average returns avoids mis-ranking issues in ex post comparisons as it accurately measures the total return accumulated over an investment period.
[21] A detailed description of the Ledoit and Wold (2008) Sharpe difference test is omitted to save space. Please refer to the original article for a more detailed description. The original article and programming code are available at: https://www.econ.uzh.ch/en/people/faculty/wolf/publications.html

higher distributional moments, the SKASR calculation employs the fourth order Cornish-Fisher expansion:

$$Z_{CF} = Z_C + \frac{1}{6}(Z_C^2 - 1)S + \frac{1}{24}(Z_C^3 - 3Z_C)K - \frac{1}{36}(2Z_C^3 - 5Z_C)S^2 \quad (4)$$

where $Z_C$ is the critical value for the probability based on a standard normal distribution, S denotes skewness, and K kurtosis of the return distribution (Cornish & Fisher 1937). The skewness and kurtosis are defined as follows:

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{ER_{i,t}-\overline{ER}_i}{\sigma}\right)^3, \quad (5)$$

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{ER_{i,t}-\overline{ER}_i}{\sigma}\right)^4 - 3\,, \quad (6)$$

where $N$ is the number of outcomes, $ER_{i,t}$ is the monthly excess return of a portfolio at time $t$, $\overline{ER}_i$ is the simple average of the excess returns of a portfolio, and $\sigma$ is the standard deviation of a portfolio. After calculating standard scores with a selected probability level (5% in this study), the skewness and kurtosis adjusted deviation (SKAD) is calculated by multiplying the standard deviation $\sigma$ with the $\frac{Z_{CF}}{Z_C}$ ratio. Finally, the SKAD is raised to the power of $\left(\frac{ER}{|ER|}\right)$ to avoid mis-ranking issues stemming from negative excess returns analogously to the refinement of Israelsen (2005). The annualized SKASR is calculated with the following formula:

$$SKASR = \frac{(1+\overline{ER})^{12}-1}{SKAD^{(ER/|ER|)}\sqrt{12}}\,, \quad (7)$$

where $\overline{ER}$ is the geometric average of the monthly excess returns of a portfolio, and the skewness and kurtosis adjusted deviation $SKAD^{(ER/|ER|)}$ substitutes standard deviation in the denominator of the Sharpe ratio described in Equation 3.

## 3.4 Risk-adjusted return, return-based style analysis, and mean-variance efficiency

To assess the risk-adjusted return of the time-series factor momentum strategies, the returns are regressed against the six-factor model of Fama and French (2018):

$$R_{i,t} - rf_t = \alpha_i + \beta_i^1(MKT_t - rf_t) + \beta_i^2 SMB_t + \beta_i^3 HML_t + \beta_i^4 RMW_t + \beta_i^5 CMA_t + \beta_i^6 UMD_t + \varepsilon_{i,t}\ , \tag{8}$$

where $R_{i,t} - rf_t$ is the expected return of an asset in excess of the risk-free rate, $\alpha_i$ is the average return unexplained by the model, $\varepsilon_{i,t}$ is an error term, and the $\beta$ coefficients are the sensitivities of a portfolio to expected factor premiums: the excess return of the market denoted by $(MKT_t - rf_t)$, a size factor denoted by $SMB_t$, a value factor denoted by $HML_t$, a profitability factor denoted by $RMW_t$, an investment factor denoted by $CMA_t$, and a momentum factor denoted by $UMD_t$.[22]

The returns are also regressed against the $q^5$-factor model of Hou, et al. (2021), described in the following equation, as it outperforms many of the popular factor models utilized in explaining variation in stock returns in the cross-section (Hou et al. 2019):

$$R_{i,t} - rf_t = \alpha_i + \beta_i^1(MKT_t - rf_t) + \beta_i^2 ME_t + \beta_i^3 (I/A)_t + \beta_i^4 ROE_t + \beta_i^5 EG_t + \varepsilon_{i,t}\ , \tag{9}$$

where $R_{i,t} - rf_t$ is the expected return of an asset in excess of the risk-free rate, $\alpha_i$ is the average return unexplained by the model, $\varepsilon_{i,t}$ is an error term, and the $\beta_i$ coefficients are the sensitivities of a portfolio to expected factor premiums: the excess return of the market denoted by $(MKT_t - rf_t)$, a size factor denoted by $ME_t$, an investment factor denoted by

[22] The risk-free rate is only deducted from long-only strategies since long-short (e.g., Winner-Loser) strategies are already in the form of excess returns as they are financed by selling assets short instead of borrowing at the risk-free rate.

$(I/A)_t$, a profitability factor denoted by $ROE_t$, and an earnings growth factor denoted by $EG_t$.[23]

A significantly positive alpha has two important take-aways. From an investment perspective, it suggests an investor would have earned a higher Sharpe ratio by including the left-hand side strategy into their investments in addition to the right-hand side strategies in the risk-adjustment equation (Huberman & Kandel 1987). From an asset pricing perspective, it implies that an asset pricing model including the left-hand side variable in addition to the right-hand side variables dominates a model that only contains the right-hand side variables; hence the model including the both the left- and right-hand side variables is more effective in explaining variation in the cross-section of expected returns (Barillas & Shanken 2017).

To complement the results of from the risk-adjusted performance analysis regarding potential factor sensitivities of the strategies, the average style exposure of the best performing strategies is studied by applying the return-based style analysis of Sharpe (1992). The return-based style analysis aims to find an optimal ex-post allocation in a mix of chosen assets to replicate the returns of the analysed strategy by minimizing tracking error between the analysed strategy and the optimized return style mimicking portfolio relying on quadratic optimization. The significances of the weight exposures to different styles are assessed by employing the standard errors calculated in accordance with Lobosco and DiBartolomeo (1997). In addition, a pre-cost and post-cost ex-post mean-variance efficiency analysis is conducted to further assess whether the strategies are assigned positive weights in the ex-post maximum attainable Sharpe ratio portfolio. The two multifactor model factors described in Equations 8 and 9 are employed in estimating the mean-variance efficient (MVE) portfolio.

[23] Hou et al. (2019) find the original q-factor model of Hou, Xue, Zhang (2015) augmented with the expected growth factor (i.e., the $q^5$-factor model introduced in Hou et al. 2021) to outperform the original q-factor model, the Fama and French (2015) five-factor model, the Stambaugh and Yuan (2017) four-factor model, the Fama and French (2018) six-factor model, the Barillas and Shanken (2018) six-factor model, and the Daniel, Hirshleifer, and Sun (2020) three-factor model.

## 3.5 Turnover and trading costs

The turnover of time series factor momentum strategies is calculated following Gupta and Kelly (2019) who define turnover as the sum of absolute changes in portfolio weights each rebalancing month, which describes the total two-sided trading (both opening and closing positions) volume as a fraction of gross asset value. The turnover of each factor is defined as the sum of the change in portfolio weights at each rebalancing point in accordance with the following formula:

$$TO_{i,t} = \sum \left| w_{i,t} - w_{i,t-1} \right| , \tag{10}$$

where $w_{i,t}$ is the new weight defined by the momentum indicator as in Equations 1 and 2 at each rebalancing month $t$ and $w_{i,t-1}$ is the weight prior to rebalancing the portfolio. The average annualized turnover is defined as the average of the sum of absolute changes in the factor weights at each rebalancing month multiplied by 12. The absolute change in the portfolio weights, the monthly turnover, is multiplied by a cost per unit of turnover to estimate how trading costs affect the returns of a strategy. Furthermore, a breakeven point is calculated for all strategies to find the maximum amount of basis points at the estimated amount of turnover, where the multifactor alpha remains positive and significant at the 1% level.

Estimating turnover from strategy weights provides an estimate of the turnover required to implement the strategy in practice using, for example, low-cost factor style indices or style ETFs targeting to capture returns of certain stylized factors. However, trading cost estimation based on turnover calculated from changes in portfolio weights offers only a simple calculation on the influence of trading costs to performance. Moreover, employing theoretical factor portfolios as proxies ignores costs from directly trading stocks associated with forming the traded factors. The long-short factors are in theory described as zero-cost portfolios requiring no capital to construct. However, costs associated with selling short are likely higher in practice overstating the net profitability of the zero-cost factors that are based on highly theoretical assumptions about real-world trading frictions and financing investments by selling short portfolios of stocks (Shleifer & Vishny 1997; Stambaugh, et al. 2015).

## 3.6 Performance decomposition based on bull and bear market periods

To assess whether the performance of factor momentum strategies depends on stock market conditions, the sample is divided into ex post bull and bear states using a peak-to-trough approach according to the turning points of the U.S. stock market similarly to Stivers and Sun (2013). Stivers and Sun (2013) employ a 15% threshold as their main market state indicator and replicate their results with 17.5% and 20% thresholds. This thesis uses a 20% threshold to define the main ex post indicator variable and for robustness purposes replicates the results with a 15% threshold following the example of Stivers and Sun (2013).[24] Hence, using cumulative log returns of the Fama and French (2015) market factor (MKT-rf), the loss of -20% (-15%) from the previous peak to the subsequent trough defines a bear state in the demarcation of market states.[25] Correspondingly, a gain of 20% (15%) in cumulative log returns from the previous trough to subsequent peak defines a bull state. To illustrate the returns of factor momentum during bullish and bearish market states, the cumulative returns of pooled bullish and bearish periods are plotted and the maximum drawdown over bearish states are reported for all strategies.

### 3.6.1 Linear effects and conditional CAPM

The relationship between factor momentum and excess market return (MKT-rf) during bullish and bearish market states is examined by applying the methodology of Giot (2005). The model definition is the following:

$$r_{i,t} - r_{m,t} = \beta_0^+(1 - D_t) + \beta_0^-(D_t) + \beta_1^+(r_{m,t})(1 - D_t) + \beta_1^-(r_{m,t})(D_t) + \varepsilon_t, \quad (11)$$

where $r_{i,t} - r_{m,t}$ is the excess return of a strategy over and above the excess return of the market ($r_{m,t}$), $D_t$ is a bear market dummy variable, $(1 - D_t)$ is a bull market dummy

[24] Replicating the results with a 15% threshold is also motivated by the lower threshold classifying more observations as bearish periods, whereas a 20% threshold isolates only deeper drawdowns of the market.
[25] The use of logarithmic returns avoids the need to use asymmetric thresholds for bull and bear market states in contrast to arithmetic returns (a higher % return is required to account for a loss of X% using arithmetic returns).

variable, and $\varepsilon_t$ is an error term.[26] The bear market dummy $D_t$ equals one during a bearish state and is zero during a bullish state, and vice versa using the bull market dummy variable $(1 - D_t)$.[27] The coefficients of interest in Equation 11 are the $\beta_1^+$ and $\beta_1^-$ coefficients that measure the sensitivity of a strategy's excess return over and above the excess market return with respect to excess market return in bullish and bearish states, respectively.

To test the hypothesis whether the possible linear relationship between the excess returns of factor momentum strategies over and above excess market return and excess market return is equal during bearish and bullish states, a Wald test using the F-statistic is conducted, which tests the significance of the difference between the $\beta_1^+$ and $\beta_1^-$ coefficients. The null hypothesis of the test is that the linear effects are equal. Therefore, if the p-value is less than 0.01 (0.05), then the null hypothesis is rejected and the alternative hypothesis is accepted resulting in the conclusion that the difference of the coefficients is not equal to zero at a 1% (5%) level of significance.

The regression in Equation 11 provides coefficient estimates that are equivalent to the interpreted conditional CAPM regression estimates employed by Daniel and Moskowitz (2016) that attempts to capture both expected return and market-beta differences in bear markets.[28] Hence, when using excess returns, the $\beta_0^+$ and $\beta_0^-$ coefficients can be interpreted as conditional CAPM alphas and the $\beta_1^+$ and $\beta_1^-$ coefficients as conditional CAPM market betas during bullish and bearish states, respectively. Moreover, the conditional CAPM market betas are equivalent to $(1 + \beta_1^+)$ and $(1 + \beta_1^-)$ when using returns over a benchmark. Also, the coefficients $\beta_0^+$ and $\beta_0^-$ remain unchanged regardless of whether excess returns are used instead of returns over a benchmark due to the regression construction.

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[26] The excess returns of a strategy denoted by $r_{i,t}$ correspond to returns of the strategy over the cost of financing (i.e., net of the risk-free rate or the returns from a portfolio that is sold short to cover the long position).

[27] Using the 20% threshold in the market state demarcation results in 151 (21.88%) bearish and 539 (78.12%) bullish observations from the full sample of 690 observations. Analogously, using a 15% threshold results in 188 (27.25%) of bearish and 502 (72.75%) bullish observations.

[28] Daniel and Moskowitz (2016) estimate a regression using excess returns (returns over the risk-free rate): $r_{i,t} = \alpha_i + \beta_1(D_t) + \beta_2(r_{m,t}) + \beta_3(r_{m,t} * D_t) + \varepsilon_t$, where the $\alpha_i$ coefficient is the conditional CAPM alpha during bull markets, $\beta_1$ coefficient is the difference in the conditional CAPM alpha during bear markets in comparison to bull markets, and $\beta_2$ coefficient is the conditional CAPM market beta during bull markets, and $\beta_3$ coefficient measures the conditional CAPM market beta difference in bear markets in comparison to bull markets.

### 3.6.2 Quadratic effects

The analysis is extended by introducing quadratic benchmark return $r_{m,t}^2$ terms to form the following equation and assess the size effect of the benchmark returns:

$$r_{i,t} - r_{m,t} = \beta_0^+(1 - D_t) + \beta_0^-(D_t) + \beta_1^+(r_{m,t})(1 - D_t) + \beta_1^-(r_{m,t})(D_t) + \beta_2^+(r_{m,t}^2)(1 - D_t) + \beta_2^-(r_{m,t}^2)(D_t) + \varepsilon_t, \quad (12)$$

where $r_{i,t} - r_{m,t}$ is the excess return of a strategy over and above the excess return of the market $(r_{m,t})$ , $D_t$ is a bear market dummy variable, $(1 - D_t)$ is a bull market dummy variable, and $\varepsilon_t$ is an error term. Analogously to Equation 11, a Wald test is used to determine whether the possible quadratic effects are equal following bullish and bearish states by testing the significance of the difference between the $\beta_2^+$ and $\beta_2^-$ coefficients.

Due to the regression construction, the $\beta_2^+$ and $\beta_2^-$ coefficients remain the same regardless of whether excess returns are used instead of returns over a benchmark. Any significant quadratic effect(s) would suggest the benchmark returns during bullish and bearish states to co-move differently with the same month's returns of the strategies over the returns of the benchmark. A significant linear return term indicates the sign and direction of the linear relationship (i.e., sensitivity) in Equation 12, whereas a significant quadratic return term captures the relationship on the size of the benchmark return. For example, a significantly positive (negative) bullish (bearish) state linear and quadratic return term coefficients would jointly indicate a strategy to perform remarkably well in bullish (bearish) states when the benchmark returns are positive (negative) on average.

# 4 Results

Table 3 reports summary statistics for the Winner-Loser strategies and decomposition of Winner-Loser strategy returns into long and short legs. Panel A of Table 3 confirms that time series factor momentum following a long-short approach is profitable on average using a small selection of factors. The monthly rebalanced Winner-Loser strategies generate positive average excess returns using formation windows of one-month up to one year with the Winner-Loser (1-1) strategy exhibiting the strongest performance, in line with the results of Avramov et al. (2017) and Gupta and Kelly (2019). The Winner-Loser strategies also earn higher average excess returns when rebalanced more frequently, thereby supporting the results of Ehsani and Linnainmaa (2022b) that longer holding period factor momentum strategies earn lower returns due to not rebalancing away from factors whose return continuation reverses.

Gupta and Kelly (2019) assess the gain from factor timing by comparing the performance of factor momentum strategies against a monthly rebalanced equally weighted (EWF) factor portfolio. In a theoretical setting, the EWF portfolio's performance is quite impressive as it earns 0.35% of monthly average raw returns with a t-value of 7.49 and volatility of 1.24% while exhibiting positive skewness (0.78), moderate kurtosis (8.38), and a minimum (maximum) monthly return of -5.57% (9.60%). However, the returns generated by timing factors on prior returns is far more impressive as all Winners in Panel A of Table 3 outperform the EWF portfolio on an average raw return basis, albeit only the best performing Winner (1-1) strategy exhibits a higher t-statistic. Moreover, in a more practical setting that assumes the EWF strategy is implemented long-only by buying ETFs financed by borrowing at the risk-free rate, the strategy's monthly average excess return drops to -0.015%, thus resulting in a negative annualized Sharpe ratio of -0.06 and SKASR of -0.04. Considering the cost of financing the portfolios further accentuates the importance of timing as Table 4 reveals that almost all Winner-Loser and Winner-rf strategies, especially the monthly rebalanced strategies, outperform the EWF portfolio on a reward-to-risk basis.

Table 3: Time series factor momentum summary statistics

This table reports the monthly average (%) return, t-values, and standard deviations in percentages, minimum (%) return, maximum (%) return, skewness, and kurtosis of the Winner-Loser strategies, Winner (long leg), and Loser (short leg) partitions with one, three, six, and 12-month formation and holding period combinations. The Winner-Loser returns are in the form of excess returns and the long- and short leg portfolios are in the form of raw returns. The higher distribution moments are calculated with equations 5 and 6. The sample starts from July 1964 and ends in December 2021. The asterisks **, (*) mark the significances at the 1%, (5%) risk levels based on the one-sample t-test.

| | Winner-Loser | | | | Winner (long leg) | | | | Loser (short leg) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Holding | Formation period | | | | Formation period | | | | Formation period | | | |
| period | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 |
| Panel A: Average (%) return | | | | | | | | | | | | |
| 1 | 0.99** | 0.67** | 0.62** | 0.64** | 0.79** | 0.64** | 0.62** | 0.66** | -0.19 | -0.02 | 0.00 | 0.03 |
| 3 | 0.61** | 0.23 | 0.47** | 0.48** | 0.61** | 0.43** | 0.58** | 0.60** | 0.01 | 0.20* | 0.12 | 0.12 |
| 6 | 0.44* | 0.29 | 0.22 | 0.29 | 0.57** | 0.54** | 0.44** | 0.52** | 0.13 | 0.25* | 0.22* | 0.23* |
| 12 | 0.33* | 0.20 | 0.19 | 0.05 | 0.54** | 0.51** | 0.39** | 0.42** | 0.20* | 0.31** | 0.02* | 0.38** |
| Panel B: t-value | | | | | | | | | | | | |
| 1 | 5.68 | 3.89 | 3.76 | 3.72 | 8.17 | 6.61 | 6.63 | 6.95 | -1.85 | -0.23 | 0.04 | 0.25 |
| 3 | 3.48 | 1.34 | 2.92 | 2.76 | 5.94 | 4.36 | 6.36 | 6.26 | 0.08 | 1.99 | 1.20 | 1.15 |
| 6 | 2.48 | 1.67 | 1.38 | 1.66 | 5.68 | 5.54 | 4.76 | 5.45 | 1.33 | 2.38 | 2.36 | 2.09 |
| 12 | 2.08 | 1.34 | 1.33 | 0.29 | 5.81 | 5.79 | 4.06 | 4.49 | 2.11 | 2.92 | 2.19 | 3.73 |
| Panel C: Standard deviation (%) | | | | | | | | | | | | |
| 1 | 4.56 | 4.50 | 4.31 | 4.51 | 2.56 | 2.56 | 2.46 | 2.51 | 2.70 | 2.71 | 2.54 | 2.72 |
| 3 | 4.58 | 4.42 | 4.22 | 4.57 | 2.71 | 2.58 | 2.41 | 2.51 | 2.55 | 2.66 | 2.52 | 2.71 |
| 6 | 4.64 | 4.59 | 4.17 | 4.64 | 2.65 | 2.58 | 2.43 | 2.51 | 2.66 | 2.76 | 2.47 | 2.86 |
| 12 | 4.22 | 3.99 | 3.71 | 4.11 | 2.43 | 2.32 | 2.53 | 2.48 | 2.54 | 2.76 | 2.45 | 2.66 |
| Panel D: Minimum monthly (%) return | | | | | | | | | | | | |
| 1 | -24.61 | -23.01 | -17.82 | -19.04 | -11.13 | -11.70 | -11.64 | -12.22 | -20.45 | -19.60 | -18.17 | -18.85 |
| 3 | -20.90 | -19.22 | -17.66 | -18.76 | -12.39 | -11.93 | -10.14 | -11.41 | -20.45 | -19.60 | -18.00 | -17.64 |
| 6 | -17.31 | -25.12 | -17.36 | -35.39 | -10.75 | -10.92 | -12.45 | -11.50 | -26.05 | -19.60 | -18.00 | -17.64 |
| 12 | -28.70 | -26.19 | -24.74 | -30.83 | -18.22 | -16.42 | -17.99 | -20.02 | -13.77 | -25.30 | -13.58 | -11.57 |

Table 3 (continued):

| Holding period | Winner-Loser | | | | Winner (long leg) | | | | Loser (short leg) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Formation period | | | | Formation period | | | | Formation period | | | |
| | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 |
| Panel E: Maximum monthly (%) return | | | | | | | | | | | | |
| 1 | 40.00 | 36.70 | 36.40 | 36.28 | 19.55 | 18.28 | 18.23 | 17.44 | 14.58 | 13.21 | 12.57 | 12.90 |
| 3 | 40.00 | 35.15 | 34.93 | 35.87 | 19.55 | 18.22 | 16.93 | 18.24 | 11.52 | 11.13 | 11.49 | 12.90 |
| 6 | 42.82 | 35.15 | 34.93 | 35.87 | 18.25 | 18.22 | 16.93 | 18.24 | 11.52 | 14.20 | 11.49 | 26.86 |
| 12 | 26.34 | 18.05 | 16.68 | 19.42 | 12.56 | 11.36 | 10.74 | 12.92 | 13.65 | 13.49 | 11.49 | 11.49 |
| Panel F: Return distribution skewness | | | | | | | | | | | | |
| 1 | 1.07 | 0.38 | 0.74 | 0.59 | 0.38 | 0.14 | 0.22 | 0.27 | -0.97 | -0.57 | -0.55 | -0.05 |
| 3 | 1.32 | 0.46 | 0.72 | 0.48 | 0.51 | 0.06 | 0.48 | 0.47 | -1.25 | -0.79 | -0.44 | 0.06 |
| 6 | 1.65 | 0.29 | 0.66 | -0.05 | 0.60 | 0.52 | 0.24 | 0.53 | -1.84 | -0.36 | -0.18 | 1.03 |
| 12 | -0.37 | -0.64 | -0.68 | -0.76 | -0.93 | -0.41 | -1.46 | -1.52 | 0.18 | -0.43 | 0.25 | 0.24 |
| Panel G: Return distribution kurtosis | | | | | | | | | | | | |
| 1 | 12.44 | 9.16 | 9.05 | 9.18 | 6.50 | 6.32 | 6.43 | 6.60 | 10.66 | 9.31 | 6.51 | 6.47 |
| 3 | 14.47 | 7.89 | 9.20 | 8.60 | 8.37 | 5.94 | 6.95 | 7.04 | 10.69 | 8.50 | 6.25 | 5.46 |
| 6 | 16.63 | 8.70 | 9.87 | 11.88 | 7.43 | 6.91 | 7.06 | 7.68 | 17.63 | 7.99 | 6.55 | 13.75 |
| 12 | 7.49 | 5.25 | 5.13 | 6.41 | 8.73 | 6.05 | 9.31 | 14.12 | 4.58 | 13.70 | 4.56 | 2.92 |

Comparing the performance of the Winners against the Losers implies that the profits of the Winner-Loser strategies mostly emanate from the long legs of the strategies, and particularly from the continuity in positive factor returns, in line with Table 2. Panels A and B of Table 3 shows that all the average raw returns of the Winners are significantly positive at the 1% level and exhibit the highest t-statistics, whereas only seven of the Winner-Loser strategies generate excess returns that are significant at the 1% level. The less significant performance of several Winner-Loser strategies stems from the poor performance of the Loser portfolio (i.e., short leg). Only two Loser strategies exhibit negative average raw returns that positively increment the average raw returns of the short position holder, albeit the deviation of the average returns from zero of the two strategies are insignificant. Consequently, the Loser portfolio increases the average excess returns of the Winner-Loser strategies only in three cases out of the sixteen reported holding and formation period combinations, while remarkably increasing the volatility of the Winner-Loser strategies compared to only trading the Winners (see Panel C of Table 3).

Panels D to F of Table 3 show that factor momentum exhibits different distributional properties compared to stock-level momentum, like the UMD factor.[29] All Winner-Loser strategies in Panel D, except the Winner-Loser (6-12) strategy, have less negative minimum monthly returns than the UMD factor (-34.40%). Panel E shows that all Winner-Loser strategies, except the Winner-Loser (3-12) and (6-12) strategies, have higher maximum monthly returns than the UMD factor (18.20%). In contrast to the UMD factor that has a skewness of -1.27 and kurtosis of 9.78, Panels F and G reveal that most of the Winner-Loser strategies are positively skewed with high kurtosis, thus implying that a part of the long-term performance of the strategies may stem from the fat right tail of the return distribution.

Comparing the Winners against the long leg of the UMD factor (i.e., long-only UMD = 0.5 x (small high prior returns portfolio + big high prior returns portfolio)) reveals that the average raw returns of the Winners are lower than the average raw returns of the long leg of the UMD factor.[30] The average raw return of the long-only UMD factor of 1.37% with a t-

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[29] For the sake of brevity, only monthly rebalanced versions of stock-level momentum are considered in this thesis to shortly compare the return characteristics of factor momentum with stock-level momentum.

[30] The long-only UMD factor is highly correlated with the MKT-rf factor with a rho of 0.92 over the period from July 1964 to December 2021. Since the purpose here is to simply compare the long leg of UMD factor, the long-only UMD factor is not hedged market neutral as it is often done in literature to isolate the premium not captured by the market portfolio.

statistic of 6.78 is higher than the average returns of all the Winner strategies in Panel A of Table 3. However, the long-only UMD factor also exhibits higher monthly volatility of 5.32% compared to the Winners in Panel C of Table 3. Nevertheless, Panel D of Table 3 shows that the Winners have considerably lower minimum monthly return values than the long-only UMD factor (-27.92%), whereas Panel E indicates that the maximum monthly returns of the Winners are for the most part at par with the long-only UMD factor. Most Winners in Panels F and G of Table 3 exhibit positive skewness and high kurtosis, whereas the Winners (1-12), (6-12), and (12-12) show more negative skewness than the long-only UMD factor (-0.61) coupled with considerably higher kurtosis (2.23), thereby indicating a tendency of the three strategies to sometimes crash.

## 4.1 Average factor weights at the outset

Time series factor momentum allocates factor weights on the absolute performance of each factor normalized based on the prior return of all factors with the same sign. Consequently, the time series factor momentum strategies are always invested in the selection of timed factor raising two questions. Are the long-short strategies on average long and short on each factor with equal magnitude? Based on Figure 1, the answer is no.

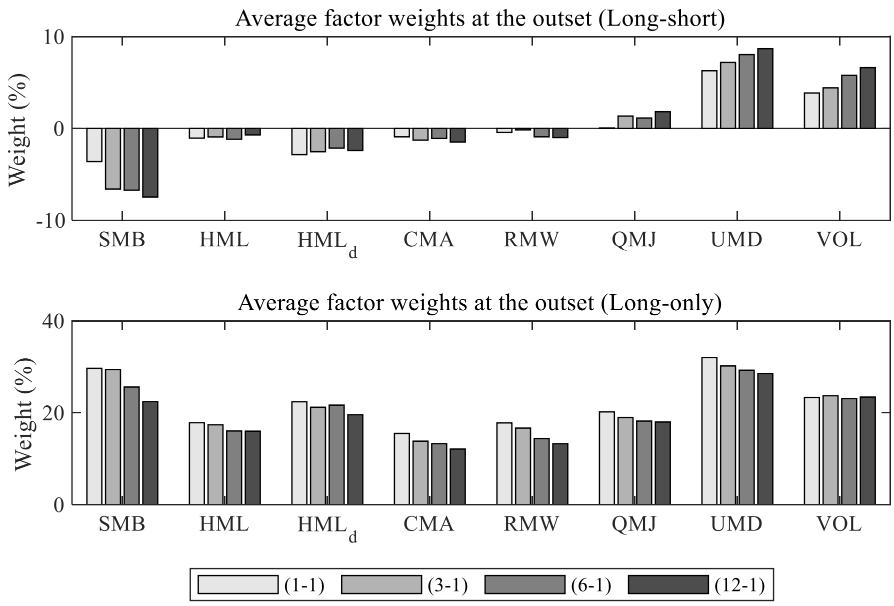



Figure 1: Average (%) factor weights at the outset, monthly rebalancing. The parentheses in the legend of each figure reports each strategy's formation and holding period combination, respectively.

The one, three, six, and 12-month formation Winner-Loser strategies are on average long on the QMJ, UMD, and VOL factors and short on the SMB, HML, $HML_D$, CMA , and RMW factors. Do the strategies allocate larger weights to certain factors? Based on Figure 1, the answer is yes. On average, the monthly rebalanced Winner-Loser strategies allocate considerably larger positive weights to the UMD and VOL factors and greater negative weights to the SMB and $HML_D$ factors on all four formation periods. Analogously, the Winner strategies on average allocate more weight to the SMB, UMD and VOL factors and less weight to the HML, CMA, and RMW factors.[31]

## 4.2 Reward-to-variability

Panel A of Table 4 reveals that most of the Winner-Loser and Winner-rf strategies lose to the market portfolio based on the Sharpe ratio. Only the monthly rebalanced Winner-Loser strategies, the Winner-Loser (3-1), and Winner-rf (1-1) strategies exhibit higher annualized Sharpe ratios than the market (0.38). However, all the Sharpe ratio differences against the market are insignificant based on the Ledoit and Wolf (2008) test. The significance test highlights the difficulty to beat the reward-to-risk performance of the market in the long-term, and even more so after considering the distributional properties of investment strategies that deviate from normality, such as non-zero skewness and high kurtosis of the factor momentum strategies. Regardless of the Ledoit and Wolf (2008) test results, the best performing monthly rebalanced Winner-Loser strategies and the Winner-rf strategy exhibit higher SKASRs than the market (0.38), hence indicating that factor momentum generates higher reward with respect to risk than the market portfolio after considering notable differences in distributional properties.[32] Moreover, the SKASRs of the monthly rebalanced Winner-Loser and Winner-rf strategies are lower compared to their corresponding Sharpe ratios, thus suggesting that their distributional asymmetries are harmful yet small in magnitude for an investor in terms of reward-to-risk. By contrast, most less frequently

[31] The average weights at the outset of longer holding-period strategies may differ from the monthly rebalanced versions. However, the monthly rebalanced strategies are by far the most interesting strategies in terms of average weights due to their strong performance and larger number of observations from which to calculate the average weights at the outset.

[32] The market is negatively skewed (-0.49) with low kurtosis (1.85), has a minimum return of -22.64%, maximum return of 16.61%, and generates an average raw monthly return of 0.95% coupled with a monthly volatility of 4.46%.

rebalanced strategies exhibit higher SKASRs than their corresponding Sharpe ratios, thus indicating the opposite when considering information about higher distributional moments.[33]

Table 4: Sharpe ratios and SKASRs of time series factor momentum

This table reports the annualized Sharpe ratios and the skewness and kurtosis adjusted Sharpe ratios (SKASR) of Pätäri (2011). The significance of the ratios is benchmarked against the excess return of the market (MKT-rf), which has an annualized Sharpe ratio and SKASR of around 0.38 over the same period. The annualized Sharpe is calculated with Equation 3, the SKASR with Equation 7, where the higher distributional moments are defined in Equations 5 and 6. The **, (*) mark the significance at 1%, (5%) risk levels of the Sharpe difference against the MKT-rf factor based on the Ledoit and Wolf test (2008). The sample starts from July 1964 and ends in December 2021.

| Holding period | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | Formation period | | | | Formation period | | | |
| | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 |
| Panel A: Sharpe ratio | | | | | | | | |
| 1 | 0.71 | 0.45 | 0.44 | 0.43 | 0.55 | 0.33 | 0.32 | 0.37 |
| 3 | 0.39 | 0.10 | 0.32 | 0.29 | 0.27 | 0.04 | 0.27 | 0.28 |
| 6 | 0.26 | 0.14 | 0.11 | 0.14 | 0.23 | 0.19 | 0.06 | 0.17 |
| 12 | 0.20 | 0.11 | 0.11 | -0.03 | 0.20 | 0.17 | -0.01 | 0.03 |
| Holding period | Winner-Loser | | | | Winner-rf | | | |
| | Formation period | | | | Formation period | | | |
| | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 |
| Panel B: Skewness and kurtosis adjusted Sharpe ratio | | | | | | | | |
| 1 | 0.69 | 0.42 | 0.45 | 0.42 | 0.51 | 0.31 | 0.30 | 0.35 |
| 3 | 0.43 | 0.15 | 0.35 | 0.31 | 0.27 | 0.07 | 0.28 | 0.28 |
| 6 | 0.33 | 0.18 | 0.16 | 0.15 | 0.25 | 0.21 | 0.09 | 0.19 |
| 12 | 0.20 | 0.13 | 0.13 | 0.03 | 0.17 | 0.17 | 0.02 | 0.05 |

How does factor momentum benchmark against stock-level momentum in terms of reward-to-risk? Panel A of Table 4 reveals that only the Winner-Loser (1-1) and (3-1) strategies exhibit higher Sharpe ratios than the UMD factor. Panel B of Table 4 shows that all monthly rebalanced Winner-Loser strategies and the Winner-Loser (1-3) strategy generate higher SKASR than the UMD factor. By contrast, the long-only UMD factor outperforms the

[33] It is noteworthy to mention that Gupta and Kelly (2019) report similar monthly rebalanced time series factor momentum strategies formed using one-month and 12-months of prior factor returns to earn annualized Sharpe ratios of 0.84 and 0.70, which are clearly much higher than the Sharpe ratios reported in Table 4. The difference between the results most likely stems from the difference in the number of employed factors. Regardless of the volatility scaling employed by Gupta and Kelly (2019), a time series factor momentum strategy allocates portfolio weights to a large variety of factors, from which many exhibits positive returns with low volatility that enhances the Sharpe ratios of the strategies.

Winner-rf strategies in terms of annualized Sharpe ratio (0.59) and SKASR (0.54) regardless of the long-only UMD factor's higher monthly volatility of 5.32%.[34]

## 4.3 Risk-adjusted return

In line with prior literature, the risk-adjusted return of the Winner-Loser (1-1) strategy reported in Table 5 is impressive, generating the highest monthly six-factor alpha of 0.93% and $q^5$-factor alpha of 0.89% significant at the 1% level.

Table 5: The risk-adjusted return of time series factor momentum

This table reports the (%) monthly alphas of the Winner-Loser and Winner strategies by regressing their returns against the Fama and French (2018) six-factor model and the $q^5$-factor model of Hou et al. (2018). The alphas are calculated using returns from January 1967 to December 2021 to make a valid comparison between the alphas as the $q^5$-factor data starts from January 1967. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors The bolded values with asterisk **, (*) indicate the significances of the alphas at 1%, (5%) risk levels.

| Holding period | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | Formation period | | | | Formation period | | | |
| | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 |
| Panel A: Six-factor alpha | | | | | | | | |
| 1 | **0.93**** | **0.60**** | **0.43*** | **0.40**** | 0.15 | -0.02 | -0.08 | -0.06 |
| | (4.29) | (2.82) | (2.57) | (2.69) | (1.23) | (-0.22) | (-0.83) | (-0.63) |
| 3 | **0.53*** | 0.11 | 0.23 | 0.17 | -0.04 | **-0.28**** | -0.13 | -0.13 |
| | (2.17) | (0.50) | (1.47) | (1.11) | (-0.30) | (-2.65) | (-1.37) | (-1.44) |
| 6 | 0.41 | 0.18 | -0.03 | 0.05 | -0.07 | -0.14 | **-0.27*** | **-0.21*** |
| | (1.67) | (0.82) | (-0.19) | (0.34) | (-0.58) | (-1.36) | (-2.51) | (-2.29) |
| 12 | 0.27 | 0.20 | 0.03 | -0.10 | -0.12 | -0.14 | **-0.34**** | **-0.34**** |
| | (1.78) | (0.96) | (0.21) | (-0.58) | (-1.36) | (-1.61) | (-3.35) | (-3.66) |
| Holding period | Winner-Loser | | | | Winner-rf | | | |
| | Formation period | | | | Formation period | | | |
| | 1 | 3 | 6 | 12 | 1 | 3 | 6 | 12 |
| Panel B: $q^5$-factor alpha | | | | | | | | |
| 1 | **0.89**** | **0.56*** | **0.42*** | 0.39 | 0.16 | -0.03 | -0.06 | -0.07 |
| | (4.07) | (2.47) | (2.10) | (1.90) | (1.25) | (-0.24) | (-0.54) | (-0.56) |
| 3 | **0.41*** | 0.09 | 0.19 | 0.20 | -0.10 | **-0.27*** | -0.13 | -0.13 |
| | (2.00) | (0.42) | (0.92) | (0.96) | (-0.75) | (-2.28) | (-1.12) | (-1.04) |
| 6 | 0.38 | 0.31 | 0.00 | 0.14 | -0.06 | -0.05 | -0.24 | -0.18 |
| | (1.79) | (1.27) | (0.01) | (0.63) | (-0.40) | (-0.36) | (-1.96) | (-1.51) |
| 12 | -0.16 | 0.16 | -0.03 | -0.06 | -0.04 | -0.09 | **-0.34**** | **-0.35**** |
| | (1.71) | (0.95) | (0.01) | (-0.77) | (-0.28) | (-0.68) | (-2.75) | (-2.79) |

[34] The Sharpe ratio and SKASR of the long-only UMD factor are calculated with Equations 3 and 7 that assume the long-only strategy is financed by borrowing at the risk-free rate.

The monthly rebalanced Winner-Loser strategies also exhibit significantly positive alpha using longer than one-month formation periods, in line with Gupta and Kelly (2019) and Ehsani and Linnainmaa (2022a, 2022b). However, the $q^5$-factor model indicates that the monthly rebalanced strategies exhibit positive alpha only on one, three, and six-month formation periods. Interestingly, only the one-month Winner-Loser strategy generates significantly positive alpha at the 5% level when rebalanced quarterly. Conversely, all other Winner-Loser strategies in Table 5 do not generate significant alpha when rebalanced less frequently, thereby corroborating that long-short factor momentum performance is stronger on short formation and holding periods also on a risk-adjusted basis. Moreover, The Winner-rf strategies in Table 5 exhibit far inferior performance compared to the Winner-Loser strategies when risk-adjusting against the six-factor or $q^5$-factor model. The Winner-rf (1-1) strategy is the sole long-only strategy that generates positive but insignificant alpha. Hence, the performance of the long-only time series factor momentum is disappointing and implies that time series factor momentum is best exploited as a long-short strategy.

## 4.4 Exposure to multifactor model risk factors

Panels A and B of Table 6 show that the adjusted $R^2$ values of the Winner-Loser (1-1) strategy given by the six-factor and $q^5$-factor model regressions are roughly 1% and 2%. The low adjusted $R^2$ values indicate that the employed multifactor models are not effective in explaining the returns of the best performing Winner-Loser (1-1) strategy in line with prior literature (Gupta & Kelly 2019; Ehsani & Linnainmaa 2022a). By contrast, the adjusted $R^2$ values of the corresponding Winner-rf (1-1) strategy whose returns are captured by both multifactor models in Panels A and B of Table 6 are roughly 20% and 13%, respectively.

The adjusted $R^2$ values of the monthly rebalanced longer formation period-strategies are considerably higher between 13% and 55% in Panel A of Table 6 and between 2% to 13% in Panel B. Table 6 shows the UMD coefficient and its significance to increase in tandem with the adjusted $R^2$ values associated with longer the formation periods, which indicates that the UMD factor is important in explaining the returns of the longer formation-period strategies. The same observation also holds for the corresponding quarterly and semi-annually rebalanced strategies, whereas the UMD factor loadings of the annually rebalanced strategies are strongest for the one- and 12-month formation strategies (Appendix 2). By contrast, the best performing the Winner-Loser (1-1) and Winner-rf (1-1) strategies have insignificant UMD factor loadings.

Table 6: The multifactor model regression coefficients of monthly rebalanced strategies

This table reports the coefficients and adjusted $R^2$ values from regressing one, three, six, and 12-month formation and one-month holding period strategy combinations against the six-factor model of Fama and French (2018) and the $q^5$-factor model of Hou et al. (2021). The coefficients are calculated using returns from January 1967 to December 2021 to make a valid comparison between the coefficients as the $q^5$-factor data starts from January 1967. The alpha coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel A: Six-factor model coefficients | | | | | | | | |
| $\hat{\alpha}$ | **0.93**** | **0.60**** | **0.43*** | **0.40**** | 0.15 | -0.02 | -0.08 | -0.06 |
| | (4.29) | (2.82) | (2.57) | (2.69) | (1.23) | (-0.22) | (-0.83) | (-0.63) |
| MKT-rf | -0.03 | -0.08 | -0.05 | 0.01 | 0.00 | -0.02 | 0.01 | 0.02 |
| | (-0.58) | (-1.27) | (-0.88) | (0.2) | (-0.13) | (-0.75) | (0.22) | (0.74) |
| SMB | 0.01 | -0.04 | 0.01 | 0.01 | **0.15*** | **0.11*** | **0.15**** | **0.16**** |
| | (0.06) | (-0.39) | (0.13) | (0.13) | (2.52) | (2.16) | (2.73) | (3.70) |
| HML | -0.14 | -0.13 | 0.01 | -0.13 | 0.12 | 0.09 | **0.18**** | **0.12*** |
| | (-1.02) | (-1.01) | (0.04) | (-1.01) | (1.59) | (1.42) | (2.96) | (2.01) |
| RMW | -0.07 | -0.28 | -0.40 | **-0.52**** | 0.17 | 0.06 | 0.00 | -0.06 |
| | (-0.33) | (-1.24) | (-1.90) | (-3.40) | (1.72) | (0.52) | (-0.04) | (-0.70) |
| CMA | **0.40*** | 0.12 | 0.01 | 0.00 | **0.35**** | **0.24**** | **0.16*** | **0.14*** |
| | (2.37) | (0.83) | (0.06) | (0.01) | (3.65) | (3.35) | (2.22) | (2.25) |
| UMD | 0.02 | **0.32**** | **0.52**** | **0.69**** | 0.13 | **0.30**** | **0.35**** | **0.44**** |
| | (0.15) | (2.65) | (5.70) | (8.70) | (1.58) | (6.03) | (7.03) | (9.53) |
| Adj. $R^2$ | 0.01 | 0.13 | 0.29 | 0.49 | 0.20 | 0.31 | 0.41 | 0.55 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel B: $q^5$-factor model coefficients | | | | | | | | |
| $\hat{\alpha}$ | **0.89**** | **0.56*** | **0.42*** | 0.39 | 0.16 | -0.03 | -0.06 | -0.07 |
| | (4.07) | (2.47) | (2.10) | (1.90) | (1.25) | (-0.24) | (-0.54) | (-0.56) |
| MKT-rf | -0.03 | -0.10 | -0.10 | -0.04 | -0.02 | -0.06 | -0.04 | -0.02 |
| | (-0.46) | (-1.36) | (-1.31) | (-0.51) | (-0.70) | (-1.42) | (-1.08) | (-0.59) |
| ME | -0.02 | 0.07 | 0.20 | 0.21 | 0.14 | 0.18 | **0.24*** | **0.27**** |
| | (-0.10) | (0.37) | (0.92) | (0.98) | (1.95) | (1.84) | (2.27) | (2.64) |
| I/A | 0.17 | -0.21 | -0.21 | -0.35 | **0.42**** | 0.22 | 0.19 | 0.13 |
| | (0.99) | (-0.99) | (-0.95) | (-1.48) | (4.44) | (1.83) | (1.65) | (1.05) |
| ROE | -0.24 | 0.00 | 0.09 | 0.11 | 0.01 | 0.16 | 0.16 | 0.16 |
| | (-1.31) | (0.03) | (0.51) | (0.58) | (0.10) | (1.62) | (1.71) | (1.58) |
| EG | 0.23 | 0.27 | 0.26 | 0.35 | 0.13 | 0.17 | 0.16 | **0.23*** |
| | (1.38) | (1.58) | (1.47) | (1.74) | (1.26) | (1.71) | (1.61) | (2.27) |
| Adj. $R^2$ | 0.02 | 0.02 | 0.03 | 0.04 | 0.13 | 0.12 | 0.13 | 0.13 |

The returns of different formation and holding period factor momentum strategies exhibit varying loadings to common factors that have been shown to be effective in capturing cross-sectional variation in stock returns (Fama & French 2018; Hou et al. 2021). For example, the Winner-Loser (1-1) strategy has a significantly positive CMA coefficient in Panel A of Table 6, thus implying exposure to low asset growth stocks. The Winner-Loser (3-1), (6-1), and (12-1) strategies have strongly positive UMD coefficients indicating exposure to winner stock-level momentum, with the Winner-Loser (12-1) strategy additionally having a strongly negative RMW coefficient that indicates of exposure to weak profitability stocks. Panel B of Table 6 reveals none of the monthly rebalanced Winner-Loser strategies to have significant loadings to the $q^5$-factors.

Analogously, Panel A of Table 6 reveals that the Winner-rf (1-1) strategy has mildly positive SMB and strongly positive CMA coefficients, thus implying exposures to small and low asset growth stocks, respectively. The Winner-rf (3-1), (6-1), and (12-1) strategies in Panel A of Table 6 have strongly positive UMD coefficients indicating an exposure to winner stock-level momentum, while the Winner-rf (6-1) and Winner-rf (12-1) strategies also have additional positive HML coefficients, thus implying additional exposure to value stocks. Panel B of Table 6 also indicates that the Winner-rf (1-1) strategy has a strongly positive I/A coefficient, suggesting an exposure to stocks with high investment-to-assets ratio. The Winner-rf (3-1), (6-1), (12-1) strategies in Panel B of Table 6 have positive ME coefficients that indicate exposure to small stocks, with the Winner-rf (12-1) strategy also loading positively on the EG factor coefficient, thereby implying an additional exposure to high expected growth stocks.

Depending on the formation and holding period combination, Appendices 2 and 3 reveal factor exposures of the corresponding less frequently rebalanced Winner-Loser and Winner-rf strategies to exhibit analogous variation in the size and sign of the factor loadings as for the strategies shown in Table 6. The less frequently rebalanced Winner-Loser strategies exhibit significant loadings to the CMA, RMW, and UMD factors, whereas the corresponding Winner-rf strategies show significant loadings to all the six-factor model factors depending on the strategy. The less frequently rebalanced Winner-Loser strategies in Appendix 3 exhibit significant loadings to the I/A and ROE factors, whereas the Winner-rf strategies load significantly to all the $q^5$-factors depending on the strategy.

## 4.5 Ex-post return-based style analysis and mean-variance efficiency

As time series factor momentum exhibits varying exposures to common factors across formation and holding period combinations, the return-based style analysis of Sharpe (1992) is applied as a complementary analysis to further study how the timed factors contribute to explaining the returns of the best performing monthly rebalanced Winner-Loser strategies (see Table 6 & Appendices 2 & 3).[35] As suggested by Table 6, Panel A of Table 7 shows that the portfolio that tracks the performance of the Winner-Loser (1-1) strategy assigns the largest significant weight to the CMA factor. Strikingly, the mimicking portfolio reveals that in addition to the CMA factor, the SMB, QMJ, and UMD factors appear to be significantly important in replicating the returns of the Winner-Loser (1-1) strategy, which is not revealed by the risk-adjustment regressions. The mimicking portfolio of the Winner-Loser (1-1) strategy tilts significantly towards size (17.28%), value (44.28%), quality (15.15%), and stock-level momentum (13.34%). Additionally, the mimicking portfolio explains 93% of the variance in the returns of the Winner-Loser (1-1) strategy, thus exhibiting the highest $R^2$ from the performance tracking portfolios.

Panel A of Table 7 reveals that the mimicking portfolios assign significant weigh to the CMA factor, especially the mimicking portfolios of the strategies relying on the 3- and 6-month momentum indicators. Surprisingly, the weight assigned to the CMA factor decreases (increases) strongly for the longer (shorter) formation-period strategies, whereas simultaneously the significant weight of the SMB and UMD factors increase (decrease) while the $R^2$ of the strategies decreases (increases). These observations jointly indicate that the CMA factor is important in explaining the returns of the strategies relying on shorter formation periods, whereas the importance of the UMD factor is greater in explaining the returns of the longer formation-period strategies.[36]

[35] Sharpe (1992) states that the asset portfolios employed in constructing the mimicking portfolios should have low correlations or different standard deviations in cases of high correlation. Consequently, the RMW factor is removed from the set of eight stylized factors in the return-based style analysis as it is strongly correlated with the QMJ factor (rho of 0.70) with a standard deviation that is close to the standard deviation of the QMJ factor.

[36] Value and momentum being important contributors in the mimicking portfolios is particularly interesting as value and momentum are known to be strongly negatively correlated in certain market environments, relating to the very essence of factor timing that strives to exploit such properties to generate higher returns (Asness, Moskowitz, Pedersen 2013; Blitz 2021).

Table 7: Pre-cost return-based style and tangency portfolio weights

This table reports weights from the return-based style analysis of Sharpe (1992) applied to the returns of the monthly rebalanced Winner-Loser strategies in Panel A. The (%) weights of the performance mimicking portfolios are optimized to minimize the tracking error between the factor momentum portfolio and the mimicking portfolio by means of quadratic optimization. Following Sharpe's (1992) style analysis, the sum of the estimated weights equal 100% and no short selling is allowed (the weights must be nonnegative). Panel A also reports the proportion of variance in the factor momentum returns that are explained by the corresponding mimicking portfolios ($R^2$). Panels B and C report ex post mean-variance efficient (MVE) tangency portfolio weights on the returns to the Fama-French (2018) six-factors and the Hou et al. (2021) $q^5$-factors separately both while omitting and including the returns to the best performing pre-cost Winner-Loser (1-1) strategy in the tangency portfolio estimation. The annualized Sharpe ratio (SR) is reported for all strategies and the MVE portfolios in Panels B and C to assess the mean-variance efficiency of the pre-cost Winner-Loser (1-1) strategy. The sample period spans from July 1964 to December 2021 in Panel A, whereas the sample period spans from January 1967 to December 2021 in Panels B and C to make a valid comparison as the $q^5$-factor data starts from January 1967. The asterisks ** (*) denote the significances of the non-zero weights in Panel A at the 1% (5%) level based on the standard errors that are calculated in accordance with Lobosco and DiBartolomeo (1997).

| Factors | Winner-Loser | | | |
|---|---|---|---|---|
| | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel A: Return-based tyle analysis (%) weights | | | | |
| SMB | 17.28** | 15.99** | 18.12** | 23.55** |
| HML | | | | |
| $HML_D$ | 9.95 | | | |
| CMA | 44.28** | 35.05** | 26.69** | 3.50 |
| QMJ | 15.15* | 9.95 | | |
| UMD | 13.34* | 39.01** | 55.2** | 72.94** |
| VOL | | | | |
| $R^2$ | 0.93 | 0.83 | 0.69 | 0.52 |
| Portfolios | SR | | Omitted | Included |
| Panel B: Pre-cost MVE portfolio weight estimation using factors from the six-factor model | | | | |
| Winner-Loser | | | | |
| (1-1) | 0.78 | | | 0.12 |
| MKT | 0.48 | | 0.17 | 0.16 |
| SMB | 0.25 | | 0.09 | 0.08 |
| HML | 0.32 | | | 0.01 |
| RMW | 0.46 | | 0.25 | 0.24 |
| CMA | 0.50 | | 0.36 | 0.29 |
| UMD | 0.50 | | 0.12 | 0.11 |
| Portfolio SR | | | 1.30 | 1.50 |
| Portfolios | SR | | Omitted | Included |
| Panel C: Pre-cost MVE portfolio weight estimation using factors from the $q^5$-factor model | | | | |
| Winner-Loser | | | | |
| (1-1) | 0.78 | | | 0.14 |
| MKT | 0.48 | | 0.18 | 0.16 |
| ME | 0.25 | | 0.10 | 0.09 |
| I/A | 0.32 | | | |
| ROE | 0.46 | | 0.31 | 0.29 |
| EG | 0.50 | | 0.40 | 0.32 |
| Portfolio SR | | | 1.13 | 1.36 |

The return-based style analysis results in Panel A of Table 7 together with the significant multifactor alphas reported in Table 6 suggests that factor momentum may provide style diversification outside of stock-level momentum, thereby motivating a mean-variance efficiency analysis on factor momentum. In line with the ex-post tangency portfolio analysis of Gupta and Kelly (2019), factor momentum is assigned weight in the mean-variance efficient (MVE) portfolio. The annualized Sharpe ratio of the MVE portfolio before including the Winner-Loser (1-1) strategy is 1.30 (1.13) in Panel B (Panel C) of Table 7, whereas the Sharpe ratio of the MVE portfolio increases to 1.50 (1.36) after including the Winner-Loser (1-1) strategy. Hence, the results in Panels B and C of Table 7 indicate that the pre-cost Winner-Loser (1-1) strategy improves the ex-post mean-variance efficiency of the tangency portfolio.

## 4.6 Average turnover and post-cost performance

The average annualized turnover of the Winner-Loser strategies, reported in Panel A of Table 8, are close to double the amount of the corresponding Winner portfolios, reported in Panel B, because of trading both long and short positions in factors.

Table 8: Average annualized turnover of time series factor momentum strategies

This table reports the average annualized turnover of the strategies defined as the two-sided trading volume (i.e., absolute changes in weights from both entering and exiting positions) as a fraction of gross asset value (see Equation 10).

| Holding period | Formation period | | | |
|---|---|---|---|---|
| | 1 | 3 | 6 | 12 |
| Panel A: Winner-Loser two-sided trading turnover | | | | |
| 1 | 29.55 | 31.45 | 30.03 | 30.80 |
| 3 | 16.80 | 30.35 | 30.29 | 32.21 |
| 6 | 11.84 | 21.71 | 29.75 | 31.38 |
| 12 | 7.72 | 14.60 | 20.87 | 30.27 |
| Panel B: Winner (long leg) two-sided trading turnover | | | | |
| 1 | 14.25 | 14.69 | 13.47 | 14.43 |
| 3 | 7.86 | 14.46 | 14.13 | 15.92 |
| 6 | 5.18 | 9.82 | 13.89 | 15.22 |
| 12 | 3.23 | 6.32 | 9.54 | 13.73 |
| Panel C: Loser (short leg) two-sided trading turnover | | | | |
| 1 | 15.29 | 16.76 | 16.56 | 16.37 |
| 3 | 8.94 | 15.89 | 16.15 | 16.29 |
| 6 | 6.66 | 11.88 | 15.86 | 16.16 |
| 12 | 4.49 | 8.28 | 11.33 | 16.54 |

The results in Table 8 suggests that infrequent rebalancing is more effective in lowering the turnover of shorter formation-period strategies. For example, Panel B of Table 8 shows that the Winner (1-12) portfolio has the lowest absolute value of average annualized turnover of 3.23, which is less than one quarter of the turnover of the Winner (1-1) portfolio. By contrast, the turnover of the Winner (12-12) portfolio is close same as the turnover of the Winner (12-1) portfolio. The annualized turnover of the Winner-Loser (1-1) portfolio is in line with the results of Gupta and Kelly (2019) on their turnover estimates of a similar factor momentum strategy with an average annualized turnover close to 30, while the turnover of the Winner-Loser (12-1) portfolio is considerably higher in comparison to their corresponding strategy with a turnover close to 10, and is thus at variance with their results.

### 4.6.1 Post-cost reward-to-variability

Despite the lower turnover and thus better resilience to trading cost considerations of the Winners, the best performing Winner-Loser (1-1) strategy exhibits superior performance in terms of net reward-to-risk compared to the best performing Winner-rf (1-1) strategy. Table 9 shows that after netting 10 basis points (bps) of trading costs per unit of turnover based on the estimates of Frazzini et al. (2018), only the Winner-Loser (1-1) strategy retains a higher annualized Sharpe ratio and SKASR than the market portfolio (MKT-rf) over the July 1964 to December 2021 period. By contrast, the post-cost Sharpe ratios and SKASRs of longer formation-period Winner-Loser strategies and all Winner-rf strategies are lower than or, they are at best, close to the Sharpe ratio and SKASR of the market portfolio. From the viewpoint of the long-only investor, Table 9 indicates that net of 5 bps of costs, the Winner-rf (1-1) has a higher annualized Sharpe ratio and SKASR than the market portfolio, whereas net of 10 bps of costs, the strategy has a Sharpe ratio and SKASR that are close to at par with reward-to-risk ratios of the market portfolio.

Table 9: Post-cost Sharpe ratios and SKASRs

This table reports the annualized Sharpe ratio and the skewness and kurtosis adjusted Sharpe ratio (SKASR) of Pätäri (2011) after trading costs over the July 1964 to December 2021 period. The significance of the ratios is benchmarked against the MKT-rf factor, which has an annualized Sharpe ratio and SKASR of around 0.38 over the same period. The annualized Sharpe ratio is calculated with Equation 3, the SKASR with Equation 7, where the higher distributional moments are defined in Equations 5 and 6.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel A: Sharpe ratio | | | | | | | | |
| 0 bps | 0.71 | 0.45 | 0.44 | 0.43 | 0.55 | 0.33 | 0.32 | 0.37 |
| 5 bps | 0.60 | 0.39 | 0.39 | 0.40 | 0.46 | 0.29 | 0.29 | 0.35 |
| 10 bps | 0.50 | 0.34 | 0.35 | 0.37 | 0.38 | 0.24 | 0.26 | 0.33 |
| 15 bps | 0.40 | 0.28 | 0.31 | 0.35 | 0.30 | 0.20 | 0.22 | 0.31 |
| 20 bps | 0.31 | 0.22 | 0.27 | 0.32 | 0.22 | 0.15 | 0.19 | 0.30 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel B: Skewness and kurtosis adjusted Sharpe ratio | | | | | | | | |
| 0 bps | 0.69 | 0.42 | 0.45 | 0.42 | 0.51 | 0.31 | 0.30 | 0.35 |
| 5 bps | 0.60 | 0.38 | 0.42 | 0.40 | 0.44 | 0.28 | 0.28 | 0.33 |
| 10 bps | 0.52 | 0.33 | 0.38 | 0.38 | 0.37 | 0.24 | 0.25 | 0.32 |
| 15 bps | 0.43 | 0.29 | 0.35 | 0.36 | 0.30 | 0.20 | 0.22 | 0.30 |
| 20 bps | 0.35 | 0.25 | 0.31 | 0.34 | 0.23 | 0.17 | 0.20 | 0.29 |

The net reward-to-risk performance of the less frequently rebalanced Winner-Loser and Winner-rf strategies are considerably inferior to the performance of the monthly rebalanced strategies even though less frequent rebalancing reduces the turnover of several strategies. Appendix 4 reveals that net of 5 bps of costs, only the Winner-Loser (3-1) strategy from the less frequently rebalanced strategies exhibits a very small improvement compared to the market portfolio in terms of annualized SKASR.

### 4.6.2 Post-cost risk-adjusted return

Table 10 reports the gross and net factor alphas for a handful of strategies that earn significant multifactor pre-cost alphas (i.e., the significantly outperforming Winner-Loser strategies). The results indicate that the Winner-Loser (1-1) strategy's multifactor alpha withstands 10 bps of trading costs while remaining significant at the 1% level, in with the results of Gupta and Kelly (2019). The multifactor alphas net of trading costs suggests that the abnormal returns (i.e., returns left unexplained by the multifactor models) generated by trading time series factor momentum is most effectively harvested with the Winner-Loser

(1-1) strategy in practice even though monthly rebalancing clearly punishes its net risk-adjusted performance.

A breakeven analysis reveals that the Winner-Loser (1-1) strategy generates monthly six-factor alpha of 0.59% and $q^5$-factor alpha of 0.59% significant at the 1% level net of 14 bps and 12 bps of trading costs per unit of turnover, respectively. Net of 20 and 18 bps of costs, Winner-Loser (1-1) strategy remains generates 0.44% of monthly six-factor and 0.44% of $q^5$-factor post-cost alpha, respectively, while remaining significant at the 5% level.

Table 10: Post-cost risk-adjusted return

For the Winner-Loser strategies, this table reports the monthly Fama and French (2018) six-factor and the Hou et al. (2021) $q^5$-factor alphas (%) net of trading costs that are significant on a pre-cost basis. The alphas are calculated using returns from January 1967 to December 2021 to make a valid comparison between the alphas as the $q^5$-factor data starts from January 1967. The t-statistics expressed in parentheses use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) indicate the significances of the alphas at 1%, (5%) risk levels.

| | Winner-Loser | | | | |
|---|---|---|---|---|---|
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-3 |
| Panel A: six-factor alpha net of costs | | | | | |
| 0 bps | **0.93**** | **0.60**** | **0.43*** | **0.40**** | **0.53*** |
| | (4.29) | (2.82) | (2.57) | (2.69) | (2.17) |
| 5 bps | **0.81**** | **0.53*** | **0.38*** | **0.37*** | **0.49*** |
| | (3.70) | (2.49) | (2.28) | (2.48) | (1.99) |
| 10 bps | **0.69**** | **0.47*** | **0.33*** | **0.34*** | 0.44 |
| | (3.12) | (2.16) | (1.99) | (2.26) | (1.81) |
| 15 bps | **0.56*** | 0.40 | 0.28 | **0.31*** | 0.40 |
| | (2.55) | (1.83) | (1.69) | (2.04) | (1.63) |
| 20 bps | **0.44*** | 0.33 | 0.24 | 0.28 | 0.36 |
| | (1.98) | (1.51) | (1.40) | (1.83) | (1.45) |
| | Winner-Loser | | | | |
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-3 |
| Panel B: $q^5$-factor alpha net of costs | | | | | |
| 0 bps | **0.89**** | **0.56*** | **0.42*** | 0.39 | **0.41*** |
| | (4.07) | (2.47) | (2.10) | (1.90) | (2.00) |
| 5 bps | **0.77**** | **0.49*** | 0.37 | 0.36 | 0.37 |
| | (3.49) | (2.16) | (1.85) | (1.74) | (1.80) |
| 10 bps | **0.64**** | 0.42 | 0.32 | 0.32 | 0.33 |
| | (2.91) | (1.84) | (1.61) | (1.58) | (1.60) |
| 15 bps | **0.52*** | 0.35 | 0.28 | 0.29 | 0.29 |
| | (2.34) | (1.53) | (1.37) | (1.43) | (1.40) |
| 20 bps | 0.39 | 0.28 | 0.23 | 0.26 | 0.25 |
| | (1.77) | (1.22) | (1.13) | (1.27) | (1.20) |

By contrast, Panel A of Table 10 shows that net of 10 bps of trading costs, the six-factor post-cost alphas of the longer formation Winner-Loser (3-1), (6-1), and (12-1) strategies are significant only at the 5% level, whereas Panel B indicates that net of 10 bps of costs none of the strategies generate significantly positive $q^5$-factor post-cost alpha. A breakeven analysis reveals that net of 3 bps and 2 bps of costs, the Winner-Loser (3-1) and Winner-Loser (12-1) strategies generate monthly post-cost alphas of 0.56% and 0.39%, respectively, while remaining significant at the 1% level. Net of 12 bps, 10 bps, and 16 bps of costs, the Winner-Loser (3-1), (6-1), and (12-1) strategies generate 0.44%, 0.33%, and 0.30% of monthly six-factor post-cost alpha significant at the 5% level, respectively.

After netting just 1 bps of trading costs, the $q^5$-factor post-cost alphas of the strategies do not remain significant at the 1% level. Nonetheless, net of 8 bps and 2 bps of trading costs, the Winner-Loser (3-1) and Winner-Loser (6-1) strategies generate 0.45% and 0.40% of $q^5$-factor post-cost alpha significant at the 5% level, respectively. From the less frequently rebalanced strategies, only the Winner-Loser (1-3) strategy returns 0.49% of monthly six-factor alpha at the 5% level after 5 bps of costs, whereas its $q^5$-factor alpha does not survive any trading costs.

#### 4.6.3 Post-cost mean-variance efficiency analysis

The mean-variance efficiency analysis in Table 11 tests whether the best performing Winner-Loser (1-1) strategy improves the performance of the MVE portfolio after netting out the maximum amount of costs per unit of turnover while the multifactor alphas of the Winner-Loser (1-1) strategy still remain significant at the 1% level. After netting out costs based on the breakeven points discussed in the previous subsection, Panels A and B of Table 11 indicate that the Winner-Loser (1-1) strategy remains a part of the MVE portfolio, albeit with less weight compared to the pre-cost results reported in Panels B and C of Table 7.

Table 11: Post-cost analysis on the optimal weights of the ex-post tangency portfolio

This table reports ex-post mean-variance efficient (MVE) tangency portfolio weights on the returns to the Fama-French (2018) six-factors and the Hou et al. (2021) $q^5$-factors separately both while omitting and including the returns to the best performing post-cost Winner-Loser (1-1) strategy in the tangency portfolio estimation. Based on the breakeven analysis discussed in Section 4.6.2, trading costs of 14 bps and 12 bps per unit of turnover are deducted from the gross returns of the Winner-Loser (1-1) strategy in Panels A and B, respectively. The annualized Sharpe ratio (SR) is reported for all strategies and the MVE portfolios to assess the mean-variance efficiency of the post-cost Winner-Loser (1-1) strategy. The sample period spans from January 1967 to December 2021 in both Panels to make a valid comparison as the $q^5$-factor data starts from January 1967.

| Portfolios | SR | Omitted | Included |
|---|---|---|---|
| Panel A: Post-cost MVE portfolio weight estimation using factors from the six-factor model | | | |
| Winner-Loser (1-1) | 0.50 | | 0.07 |
| MKT | 0.48 | 0.17 | 0.16 |
| SMB | 0.25 | 0.09 | 0.08 |
| HML | 0.32 | | |
| RMW | 0.46 | 0.25 | 0.25 |
| CMA | 0.50 | 0.36 | 0.32 |
| UMD | 0.50 | 0.12 | 0.11 |
| Portfolio SR | | 1.30 | 1.38 |
| Portfolios | SR | Omitted | Included |
| Panel B: Post-cost MVE portfolio weight estimation using factors from the $q^5$-factor model | | | |
| Winner-Loser (1-1) | 0.54 | | 0.10 |
| MKT | 0.48 | 0.18 | 0.17 |
| ME | 0.25 | 0.10 | 0.09 |
| I/A | 0.32 | | |
| ROE | 0.46 | 0.31 | 0.30 |
| EG | 0.50 | 0.40 | 0.34 |
| Portfolio SR | | 1.13 | 1.25 |

Although the trading costs lower the performance of the Winner-Loser (1-1) strategy, the maximum attainable Sharpe ratio of the MVE portfolio remains higher when including the post-cost Winner-Loser (1-1) strategy in both Panels A and B of Table 11.[37] Hence, the Table 11 confirms that the Winner-Loser (1-1) strategy improves the ex-post mean-variance efficiency of the tangency portfolio also net of trading costs.

[37] It is noteworthy to mention that the Fama-French six-factors and the Hou et al. (2021) $q^5$-factors are included pre-cost in the opportunity set in all post-cost comparisons, hence making the mean-variance efficiency test harder for the post-cost Winner-Loser (1-1) strategy. Nevertheless, the results can be very different in the instance of netting costs from the rest of the strategies included in the post-cost opportunity set.

## 4.7 Market state decomposition

The subplots a) and d) reported in Figure 2 shows that the monthly rebalanced Winner-Loser strategies avoided the momentum crash while the UMD factor experienced a drawdown of -42.1% from March to May 2009, as noted by Gupta and Kelly (2019). Over the same period, the best-performing Winner-Loser (1-1) and Winner-rf (1-1) strategies gained 59.4% and 23.9%, respectively. In addition to avoiding momentum crashes, the Winner-Loser and Winner-rf strategies have also avoided large market drawdowns. Two of the largest market drawdowns in the modern equity return sample are the ICT bubble burst from March 2000 to September 2002 and the Global financial crisis from October 2007 to February 2009 when the market portfolio suffered a drawdown of -50.1% and a drawdown of -51.5%, respectively. By contrast, the best performing Winner-Loser (1-1) and Winner-rf (1-1) strategies generated 18.6% and 66.7% during the Tech bubble burst and 17.2% and 10.7% during the Global financial crisis, respectively (see Table 12).

Table 12: Maximum (%) drawdown of the market factor and monthly rebalanced Winner-Loser and Winner-rf strategies over bearish states

This table reports the maximum (%) drawdown of the MKT-rf factor and the monthly rebalanced factor momentum strategies over bearish states. The returns are in the form of geometric excess returns (i.e., returns over the cost of financing the investment). The values are sorted on the worst drawdowns of the MKT-rf factor in ascending order. The bear market threshold is a loss of -20% in cumulative (%) log return from the previous peak to the subsequent trough of the market factor.

| Bear state | | MKT-rf | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Peak | Trough | | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Dec-72 | Sep-74 | -53.0 | 30.6 | 30.7 | 44.5 | 58.5 | 17.1 | 12.0 | 13.9 | 20.8 |
| Oct-07 | Feb-09 | -51.5 | 17.2 | 19.8 | 36.2 | 52.9 | 10.7 | 17.2 | 19.9 | 28.0 |
| Mar-00 | Sep-02 | -50.1 | 18.6 | -2.6 | 6.1 | -36.6 | 66.7 | 42.6 | 49.3 | 34.0 |
| Nov-68 | Jun-70 | -40.2 | 36.9 | 30.6 | 26.2 | 8.3 | 14.4 | 6.3 | 6.3 | -0.6 |
| Nov-80 | Jul-82 | -33.3 | -0.7 | -6.5 | -10.4 | -26.0 | -7.0 | -11.0 | -11.1 | -18.8 |
| Aug-87 | Nov-87 | -31.0 | -5.5 | -0.5 | 9.2 | -2.4 | -2.2 | -1.5 | 1.7 | -0.9 |
| Aug-89 | Oct-90 | -22.0 | 49.1 | 42.4 | 46.3 | 50.8 | 8.8 | 13.1 | 15.5 | 16.0 |
| Dec-19 | Mar-20 | -20.5 | -11.2 | 11.3 | 4.2 | 19.5 | -15.8 | 2.7 | -4.4 | 2.1 |
| Jun-83 | Jul-84 | -18.8 | 24.8 | 19.4 | 19.7 | 2.1 | 12.8 | 9.1 | 6.1 | 3.1 |
| Jun-98 | Aug-98 | -18.1 | 10.1 | 11.6 | 8.3 | 10.3 | 6.1 | 4.6 | 3.3 | 1.4 |

The subplots b) and e) in Figure 2 report the accumulated returns of the Winner-Loser and Winner-rf strategies over bearish market periods, thus illustrating the property of the strategies to hedge against market drawdowns.

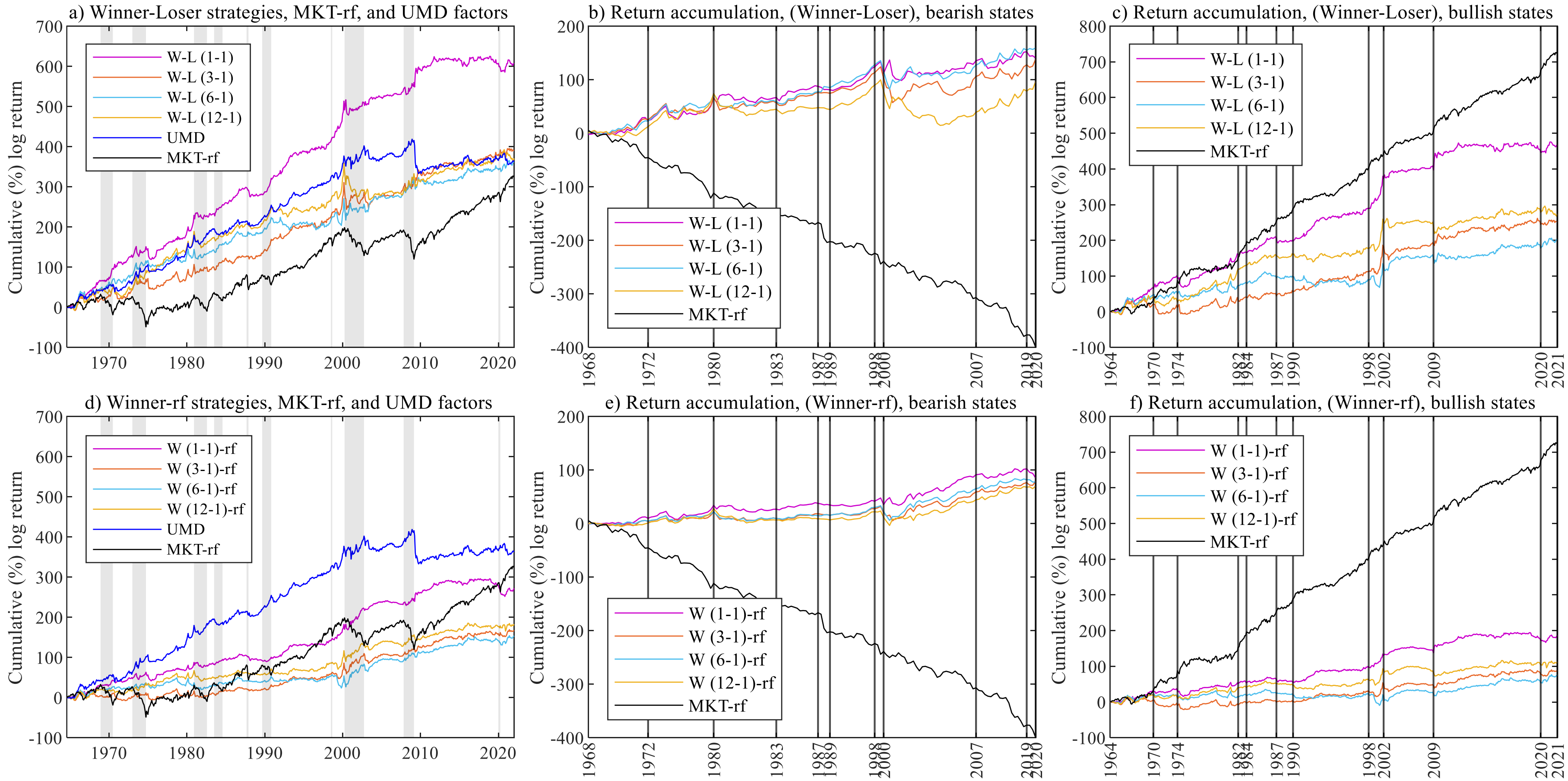



Figure 2: This figure reports the cumulative (%) log return from July 1964 to December 2021 and the return accumulation during bullish and bearish periods for the monthly rebalanced Winner-Loser and Winner-rf strategies, the MKT-rf, and the UMD factors. The grey shaded bars mark the bear market periods based on market turning points, when the cumulative loss of the market from the previous peak to the subsequent trough is -20% or less. The black vertical lines mark the temporal breaks in the time series with November 1968 (July 1964) and March 2020 (December 2021) marking the start and end of the first and last bearish (bullish) period, respectively.

However, the accumulated returns of the Winner-Loser and Winner-rf strategies over bullish states reported in subplots c) and f) in Figure 2 reveals that the strategies exhibit inferior performance compared to the market during bullish states. Appendix 5 reveals that the same two observations also apply to the less frequently rebalanced strategies based on the accumulated returns during bearish and bullish states Appendix 5, albeit a handful of the less frequently rebalanced Winner-Loser strategies exhibit slightly larger maximum drawdowns than the market over several periods ( see Appendix 6).[38]

### 4.7.1 Conditional CAPM

Despite Figure 2 suggesting that the Winner-Loser and Winner-rf strategies do not earn as large positive returns as the market during bullish states, the conditional CAPM results in Table 13 indicates that a handful of the strategies earn significantly positive returns over bullish states after adjusting for excess market return. The results with a 20% threshold reported in Panel A of Table 13 shows that the conditional alphas $(\hat{\beta}_0^+)$ and $(\hat{\beta}_0^-)$ of all monthly rebalanced, except for the Winner-rf (6-1) strategy, are significantly positive in bullish states. By contrast, the conditional alphas of the strategies in bearish states in Panel A of Table 13 are positive yet insignificant for the monthly rebalanced strategies. The bullish state conditional CAPM alphas $(\hat{\beta}_0^+)$ of the monthly rebalanced Winner-Loser and Winner-rf strategies with a 15% threshold reported in Panel B of Table 13 are in line with the results of Panel A with only small deviations in coefficient size and t-values.

The conditional CAPM betas $(1 + \hat{\beta}_0^+)$ and $(1 + \hat{\beta}_0^-)$ in Panel A of Table 13 suggest that the factor momentum strategies are not sensitive to the return of the market portfolio during bullish states and partially hedge against the market portfolio during bearish states. The conditional market betas of the strategies in Panel A of Table 13 are close to zero in bullish states, whereas the betas are negative and vary from -0.25 to -0.10 in bearish states. In line with the results of Panel A of Table 13, the conditional CAPM market betas $(1 + \hat{\beta}_0^+)$ and $(1 + \hat{\beta}_0^-)$ in Panel B are close to zero in bullish states and more negative in bearish states,

[38] The performance of factor momentum compared against the market during bullish and bearish states likely emanates directly from the timed factors as Arnott et al. (2019) show most factors from a sample of 14 well-known U.S. factors to be at their best (worst) when the market return is one standard deviation below (above) its historical mean.

albeit the bearish state coefficients are not as strong (i.e., as negative) in magnitude as in Panel A.

Table 13: Conditional CAPM and linear effects

This table reports the contemporaneous relative changes in excess factor momentum strategy returns over and above excess market return following ex post bullish and bearish market states as described in Equation 11. The third and fourth coefficients measure the positive and negative linear effects, the fifth coefficient reports the difference (linear asymmetry) in the coefficients followed by the p-value of the Wald test in square brackets, and the last row reports the adjusted $R^2$ value of each regression. The first and second coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels. The sample starts from July 1964 and ends in December 2021.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel A: Linear effects with a 20% threshold | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.93**** | **0.59**** | **0.42*** | **0.56**** | **0.41**** | **0.26*** | 0.18 | **0.26*** |
| | (5.84) | (3.06) | (2.27) | (2.94) | (4.57) | (2.31) | (1.55) | (2.26) |
| $\hat{\beta}_0^-$ | 0.47 | 0.54 | 0.64 | 0.58 | 0.15 | 0.05 | 0.15 | 0.24 |
| | (0.85) | (0.89) | (1.54) | (1.28) | (0.50) | (0.19) | (0.63) | (0.91) |
| $\hat{\beta}_1^+$ | **-0.98**** | **-1.03**** | **-0.98**** | **-0.98**** | **-1.03**** | **-1.05**** | **-1.01**** | **-1.02**** |
| | (-12.74) | (-14.5) | (-15.26) | (-13.43) | (-24.65) | (-22.84) | (-24.52) | (-22.95) |
| $\hat{\beta}_1^-$ | **-1.25**** | **-1.23**** | **-1.23**** | **-1.10**** | **-1.19**** | **-1.21**** | **-1.17**** | **-1.11**** |
| | (-9.61) | (-10.62) | (-12.29) | (-7.77) | (-13.70) | (-17.25) | (-21.21) | (-17.01) |
| Linear | **0.27**** | **0.19*** | **0.25**** | 0.12 | **0.16**** | **0.16**** | **0.16**** | **0.10*** |
| | [0.00] | [0.02] | [0.00] | [0.18] | [0.00] | [0.00] | [0.00] | [0.05] |
| Adj. $R^2$ | 0.53 | 0.55 | 0.57 | 0.51 | 0.79 | 0.80 | 0.79 | 0.78 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel B: Linear effects with a 15% threshold | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.88**** | **0.53**** | **0.42*** | **0.55**** | **0.42**** | **0.25*** | 0.20 | **0.29*** |
| | (5.33) | (2.61) | (2.16) | (2.77) | (4.99) | (2.18) | (1.72) | (2.56) |
| $\hat{\beta}_0^-$ | 0.81 | 0.87 | **0.84*** | **0.85*** | 0.33 | 0.30 | 0.33 | 0.38 |
| | (1.68) | (1.70) | (2.26) | (2.14) | (1.28) | (1.26) | (1.51) | (1.65) |
| $\hat{\beta}_1^+$ | **-0.99**** | **-1.04**** | **-1.01**** | **-1.01**** | **-1.05**** | **-1.07**** | **-1.03**** | **-1.04**** |
| | (-12.20) | (-14.31) | (-15.40) | (-13.35) | (-26.02) | (-24.13) | (-27.21) | (-24.16) |
| $\hat{\beta}_1^-$ | **-1.18**** | **-1.15**** | **-1.14**** | **-1.02**** | **-1.14**** | **-1.15**** | **-1.10**** | **-1.05**** |
| | (-9.88) | (-10.54) | (-11.10) | (-7.79) | (-13.85) | (-16.08) | (-17.68) | (-15.71) |
| Linear | **0.19*** | 0.11 | 0.14 | 0.02 | 0.09 | 0.08 | 0.07 | 0.01 |
| | [0.03] | [0.20] | [0.09] | [0.82] | [0.05] | [0.09] | [0.16] | [0.84] |
| Adj. $R^2$ | 0.53 | 0.55 | 0.56 | 0.51 | 0.79 | 0.79 | 0.79 | 0.78 |

Only five (four) out of twelve less frequently rebalanced Winner-Loser and three (four) out of twelve Winner-rf strategies with 20% (15%) thresholds in Appendix 7 (Appendix 8) exhibit significantly positive alpha in bullish states while none of the strategies exhibit significant bearish state alpha. Moreover, most of the corresponding less frequently rebalanced strategies in Appendices 7 and 8 exhibit conditional betas that are similar in sign but smaller in magnitude compared to the conditional beta estimates of Table 13.

### 4.7.2 Linear effects

Based on the $\hat{\beta}_1^+$ and $\hat{\beta}_1^-$ coefficients in Panels A and B of Table 13, the linear relationship between the Winner-Loser and Winner-rf strategy returns over and above the market return is significantly negative at the 1% level both in bullish and bearish states. The negative linear relationship indicates that factor momentum returns over and above the market return change in the opposite direction than the market return in bearish and bullish states. On average, factor momentum generates higher (lower) returns than the market during bearish (bullish) states when the average market return is negative (positive). The $\hat{\beta}_1^-$ coefficients are more negative than the $\hat{\beta}_1^+$ coefficients in Panel A of Table 13, thus corroborating the implications of Figure 2 that factor momentum returns relative to the market return are different in bullish and bearish states.

The Wald test results in Panel A of Table 13 confirm that the $\hat{\beta}_1^+$ and $\hat{\beta}_1^-$ coefficients are sharply different at the 1% level of significance in all cases with less than 12 months of prior returns used to construct the momentum indicator. The asymmetry $(\hat{\beta}_1^+ - \hat{\beta}_1^-)$ is larger for the Winner-Loser strategies. However, the $\hat{\beta}_1^+$ and $\hat{\beta}_1^-$ coefficients of the Winner-rf strategies are more significant based on the higher absolute t-statistics and higher adjusted $R^2$ values, thus implying that a larger portion of the returns of the Winner-rf strategies over the benchmark is related to the returns of the market in contrast to the Winner-Loser strategies. The less frequently rebalanced Winner-rf strategies also exhibit higher adjusted $R^2$ values compared to the corresponding Winner-Loser strategies in Appendix 7. Conversely, the results in Panel B of Table 13 are for the most part at variance with the results in Panel A on the asymmetry of the linear dependency between market states. In contrast to Panel A of Table 13, the results in Panel B indicates that only the Winner-Loser (1-1) strategy exhibits stronger negative relationship at the 5% level of significance in bearish states based on the Wald test. Therefore, the difference in results with a 15% threshold implies that the linear asymmetry is stronger during more severe market drawdowns captured by the larger threshold in the demarcation of market states.

The property of factor momentum to hedge against a drawdown of the market is stronger for monthly rebalanced strategies as the returns of most less frequently rebalanced strategies over and above the market return do not exhibit linear asymmetry with respect to market return between market states. Only the Winner-Loser (3-12) and Winner-rf (6-3), (3-6), (3-12), and (6-12) strategies have significantly lower $\hat{\beta}_1^-$ coefficients based on the Wald test with a 20% threshold in Appendix 7, whereas the linear asymmetry is significant only for the Winner-rf (3-12) strategy with a 15% threshold in Appendix 8.

### 4.7.3 Linear effects after including quadratic terms

By adding the quadratic return terms $(\beta_1^+)^2$ and $(\beta_1^-)^2$, the linear return term coefficients $\hat{\beta}_1^+$ and $\hat{\beta}_1^-$ are negative and remain significant. The linear asymmetry in Panel A of Table 14 is also stronger after adding the quadratic terms based on the larger difference between the $\hat{\beta}_1^+$ and $\hat{\beta}_1^-$ coefficients, albeit the absolute t-values of the $\hat{\beta}_1^-$ coefficients are considerably lower compared to Panel A of Table 13. In line with Panel A of Table 14, the results of Panel B reveal that the significance and magnitude of the linear asymmetry increases when the quadratic terms are included in the model specification, even though the linear asymmetry is not as large or as significant with a 15% threshold. All except the one-month formation strategies in Panel B of Table 14 have significantly negative bullish state linear term coefficients and quadratic term coefficients in line with Panel A. The Wald test results in Panel B of Table 14 also corroborates that an asymmetric linear relationship exists in most cases after considering the quadratic effects.

The linear asymmetry is stronger also for the less frequently rebalanced strategies with a 20% (15%) threshold reported in Appendix 9 (Appendix 10) after including the quadratic terms, in line with the results of Panel A (Panel B) of Table 14. Before including the quadratic terms, only the linear asymmetry of four (one) out of twelve Winner-rf strategies in Appendix 7 (Appendix 8) are significant. By contrast, after including the quadratic terms in Appendix 9 (Appendix 10), two (two) out of twelve of the Winner-Loser strategies and eight (five) out of twelve of the Winner-rf strategies exhibit significant linear asymmetry between states.

Table 14: Linear and quadratic effects

This table reports the contemporaneous relative changes in excess factor momentum strategy returns over and above excess market return following ex post bullish and bearish market states as described in Equation 12. The third and fourth coefficients measure the positive and negative linear effects, the fifth and sixth coefficients measure corresponding quadratic effects, the seventh coefficient reports the difference (linear asymmetry) of the third and fourth coefficients followed by the p-value of the Wald test in square brackets, the eight coefficient reports the difference (quadratic asymmetry) between the fifth and sixth coefficient followed by the p-value of the Wald test in square brackets, and the last row reports the adjusted $R^2$ value of each regression. The first and second coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels. The sample starts from July 1964 and ends in December 2021.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel A: Linear and quadratic effects with a 20% threshold | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.99**** | **1.01**** | **0.85**** | **1.03**** | **0.51**** | **0.53**** | **0.46**** | **0.57**** |
| | (4.36) | (4.61) | (4.01) | (4.67) | (4.53) | (4.48) | (3.79) | (4.34) |
| $\hat{\beta}_0^-$ | 0.65 | 0.56 | 0.43 | 0.30 | 0.33 | 0.16 | 0.20 | 0.19 |
| | (1.44) | (1.03) | (1.04) | (0.59) | (1.30) | (0.64) | (0.86) | (0.73) |
| $\hat{\beta}_1^+$ | **-0.97**** | **-0.93**** | **-0.88**** | **-0.87**** | **-1.01**** | **-0.98**** | **-0.94**** | **-0.94**** |
| | (-14.47) | (-16.98) | (-16.27) | (-13.93) | (-24.6) | (-24.29) | (-24.16) | (-23.26) |
| $\hat{\beta}_1^-$ | **-1.34**** | **-1.24**** | **-1.12**** | **-0.95**** | **-1.29**** | **-1.27**** | **-1.20**** | **-1.09**** |
| | (-6.34) | (-6.29) | (-6.82) | (-4.89) | (-10.23) | (-11.7) | (-13.92) | (-10.33) |
| $(\beta_1^+)^2$ | 0.00 | **-0.03**** | **-0.03**** | **-0.04**** | -0.01 | **-0.02**** | **-0.02**** | **-0.03**** |
| | (-0.30) | (-3.95) | (-4.71) | (-4.22) | (-1.00) | (-3.76) | (-4.38) | (-3.91) |
| $(\beta_1^-)^2$ | -0.010 | 0.00 | 0.01 | 0.02 | -0.01 | -0.01 | 0.00 | 0.00 |
| | (-0.81) | (-0.12) | (1.37) | (1.20) | (-1.55) | (-0.91) | (-0.74) | (0.38) |
| Linear | **0.37**** | **0.31**** | **0.24*** | 0.08 | **0.28**** | **0.29**** | **0.26**** | **0.15*** |
| | [0.00] | [0.00] | [0.02] | [0.46] | [0.00] | [0.00] | [0.00] | [0.01] |
| Quadratic | 0.01 | **-0.03**** | **-0.05**** | **-0.06**** | 0.00 | **-0.01*** | **-0.02**** | **-0.03**** |
| | [0.49] | [0.00] | [0.00] | [0.00] | [0.43] | [0.02] | [0.00] | [0.00] |
| Adj. $R^2$ | 0.53 | 0.56 | 0.58 | 0.53 | 0.79 | 0.81 | 0.80 | 0.79 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-1 | 3-1 | 6-1 | 12-1 | 1-1 | 3-1 | 6-1 | 12-1 |
| Panel B: Linear and quadratic effects with a 15% threshold | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.88**** | **0.87**** | **0.74**** | **0.92**** | **0.45**** | **0.44**** | **0.39**** | **0.52**** |
| | (3.80) | (3.95) | (3.57) | (4.21) | (4.00) | (3.78) | (3.26) | (3.95) |
| $\hat{\beta}_0^-$ | **0.97*** | **0.92*** | 0.66 | 0.62 | **0.49*** | 0.40 | 0.38 | 0.35 |
| | (2.46) | (1.97) | (1.77) | (1.42) | (2.19) | (1.8) | (1.72) | (1.48) |
| $\hat{\beta}_1^+$ | **-1.00**** | **-0.90**** | **-0.87**** | **-0.86**** | **-1.03**** | **-0.99**** | **-0.96**** | **-0.95**** |
| | (-15.65) | (-17.76) | (-15.93) | (-13.12) | (-34.72) | (-26.8) | (-26.25) | (-23.24) |
| $\hat{\beta}_1^-$ | **-1.27**** | **-1.18**** | **-1.04**** | **-0.90**** | **-1.23**** | **-1.20**** | **-1.13**** | **-1.04**** |
| | (-6.78) | (-6.75) | (-7.17) | (-5.35) | (-10.87) | (-12.06) | (-13.99) | (-11.04) |
| $(\beta_1^+)^2$ | 0.00 | **-0.03**** | **-0.03**** | **-0.04**** | 0.00 | **-0.02**** | **-0.02**** | **-0.02**** |
| | (0.05) | (-3.97) | (-4.52) | (-3.91) | (-0.36) | (-3.56) | (-4.20) | (-3.40) |
| $(\beta_1^-)^2$ | -0.01 | 0.00 | 0.01 | 0.02 | -0.01 | -0.01 | 0.00 | 0.00 |
| | (-0.92) | (-0.25) | (1.35) | (1.24) | (-1.70) | (-1.10) | (-0.85) | (0.34) |
| Linear | **0.27*** | **0.27*** | 0.17 | 0.04 | **0.19**** | **0.22**** | **0.17**** | 0.08 |
| | [0.01] | [0.01] | [0.09] | [0.69] | [0.00] | [0.00] | [0.00] | [0.16] |
| Quadratic | 0.01 | **-0.03**** | **-0.05**** | **-0.05**** | 0.01 | -0.01 | **-0.02*** | **-0.03**** |
| | [0.28] | [0.01] | [0.00] | [0.00] | [0.15] | [0.06] | [0.01] | [0.00] |
| Adj. $R^2$ | 0.53 | 0.56 | 0.57 | 0.52 | 0.79 | 0.80 | 0.80 | 0.79 |

### 4.7.4 Quadratic effects

The Winner-Loser (1-1) and Winner-rf (1-1) strategies in Table 14 do not exhibit significant quadratic return terms $(\beta_1^+)^2$ and $(\beta_1^-)^2$ indicating that the returns over and above the market return of the two strategies do not have a significant quadratic relationship with the market return. By contrast, the longer formation-period strategies in Table 14 have significantly negative bullish state quadratic term coefficients. The significantly negative bullish state linear $(\beta_1^+)$ and quadratic $(\beta_1^+)^2$ return term coefficients jointly suggest that the Winner-Loser (3-1), (6-1), and (12-1) and Winner-rf (3-1), (6-1), and (12-1) strategies have a significantly negative relationship with the market return during bullish states that is stronger in magnitude when the size of the market return is larger. The Wald tests in Table 14 confirm a quadratic asymmetry to exist for these strategies between states, albeit the quadratic asymmetry of the Winner-rf (3-1) strategy in Panel B of Table 14 is significant at the 10% level instead of 5%. Table 14 also shows that the relationship is strictly linear during bearish states as none of the bearish state quadratic terms are significant for the strategies.

Most of the less frequently rebalanced strategies, particularly the longer formation-period strategies, also exhibit negative bullish state quadratic term coefficients that are more negative in bullish states based on the Wald test with 20% and 15% thresholds (see Appendices 9 & 10). Appendices 9 and 10 reveal that the Winner-rf (3-3) strategy has a significantly negative bearish state linear term and quadratic term coefficients that jointly indicate that the strategy's returns over and above the market return have a negative relationship with the market return that is stronger when the size of the market return is larger. Conversely, the Winner-Loser (12-6), (1-12), and (12-12) strategies exhibit significantly negative bearish state linear term and significantly positive bullish state quadratic term coefficients that jointly indicate that the strategies have a negative relationship with the market return that is less negative when the size of the market return is larger.

# 5 Conclusions

Prior literature shows that factor momentum strategies generate high returns. However, most prior studies employ large factor sets omitting the possible nonexistence of investment products that track returns from less popular factors, the difficulty to implement long-short factors in practice due to trading frictions (i.e., short selling constraints), and the possibility of the results being driven by obscure factors. In spite of these limitations, factor investing can be implemented using financial investment products, such as available factor ETFs that track different individual stylized factors. Motivated by prior literature on real-world profits from momentum, this thesis contributes to existing literature by analyzing time series factor momentum from a viewpoint that is a few steps closer to practical implementation. For this purpose, a small set of eight publicly available long-short factors are employed as proxies for stylized ETFs that capture size, value , quality, momentum, and low risk. As noted by Blitz (2021), these factor styles are frequently targeted by investors, having existing coverage by market makers. The following paragraphs summarizes the results, answers the research questions, and briefly discusses possible topics of future research.

As suggested by the full sample autocorrelation tests on individual factor returns, factor momentum is stronger on the long side based on the higher average raw returns of the Winner portfolios relative to the corresponding Loser portfolios. All long legs of the Winner-Loser strategies also generate higher average raw returns than a monthly rebalanced equally weighted factor (EWF) portfolio, thus accentuating the role of timing in generating higher returns. Moreover, nearly all factor momentum strategies outperform the EWF portfolio also after considering costs from financing the investments following a more practical perspective towards factor investing. In line with existing literature, several of the best performing monthly rebalanced Winner-Loser strategies generate significantly positive Fama-French (2018) six-factor and Hou et al. (2021) $q^5$-factor pre-cost alphas. Confirming the results of Gupta and Kelly (2019), the Winner-Loser (1-1) strategy exhibits the strongest performance as it outperforms all strategies in pre-cost and post-cost performance comparisons. Conversely, a long-only investor may be disappointed as the long-only Winner-rf strategies are inferior to their Winner-Loser strategy counterparts in performance comparisons, thereby suggesting that factor momentum is best exploited as a long-short strategy.

The risk-adjustment regressions reveal that most longer formation-period strategies load strongly to the UMD factor, thereby suggesting that the UMD factor is important in explaining the returns of a number of longer formation-period strategies on various rebalancing frequencies. An ex-post return-based style analysis reveals that the best performing monthly rebalanced Winner-Loser strategies significantly tilt towards size, value, and momentum, which the risk-adjustment regressions do not fully reveal. Moreover, the CMA (UMD) factor is assigned more weight in the portfolios mimicking the performance of the shorter (longer) formation-period strategies and less weight in the portfolios mimicking the performance of longer (shorter) formation-period strategies. The pre-cost and post-cost Winner-Loser (1-1) strategy increases the maximum attainable Sharpe ratio in estimating the ex-post tangency portfolio, thereby indicating that factor momentum is valuable in augmenting the performance of the tangency portfolio.

Factor momentum strategies have also avoided large market drawdowns. A conditional CAPM model suggests that factor momentum hedges against market return declines during bearish states and exhibits neutral performance with respect to market return in bullish states. The linear model indicates that returns from factor momentum over and above the market return have a negative linear relationship with market return in bullish and bearish states, which is stronger in bearish states confirmed by the Wald test. Hence, when the average market return is positive (negative) in bullish (bearish) states, the strategies tend to exhibit inferior (superior) performance compared to the market return in bullish (bearish) states, on average. The negative linear dependency is also stronger when quadratic terms are included in the model. Longer formation-period strategies, regardless of the rebalancing frequency, also exhibit significantly negative quadratic effects in addition to negative linear effects in bullish states. Hence, the return dependency of the longer formation-period strategies is stronger with respect to the market return during bullish states when the size of the market return is large.

Finally, this thesis aims to open discussion on the viability of real-world applications of factor momentum. The use of theoretical factor portfolios of well-known factors to substitute for real-world factor ETFs is convenient due to data restrictions but also leaves much room for improvement. Apart from less frequent rebalancing, this thesis does not consider other cost-mitigation methods that aim to improve the post-cost performance of factor momentum by e.g., lowering turnover, excluding high-cost securities from portfolios, or considering cross-factor exposures of individual stocks or portfolios with respect to different factors. Therefore, future research could test how factor momentum performs in the instance of employing factors that follow more efficient factor or portfolio construction. The cross-factor exposures could be considered by, for example, utilizing factor sleeves as suggested by Blitz (2023) for traditional multifactor strategies or employing composite portfolio formation indicators that considers information on the aggregate (i.e., total) exposure of the strategies to a few important themes, such as the relationship between value and momentum as they tend to be negatively correlated at times (Asness et al. 2013; Blitz 2021, 2023).

# References

Asness, C. & Frazzini, A. (2013) The devil in HML’s details. *Journal of Portfolio Management*, 39 (4), 49–68.

Asness, C. S., Moskowitz, T. J. & Pedersen, L. H. (2013) Value and momentum everywhere. *Journal of Finance*, 68 (3), 929–985.

Asness, C., Frazzini, A., Israel, R. & Moskowitz, T. (2014) Fact, fiction, and momentum investing. *Journal of Portfolio Management*, 40 (5), 75–92.

Asness, C. S. (2016) The siren song of factor timing aka ‘smart beta timing’ aka ‘style timing’. *Journal of Portfolio Management*, 42 (5), 1–6.

Asness, C. S., Frazzini, A. & Pedersen L. H. (2019) Quality minus junk. *Review of Accounting Studies*, 24 (1), 34–112.

Arnott, R., Harvey C. R., Kalesnik V. & Linnainmaa, J. T. (2019) Alice’s adventures in factorland: Three blunders that plague factor investing. *Journal of Portfolio Management*, 45 (4), 18–36.

Arnott, R. D., Clements, M., Kalesnik, V. & Linnainmaa, J. T. (2021) Factor momentum. Working Paper. SSRN.

Asem, E. & Tian, G. Y. (2010) Market dynamics and momentum profits. *Journal of Financial and Quantitative Analysis*, 45 (6), 1549–1562.

Avramov, D., Cheng, S., Schreiber, A. & Shemer, K. (2017) Scaling up market anomalies. *Journal of Investing*, 26 (3), 89–105.

Banz, R. W. (1981) The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9 (1), 3–18.

Barillas, F. & Shanken, J. (2017) Which alpha?. *Review of Financial Studies*, 30 (4), 1316–1338.

Barillas, F. & Shanken, J. (2018) Comparing asset pricing models. *Journal of Finance*, 73 (2), 715–754.

Barroso, P. & Detzel, A. (2021) Do limits to arbitrage explain the benefits of volatility-managed portfolios?. *Journal of Financial Economics*, 140 (3), 744–767.

Barroso, P. & Santa-Clara, P. (2015) Momentum has its moments. *Journal of Financial Economics*, 116 (1), 111–120.

Blitz, D. C. & van Vliet, P. (2007) The volatility effect: Lower risk without lower return. *Journal of Portfolio Management*, 34 (1), 102–113.

Blitz, D., Huij, J. & Martens, M. (2011) Residual momentum. *Journal of Empirical Finance*, 18 (3), 506–521.

Blitz, D. (2021) The Quant Cycle. *Journal of Portfolio Management*, 48 (2), 26–43.

Blitz, D. (2023) Factor investing: The best is yet to come. *Journal of Portfolio Management Quantitative Special Issue*, 49 (2), 10–18.

Carhart, M. M. (1997) On persistence in mutual fund Performance. *Journal of Finance,* 52 (1), 57–82.

Cederburg, S., O'Doherty, M. S., Wang, F. & Yan, X. (2020) On the performance of volatility-managed portfolios. *Journal of Financial Economics*, 138 (1), 95–117.

Chan, L. K., Jegadeesh, N. & Lakonishok, J. (1996) Momentum strategies. *Journal of Finance*, 51 (5), 1681–1713.

Chordia, T. & Shivakumar, L. (2002) Momentum, business cycle, and time-varying expected returns. *Journal of Finance*, 57 (2), 985–1019.

Cohen, R. B., & Polk, C. K. (1998) The impact of industry factors in asset-pricing tests. Kellogg Graduate School of Management working paper.

Conrad, J. & Kaul, G. (1998) An anatomy of trading strategies. *Review of Financial Studies*, 11 (3), 489–519.

Cooper, M. J., Gutierrez R., C. & Hameed, A. (2004) Market states and momentum. *Journal of Finance*, 59 (3), 1345–1365.

Daniel, K. & Moskowitz, T. J. (2016) Momentum crashes. *Journal of Financial Economics*, 122 (2), 221–247.

Daniel, K., Hirshleifer, D. & Sun, L. (2020) Short- and long-horizon behavioral factors. *Review of Financial studies*, 33 (4), 1673–1736.

Dierkes, M. & Krupski, J. (2022) Isolating momentum crashes. *Journal of Empirical Finance*, 66, 1–22.

Ehsani, S. & Linnainmaa, J. T. (2022a) Factor momentum and the momentum factor. *Journal of Finance*, 77 (3), 1877–1919.

Ehsani, S. & Linnainmaa, J. T. (2022b) Internet appendix for "Factor momentum and the momentum factor". *Journal of Finance*. Available at: https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjofi.13131&file=jofi13131-sup-0001-InternetAppendix.pdf

Fama, E. F. & French, K. R. (1993) Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33 (1), 3–56.

Fama, E. F. & French, K. R. (1996) Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51 (1), 55–84.

Fama, E. F. & French, K. R. (2008) Dissecting anomalies. *Journal of Finance*, 63 (4), 1653–1678.

Fama, E. F. & French, K. R. (2015) A five-factor asset pricing model. *Journal of Financial Economics*, 116 (1), 1–22.

Fama, E. F. & French, K. R. (2018) Choosing factors. *Journal of Financial Economics*, 128 (2), 234–252.

Feng, G., Giglio, S. & Xiu, D. (2020) Taming the factor zoo: A test of new factors. *Journal of Finance*, 75 (3), 1327–1370.

Ferson, W. E. & Siegel, A. F. (2001) The efficient use of conditioning information in portfolios. *Journal of Finance*, 56 (3), 967–982.

Frazzini, A. & Pedersen, L. H. (2014) Betting against beta. *Journal of Financial Economics*, 111 (1), 1–25.

Frazzini, A., Israel, R. & Moskowitz, T. J. (2018) Trading costs. Working Paper. SSRN.

Geczy, C. C. & Samonov, M (2016) Two centuries of price-return momentum. *Financial Analysts Journal*, 72 (5), 32–56.

Giot, P. (2005) Relationships between implied volatility indexes and stock index returns: Are implied volatility indexes leading indicators?. *Journal of Portfolio Management*, 31 (3), 92–100.

Griffin, J. M., Ji, X. & Martin, J. S. (2003) Momentum investing and business cycle risk: Evidence from pole to pole. *Journal of Finance*, 58 (6), 2515–2547.

Grundy, B. D. & Martin, J. S. M. (2001) Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies*, 14 (1), 29–78.

Gupta, T. & Kelly, B. (2019) Factor momentum everywhere. *Journal of Portfolio Management*, 45 (3), 13–36.

Haddad, V., Kozak, S. & Santosh, S. (2020) Factor Timing. *Review of Financial Studies*, 33 (5), 1980–2018.

Harvey, C. R., Liu, Y. & Zhu, H. (2016) … and the cross-section of expected returns. *Review of Financial Studies*, 29 (1), 5–68.

Harvey, C. R. & Liu, Y. (2021) Lucky factors. *Journal of Financial Economics*, 141 (2), 413–435.

Hou, K., Mo, H., Xue, C. & Zhang, L. (2019) Which factors?. *Review of Finance*, 23 (1), 1–35.

Hou, K., Xue, C. & Zhang, L. (2015) Digesting anomalies: An investment approach. *Review of Financial Studies*, 28 (3), 650–705.

Hou, K., Xue, C. & Zhang, L. (2020) Replicating anomalies. *Review of Financial Studies*, 33 (5), 2019–2133.

Hou, K., Mo, H., Xue, C. & Zhang, L. (2021) An augmented q -factor model with expected growth. *Review of Finance*, 25 (1), 1–41.

Huberman, G. & Kandel, S. (1987) Mean-variance spanning. *Journal of Finance*, 42 (4), 873–888.

Ilmanen A., Israel, R., Moskowitz, T. J., Thapar, A. K. & Lee, R. (2021) How do factor premia vary over time? A century of evidence. Working Paper. SSRN.

Israelsen, C. (2005) A refinement to the Sharpe ratio and information ratio. *Journal of Asset Management*, 5 (6), 423–427.

Jegadeesh, N. & Titman, S. (1993) Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48 (1), 65–91.

Jegadeesh, N. & Titman, S. (2001) Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance*, 56 (2), 699–720.

Kan, R. & Zhou, G. (2007) Optimal portfolio choice with parameter uncertainty. *Journal of Financial and Quantitative Analysis*, 42 (3), 621–656.

Korajczyk, R. A. & Sadka, R. (2004) Are momentum profits robust to trading costs?. *Journal of Finance*, 59 (3), 1039–1082.

Kothari, S. P. & Shanken, J. (1992) Stock return variation and expected dividends: A time-series and cross-sectional analysis. *Journal of Financial Economics*, 31 (2), 177–210.

Ledoit, O. & Wolf, M. (2008) Robust performance hypothesis testing with the Sharpe ratio. *Journal of Empirical Finance*, 15 (5), 850–859.

Leippold, M. & Rueegg, R. (2021) Fama–French factor timing: The long-only integrated approach. *European Financial Management*, 27 (4), 666–700.

Lesmond, D. A., Schill, M. J. & Zhou, C. (2004) The illusory nature of momentum profits. *Journal of Financial Economics*, 71 (2), 349–380.

Liu, F., Tang, X. & Zhou, G. (2019) Volatility-managed portfolio: Does it really work?. *Journal of Portfolio Management*, 46 (1), 38–51.

Liu, L. X. & Zhang, L. (2008) Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies*, 21 (6), 2417–2448.

Lo, A. W. & MacKinlay, A. C. (1990) When are contrarian profits due to stock market overreaction?. *Review of Financial Studies*, 3 (2), 175–205.

Lobosco, A. & DiBartolomeo, D. (1997) Approximating the confidence intervals for Sharpe style weights. *Financial Analysts Journal*, 53 (4), 80–85.

Martens, M. & van Oord, A. (2014) Hedging the time-varying risk exposures of momentum returns. *Journal of Empirical Finance*, 28, 78–89.

McLean, R. D. & Pontiff, J. (2016) Does academic research destroy stock return predictability?. *Journal of Finance*, 71 (1), 5–32.

Moreira, A. & Muir, T. (2017) Volatility-managed portfolios. *Journal of Finance*, 72 (4), 1611–1643.

Moskowitz, T. J. & Grinblatt, M. (1999) Do industries explain momentum?. *Journal of Finance*, 54 (4), 1249–1290.

Newey, W. K., & West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55 (3), 703–708.

Novy-Marx, R. (2012) Is momentum really momentum?. *Journal of Financial Economics*, 103 (3), 429–453.

Novy-Marx, R. (2013) The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108 (1), 1–28.

Novy-Marx, R. & Velikov, M. (2016) A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29 (1), 104–147.

Novy-Marx, R. & Velikov, M. (2022) Betting against betting against beta. *Journal of Financial Economics*, 143 (1), 80–106.

Patton, A. J. & Weller, B. M. (2020) What you see is not what you get: The costs of trading market anomalies. *Journal of Financial Economics*, 137 (2), 515–549.

Politis, D. N. & Romano, J. P. (1992) A circular block-resampling procedure for stationary data. Purdue University. Department of Statistics.

Pätäri, E. (2011) Does the risk-adjustment method matter at all in hedge fund rankings?. *International Research Journal of Finance and Economics*, 75, 69–99.

Rachev, S., Jašić, T., Stoyanov, S. & Fabozzi, F. J. (2007) Momentum strategies based on reward–risk stock selection criteria. *Journal of Banking & Finance*, 31 (8), 2325–2346.

Rosenberg, B., Reid, K. & Lanstein, R. (1985) Persuasive evidence of market inefficiency. *Journal of Portfolio Management*, 11 (3), 9–16.

Sharpe, W. F. (1966) Mutual Fund Performance. *Journal of Business*, 39 (1), 119–138.

Sharpe, W. F. (1992) Asset allocation: Management style and performance measurement. *Journal of Portfolio Management*, 18 (2), 7–19.

Shleifer, A. & Vishny, R. W. (1997) The limits of arbitrage. *Journal of Finance*, 52 (1), 35–55.

Siganos, A. & Chelley-Steeley, P. (2006) Momentum profits following bull and bear markets. *Journal of Asset Management*, 6 (5), 381–388.

Stambaugh, R. F., Yu, J. & Yuan, Y. (2015) Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, 70 (5), 1903–1948.

Stambaugh, R. F. & Yuan, Y. (2017) Mispricing factors. *Review of Financial Studies*, 30 (4), 1270–1315.

Stivers, C. & Sun, L. (2010) Cross-sectional return dispersion and time variation in value and momentum premiums. *Journal of Financial and Quantitative Analysis*, 45 (4), 987–1014.

Stivers, C. & Sun, L. (2013) Market cycles and the performance of relative strength strategies. *Financial Management*, 42 (2), 263–290.

Titman, S., Wei, K. J. & Xie, F. (2004) Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39 (4), 677–700.

Zaremba, A. & Andreu, L. (2018) Paper profits or real money? Trading costs and stock market anomalies in country ETFs. *International Review of Financial Analysis*, 56, 181–192.

Zaremba, A. & Shemer, J. (2018) Is there momentum in factor premia? Evidence from international equity markets. *Research in International Business and Finance*, 46, 120–130.

## Appendix 1: Autocorrelation in mean returns of factors

This table reports univariate (return-on-return) regressions following Ehsani and Linnainmaa (2022a), where the dependent variable is a factor's monthly (%) return, and the independent variable $R_{i,k}$ is a factor's average (%) return over the prior $k$ month period. For each factor, the following regressions are estimated: $R_{i,t} = \alpha_i + \beta_i R_{i,k} + \varepsilon$, where the intercept $\alpha_i$ measures a factors average return adjusted for the prior average return of a factor, the slope $\beta_i$ measures the linear relationship between a factor and its average return over the prior return period, and $\varepsilon$ is an error term. The dependent variable covers the period from June 1964 to December 2021 in all regressions. The alpha coefficients are in % per month. The t-statistics expressed in parenthesis utilize Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels.

| | Conditional on prior 1-month return | | | | Conditional on prior 3-month return | | | |
|---|---|---|---|---|---|---|---|---|
| | Intercept | | Slope | | Intercept | | Slope | |
| Factor | $\hat{\alpha}$ | t($\hat{\alpha}$) | $\hat{\beta}$ | t($\hat{\beta}$) | $\hat{\alpha}$ | t($\hat{\alpha}$) | $\hat{\beta}$ | t($\hat{\beta}$) |
| SMB | 0.22 | (1.90) | 0.07 | (1.41) | 0.23 | (1.84) | 0.06 | (0.68) |
| HML | 0.22 | (1.84) | **0.17**** | (3.76) | 0.20 | (1.71) | **0.23**** | (2.91) |
| $HML_D$ | 0.23 | (1.71) | **0.13*** | (2.32) | 0.24 | (1.62) | 0.10 | (1.13) |
| CMA | **0.24**** | (3.12) | **0.12*** | (2.41) | **0.22**** | (3.07) | **0.19*** | (2.45) |
| RMW | **0.24**** | (2.80) | **0.16*** | (2.53) | **0.26*** | (2.58) | 0.10 | (0.83) |
| QMJ | **0.32**** | (3.72) | **0.17**** | (3.98) | **0.35**** | (3.60) | 0.09 | (1.23) |
| UMD | **0.59**** | (3.24) | 0.05 | (0.60) | **0.62**** | (3.17) | 0.00 | (-0.01) |
| VOL | **0.43**** | (2.86) | **0.16**** | (2.62) | **0.39*** | (2.43) | **0.23*** | (2.08) |

| | Conditional on prior 6-month return | | | | Conditional on prior 12-month return | | | |
|---|---|---|---|---|---|---|---|---|
| | Intercept | | Slope | | Intercept | | Slope | |
| Factor | $\hat{\alpha}$ | t($\hat{\alpha}$) | $\hat{\beta}$ | t($\hat{\beta}$) | $\hat{\alpha}$ | t($\hat{\alpha}$) | $\hat{\beta}$ | t($\hat{\beta}$) |
| SMB | 0.21 | (1.75) | 0.11 | (1.05) | 0.18 | (1.46) | 0.25 | (1.69) |
| HML | 0.20 | (1.63) | **0.22*** | (2.30) | 0.19 | (1.34) | 0.25 | (1.73) |
| $HML_D$ | 0.22 | (1.49) | 0.17 | (1.78) | 0.20 | (1.23) | **0.24*** | (2.02) |
| CMA | **0.22**** | (3.00) | **0.19*** | (2.02) | **0.20*** | (2.52) | **0.25*** | (2.19) |
| RMW | **0.24*** | (2.55) | 0.14 | (1.03) | 0.22 | (1.95) | 0.23 | (1.19) |
| QMJ | **0.31**** | (3.5) | 0.18 | (1.88) | **0.29**** | (3.10) | 0.26 | (1.68) |
| UMD | **0.57**** | (3.03) | 0.08 | (0.64) | **0.63**** | (3.28) | -0.01 | (-0.06) |
| VOL | **0.37*** | (2.28) | **0.27*** | (2.09) | 0.34 | (1.69) | 0.33 | (1.68) |

Appendix 2: Six-factor model regression coefficients of less frequently rebalanced strategies

This table reports the coefficients and adjusted $R^2$ values from regressing three, six, and 12-month holding period time series factor momentum strategies against the six-factor model of Fama and French (2018). The coefficients are calculated using returns from January 1967 to December 2021 to make a valid comparison between the coefficients as the $q^5$-factor data starts from January 1967. The alpha coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Six-factor coefficients (quarterly rebalanced) | | | | | | | | |
| α | **0.53*** | 0.11 | 0.23 | 0.17 | -0.04 | **-0.28**** | -0.13 | -0.13 |
| | (2.17) | (0.50) | (1.47) | (1.11) | (-0.30) | (-2.65) | (-1.37) | (-1.44) |
| MKT-rf | -0.04 | -0.02 | 0.01 | 0.01 | 0.00 | 0.01 | 0.02 | 0.03 |
| | (-0.69) | (-0.43) | (0.21) | (0.29) | (-0.09) | (0.39) | (0.94) | (1.09) |
| SMB | 0.11 | 0.01 | -0.01 | 0.04 | **0.18**** | **0.14*** | **0.15**** | **0.15**** |
| | (0.91) | (0.08) | (-0.13) | (0.5) | (2.93) | (2.31) | (2.81) | (3.74) |
| HML | 0.16 | 0.06 | 0.02 | -0.03 | **0.25**** | **0.21**** | **0.18**** | **0.16**** |
| | (1.05) | (0.38) | (0.21) | (-0.27) | (3.18) | (2.68) | (3.16) | (2.92) |
| CMA | -0.07 | -0.24 | -0.37 | **-0.44**** | 0.13 | 0.08 | 0.01 | -0.07 |
| | (-0.34) | (-1.05) | (-1.77) | (-2.85) | (1.14) | (0.70) | (0.09) | (-0.79) |
| RMW | -0.20 | -0.25 | -0.01 | -0.09 | 0.10 | 0.06 | **0.16*** | 0.09 |
| | (-1.06) | (-1.66) | (-0.07) | (-0.67) | (1.02) | (0.72) | (2.23) | (1.52) |
| UMD | 0.23 | **0.41**** | **0.54**** | **0.74**** | **0.23*** | **0.36**** | **0.36**** | **0.45**** |
| | (1.31) | (3.49) | (6.59) | (10.19) | (2.47) | (7.28) | (7.47) | (9.48) |
| Adj. R^2 | 0.04 | 0.16 | 0.30 | 0.51 | 0.22 | 0.36 | 0.42 | 0.56 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel B: Six-factor coefficients (semi-annually rebalanced) | | | | | | | | |
| α | 0.41 | 0.18 | -0.03 | 0.05 | -0.07 | -0.14 | **-0.27*** | **-0.21*** |
| | (1.67) | (0.82) | (-0.19) | (0.34) | (-0.58) | (-1.36) | (-2.51) | (-2.29) |
| MKT-rf | -0.01 | -0.05 | 0.02 | -0.01 | 0.01 | 0.01 | 0.02 | 0.02 |
| | (-0.11) | (-0.71) | (0.54) | (-0.24) | (0.40) | (0.33) | (0.64) | (0.54) |
| SMB | 0.15 | 0.03 | 0.02 | -0.01 | **0.22**** | **0.17*** | **0.13**** | **0.16**** |
| | (1.24) | (0.22) | (0.19) | (-0.09) | (3.43) | (2.51) | (2.83) | (3.49) |
| HML | 0.09 | -0.04 | 0.03 | -0.06 | **0.22**** | **0.15*** | **0.17**** | **0.14*** |
| | (0.62) | (-0.23) | (0.25) | (-0.58) | (3.05) | (1.97) | (2.93) | (2.32) |
| CMA | -0.36 | -0.14 | **-0.36*** | **-0.50**** | -0.02 | 0.10 | 0.02 | -0.04 |
| | (-1.69) | (-0.66) | (-2.28) | (-3.55) | (-0.15) | (0.84) | (0.20) | (-0.51) |
| RMW | **-0.38*** | -0.18 | -0.07 | -0.10 | -0.03 | 0.12 | **0.16*** | 0.13 |
| | (-2.37) | (-0.92) | (-0.51) | (-0.66) | (-0.34) | (1.27) | (2.12) | (1.91) |
| UMD | 0.39 | **0.41**** | **0.54**** | **0.73**** | **0.34**** | **0.32**** | **0.34**** | **0.43**** |
| | (1.96) | (3.40) | (6.13) | (10.29) | (3.57) | (6.19) | (7.31) | (10.14) |
| Adj. R^2 | 0.16 | 0.16 | 0.31 | 0.49 | 0.32 | 0.31 | 0.39 | 0.54 |

Appendix 2 (continued):

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel C: Six-factor coefficients (annually rebalanced) | | | | | | | | |
| α | 0.27 | 0.20 | 0.03 | -0.10 | -0.12 | -0.14 | **-0.34**** | **-0.34**** |
| | (1.78) | (0.96) | (0.21) | (-0.58) | (-1.36) | (-1.61) | (-3.35) | (-3.66) |
| MKT-rf | -0.06 | -0.10 | 0.03 | 0.03 | -0.02 | -0.01 | 0.03 | 0.04 |
| | (-1.12) | (-1.71) | (0.65) | (0.55) | (-0.96) | (-0.49) | (1.32) | (1.23) |
| SMB | -0.04 | -0.16 | -0.15 | **-0.21*** | **0.13**** | **0.11*** | -0.01 | 0.03 |
| | (-0.46) | (-1.64) | (-1.47) | (-2.29) | (3.18) | (2.15) | (-0.17) | (0.57) |
| HML | -0.08 | -0.01 | 0.15 | -0.12 | **0.14**** | **0.18**** | **0.30**** | **0.17*** |
| | (-0.72) | (-0.04) | (1.10) | (-1.01) | (2.86) | (2.96) | (3.84) | (2.49) |
| CMA | **-0.32**** | 0.21 | -0.21 | **-0.32**** | 0.00 | **0.19**** | 0.26 | 0.13 |
| | (-2.81) | (1.34) | (-1.43) | (-2.88) | (-0.05) | (2.76) | (1.90) | (1.92) |
| RMW | **-0.32**** | -0.17 | -0.17 | 0.03 | 0.02 | 0.14 | 0.13 | **0.21**** |
| | (-2.74) | (-1.03) | (-1.03) | (0.18) | (0.27) | (1.83) | (1.57) | (2.79) |
| UMD | **0.63**** | 0.22 | **0.37**** | **0.52**** | **0.44**** | **0.28**** | **0.25**** | **0.38**** |
| | (10.38) | (1.78) | (4.61) | (7.31) | (12.05) | (6.44) | (3.95) | (7.86) |
| Adj. R^2 | 0.48 | 0.13 | 0.18 | 0.34 | 0.56 | 0.36 | 0.35 | 0.48 |

Appendix 3: The $q^5$-factor model regression coefficients of less frequently rebalanced strategies

This table reports the coefficients and adjusted $R^2$ values from regressing three, six, and 12-month holding period time series factor momentum strategies against the $q^5$-factor model of Hou et al. (2021). The coefficients are calculated using returns from January 1967 to December 2021 to make a valid comparison between the coefficients as the $q^5$-factor data starts from January 1967. The alpha coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: $q^5$-factor model coefficients (quarterly rebalanced) | | | | | | | | |
| α | **0.41*** | 0.09 | 0.19 | 0.20 | -0.10 | **-0.27*** | -0.13 | -0.13 |
| | (2.00) | (0.42) | (0.92) | (0.96) | (-0.75) | (-2.28) | (-1.12) | (-1.04) |
| MKT-rf | -0.03 | -0.05 | -0.03 | -0.05 | -0.02 | -0.03 | -0.02 | -0.02 |
| | (-0.38) | (-0.75) | (-0.47) | (-0.59) | (-0.35) | (-0.74) | (-0.55) | (-0.43) |
| Size | 0.19 | 0.15 | 0.18 | 0.24 | **0.24**** | **0.23*** | **0.25*** | **0.27**** |
| | (1.14) | (0.70) | (0.84) | (1.13) | (2.67) | (2.16) | (2.43) | (2.63) |
| I/A | -0.07 | -0.32 | -0.18 | -0.31 | **0.32**** | 0.18 | **0.22*** | 0.14 |
| | (-0.35) | (-1.63) | (-0.84) | (-1.33) | (2.76) | (1.57) | (2.07) | (1.17) |
| ROE | 0.05 | 0.13 | 0.07 | 0.20 | 0.13 | **0.23*** | **0.16*** | 0.18 |
| | (0.22) | (0.77) | (0.43) | (1.00) | (1.10) | (2.48) | (1.98) | (1.70) |
| EG | 0.24 | 0.20 | 0.33 | 0.29 | 0.17 | 0.14 | 0.17 | **0.19*** |
| | (1.15) | (1.18) | (1.86) | (1.54) | (1.45) | (1.4) | (1.94) | (1.97) |
| Adj. R^2 | 0.01 | 0.03 | 0.03 | 0.05 | 0.12 | 0.12 | 0.14 | 0.13 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel B: $q^5$-factor model coefficients (semi-annually rebalanced) | | | | | | | | |
| α | 0.38 | 0.31 | 0.00 | 0.14 | -0.06 | -0.05 | -0.24 | -0.18 |
| | (1.79) | (1.27) | (0.01) | (0.63) | (-0.4) | (-0.36) | (-1.96) | (-1.51) |
| MKT-rf | -0.01 | -0.10 | -0.02 | -0.08 | -0.01 | -0.04 | -0.03 | -0.03 |
| | (-0.12) | (-1.27) | (-0.36) | (-0.84) | (-0.25) | (-0.93) | (-0.75) | (-0.66) |
| Size | 0.25 | 0.12 | 0.17 | 0.17 | **0.27**** | **0.22*** | **0.22*** | **0.26*** |
| | (1.30) | (0.55) | (0.88) | (0.80) | (2.68) | (1.97) | (2.34) | (2.50) |
| I/A | -0.27 | **-0.35*** | -0.18 | -0.33 | 0.18 | 0.18 | **0.23**** | 0.17 |
| | (-1.27) | (-1.99) | (-1.03) | (-1.56) | (1.49) | (1.62) | (2.60) | (1.67) |
| ROE | -0.07 | 0.22 | 0.09 | 0.19 | 0.08 | **0.19*** | **0.19*** | **0.20*** |
| | (-0.27) | (1.28) | (0.61) | (0.83) | (0.71) | (2.00) | (2.57) | (2.04) |
| EG | 0.21 | 0.03 | 0.22 | 0.21 | 0.15 | 0.06 | 0.11 | 0.15 |
| | (1.01) | (0.19) | (1.55) | (1.16) | (1.26) | (0.59) | (1.41) | (1.76) |
| Adj. R^2 | 0.03 | 0.03 | 0.02 | 0.04 | 0.09 | 0.09 | 0.13 | 0.13 |

Appendix 3 (continued):

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel C: $q^5$-factor model coefficients (annually rebalanced) | | | | | | | | |
| α | 0.38 | 0.23 | 0.00 | -0.16 | -0.04 | -0.09 | **-0.34**** | **-0.35**** |
| | (1.71) | (0.95) | (0.01) | (-0.77) | (-0.28) | (-0.68) | (-2.75) | (-2.79) |
| MKT-rf | -0.11 | -0.11 | 0.01 | 0.01 | -0.07 | -0.05 | 0.01 | 0.00 |
| | (-1.49) | (-1.81) | (0.22) | (0.10) | (-1.72) | (-1.44) | (0.30) | (0.05) |
| Size | 0.10 | -0.16 | -0.06 | -0.04 | **0.20*** | **0.14*** | 0.02 | **0.11*** |
| | (0.53) | (-1.69) | (-0.58) | (-0.32) | (2.28) | (1.97) | (0.21) | (2.15) |
| I/A | **-0.46*** | -0.21 | -0.13 | -0.19 | 0.10 | **0.25**** | **0.39**** | **0.30**** |
| | (-2.21) | (-1.37) | (-1.12) | (-1.23) | (0.91) | (2.99) | (3.72) | (3.62) |
| ROE | 0.34 | **0.31*** | 0.06 | 0.23 | **0.25*** | **0.20*** | **0.25*** | **0.30**** |
| | (1.80) | (2.00) | (0.37) | (1.22) | (2.24) | (2.03) | (2.48) | (2.64) |
| EG | 0.05 | 0.05 | 0.24 | 0.24 | 0.07 | 0.09 | 0.11 | 0.15 |
| | (0.26) | (0.33) | (1.72) | (1.41) | (0.7) | (1.03) | (1.15) | (1.64) |
| Adj. R^2 | 0.08 | 0.10 | 0.02 | 0.05 | 0.12 | 0.14 | 0.18 | 0.19 |

Appendix 4: Post-cost Sharpe ratios and SKASRs of less frequently rebalanced strategies

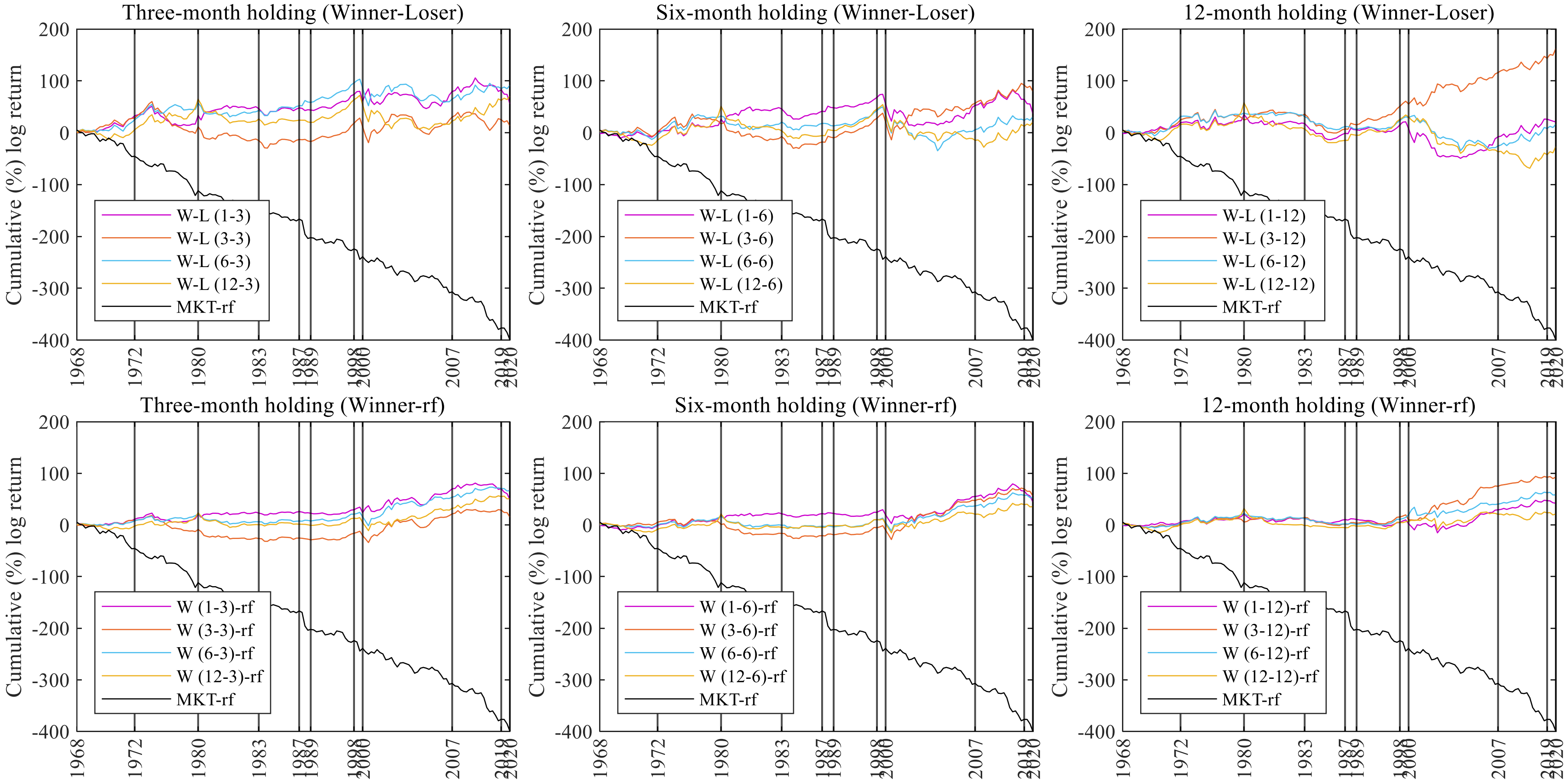
This table reports the annualized Sharpe ratio and the skewness and kurtosis adjusted Sharpe ratio (SKASR) of Pätäri (2011) after trading costs of three, six, and 12-month holding period combinations over the July 1964 to December 2021 period. The significance of the ratios is benchmarked against the MKT-rf factor, which has an annualized Sharpe ratio and SKASR of around 0.38 over the same period. The annualized Sharpe is calculated with Equation 3, the SKASR with Equation 7, where the higher distributional moments are defined in Equations 5 and 6.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Sharpe ratio (quarterly rebalanced) | | | | | | | | |
| 0 bps | 0.39 | 0.10 | 0.32 | 0.29 | 0.27 | 0.04 | 0.27 | 0.28 |
| 5 bps | 0.36 | 0.07 | 0.29 | 0.28 | 0.24 | 0.01 | 0.25 | 0.27 |
| 10 bps | 0.32 | 0.03 | 0.27 | 0.26 | 0.22 | -0.02 | 0.23 | 0.25 |
| 15 bps | 0.29 | 0.00 | 0.24 | 0.24 | 0.19 | -0.04 | 0.21 | 0.24 |
| 20 bps | 0.25 | -0.03 | 0.22 | 0.23 | 0.16 | -0.07 | 0.19 | 0.23 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel B: Skewness and kurtosis adjusted Sharpe ratio (quarterly rebalanced) | | | | | | | | |
| 0 bps | 0.43 | 0.15 | 0.35 | 0.31 | 0.27 | 0.07 | 0.28 | 0.28 |
| 5 bps | 0.40 | 0.12 | 0.32 | 0.30 | 0.25 | 0.04 | 0.26 | 0.27 |
| 10 bps | 0.37 | 0.10 | 0.30 | 0.28 | 0.23 | 0.02 | 0.24 | 0.26 |
| 15 bps | 0.34 | 0.07 | 0.28 | 0.27 | 0.20 | 0.00 | 0.22 | 0.25 |
| 20 bps | 0.31 | 0.04 | 0.26 | 0.26 | 0.18 | -0.02 | 0.21 | 0.24 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel C: Sharpe ratio (semi-annually rebalanced) | | | | | | | | |
| 0 bps | 0.26 | 0.14 | 0.11 | 0.14 | 0.23 | 0.19 | 0.06 | 0.17 |
| 5 bps | 0.24 | 0.13 | 0.09 | 0.13 | 0.21 | 0.18 | 0.05 | 0.16 |
| 10 bps | 0.22 | 0.11 | 0.08 | 0.12 | 0.20 | 0.16 | 0.03 | 0.15 |
| 15 bps | 0.21 | 0.09 | 0.06 | 0.11 | 0.19 | 0.15 | 0.02 | 0.14 |
| 20 bps | 0.19 | 0.08 | 0.04 | 0.10 | 0.18 | 0.14 | 0.01 | 0.13 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel D: Skewness and kurtosis adjusted Sharpe ratio (semi-annually rebalanced) | | | | | | | | |
| 0 bps | 0.33 | 0.18 | 0.16 | 0.15 | 0.23 | 0.19 | 0.06 | 0.17 |
| 5 bps | 0.32 | 0.17 | 0.14 | 0.15 | 0.21 | 0.18 | 0.05 | 0.16 |
| 10 bps | 0.30 | 0.15 | 0.13 | 0.14 | 0.20 | 0.16 | 0.03 | 0.15 |
| 15 bps | 0.28 | 0.14 | 0.11 | 0.13 | 0.19 | 0.15 | 0.02 | 0.14 |
| 20 bps | 0.27 | 0.13 | 0.10 | 0.12 | 0.18 | 0.14 | 0.01 | 0.13 |

Appendix 4 (continued):

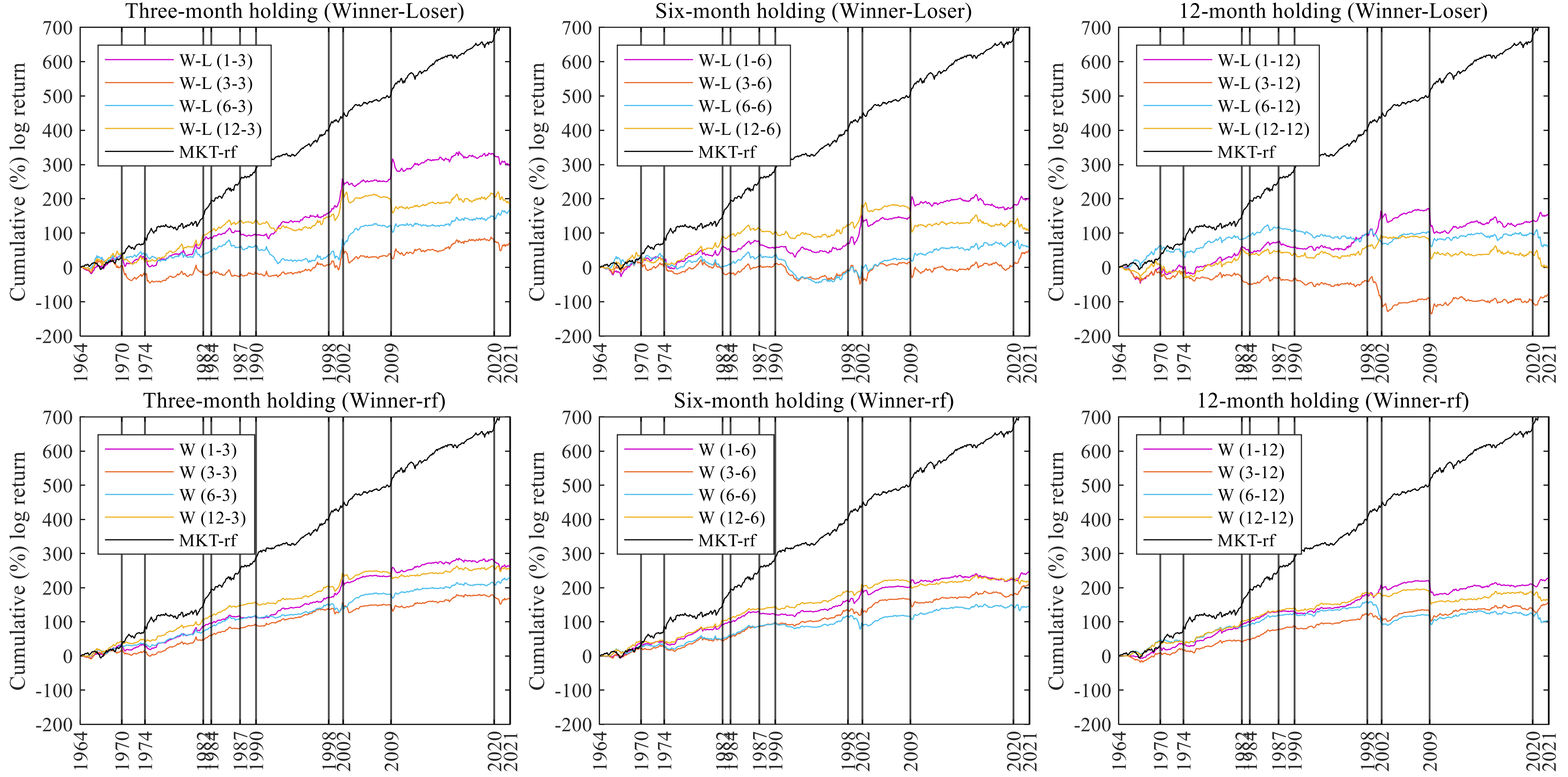
| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel E: Sharpe ratio (annually rebalanced) | | | | | | | | |
| 0 bps | 0.20 | 0.11 | 0.11 | -0.03 | 0.20 | 0.17 | -0.01 | 0.03 |
| 5 bps | 0.19 | 0.10 | 0.10 | -0.04 | 0.19 | 0.17 | -0.02 | 0.03 |
| 10 bps | 0.18 | 0.09 | 0.09 | -0.05 | 0.19 | 0.16 | -0.03 | 0.02 |
| 15 bps | 0.18 | 0.08 | 0.08 | -0.06 | 0.18 | 0.15 | -0.03 | 0.01 |
| 20 bps | 0.17 | 0.07 | 0.07 | -0.07 | 0.17 | 0.14 | -0.04 | 0.01 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel F: Skewness and kurtosis adjusted Sharpe ratio (annually rebalanced) | | | | | | | | |
| 0 bps | 0.20 | 0.13 | 0.13 | 0.03 | 0.17 | 0.17 | 0.02 | 0.05 |
| 5 bps | 0.20 | 0.13 | 0.13 | 0.02 | 0.16 | 0.16 | 0.02 | 0.04 |
| 10 bps | 0.19 | 0.12 | 0.12 | 0.01 | 0.16 | 0.15 | 0.01 | 0.04 |
| 15 bps | 0.18 | 0.11 | 0.11 | 0.01 | 0.15 | 0.15 | 0.01 | 0.03 |
| 20 bps | 0.18 | 0.10 | 0.10 | 0.00 | 0.15 | 0.14 | 0.00 | 0.03 |

Appendix 5: Log (%) return accumulation of the excess market return and excess return of less frequently rebalanced strategies during bullish and bearish states




This figure shows the log (%) return accumulation of MKT-rf the quarterly, semi-annually, and annually rebalanced Winner-Loser and Winner strategies during bearish states. The black vertical lines mark the temporal breaks in the time series with November 1968 marking the start and March 2020 the end of the first and last bearish period, respectively.

Appendix 5 (continued):




This figure shows the log (%) return accumulation of the MKT-rf and quarterly, semi-annually, and annually rebalanced Winner-Loser and Winner strategies during bullish states. The black vertical lines mark the temporal breaks in the time series with July 1964 and December 2021 marking the start and end of the first and last bullish period, respectively.

Appendix 6: Maximum (%) drawdown of the market factor and less frequently rebalanced strategies over bearish states

This table reports the maximum (%) drawdown of the MKT-rf factor and the less frequently rebalanced factor momentum strategies over bearish states. The returns are in the form of geometric excess returns (i.e., returns over the cost of financing the investment). The values are sorted on the worst drawdowns of the MKT-rf factor in ascending order. The bear market threshold is a loss of -20% in cumulative (%) log return from the previous peak to the subsequent trough of the market factor.

| Bear state | | MKT-rf | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Peak | Trough | | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Maximum drawdown (quarterly rebalanced) | | | | | | | | | | |
| Dec-72 | Sep-74 | -53.0 | -14.6 | -25.5 | 22.2 | 52.9 | 1.2 | -18.8 | 10.4 | 18.1 |
| Oct-07 | Feb-09 | -51.5 | 0.1 | -3.0 | 26.3 | 53.3 | -1.1 | 8.6 | 19.8 | 27.4 |
| Mar-00 | Sep-02 | -50.1 | 12.4 | 13.8 | -23.4 | -31.4 | 51.1 | 47.7 | 42.6 | 27.1 |
| Nov-68 | Jun-70 | -40.2 | 30.4 | 32.1 | 20.1 | -1.3 | 8.6 | 10.1 | 4.9 | -5.6 |
| Nov-80 | Jul-82 | -33.3 | 18.7 | -20.7 | -15.2 | -34.5 | 4.0 | -15.2 | -13.7 | -20.3 |
| Aug-87 | Nov-87 | -31.0 | -3.4 | -2.7 | 7.4 | -3.4 | -2.2 | -2.1 | 1.3 | -1.1 |
| Aug-89 | Oct-90 | -22.0 | 31.6 | 35.2 | 39.8 | 47.3 | 6.3 | 11.8 | 14.2 | 14.0 |
| Dec-19 | Mar-20 | -20.5 | -23.9 | -11.1 | 6.4 | 8.5 | -18.9 | -12.7 | -4.0 | -4.0 |
| Jun-83 | Jul-84 | -18.8 | -0.9 | 0.5 | 7.8 | -3.1 | 1.9 | 0.7 | 1.2 | 1.4 |
| Jun-98 | Aug-98 | -18.1 | 6.3 | 10.5 | 7.5 | 9.0 | 5.2 | 4.1 | 3.5 | 1.2 |
| Bear state | | MKT-rf | Winner-Loser | | | | Winner-rf | | | |
| Peak | Trough | | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel A: Maximum drawdown (semi-annually rebalanced) | | | | | | | | | | |
| Dec-72 | Sep-74 | -53.0 | 13.8 | 22.7 | 39.7 | 60.8 | 14.7 | 1.2 | 14.7 | 20.1 |
| Oct-07 | Feb-09 | -51.5 | 12.5 | 46.6 | 22.6 | 35.5 | 11.9 | 27.3 | 24.4 | 22.4 |
| Mar-00 | Sep-02 | -50.1 | -6.2 | 39.7 | -26.4 | -37.7 | 42.4 | 78.4 | 36.9 | 22.8 |
| Nov-68 | Jun-70 | -40.2 | -2.9 | -7.2 | -9.9 | -20.4 | -3.0 | 0.4 | -2.7 | -11.9 |
| Nov-80 | Jul-82 | -33.3 | 25.5 | -24.7 | -14.6 | -35.8 | 5.9 | -15.7 | -14.9 | -22.1 |
| Aug-87 | Nov-87 | -31.0 | 7.4 | 9.7 | -4.2 | 11.1 | 1.3 | 3.2 | 0.0 | 4.2 |
| Aug-89 | Oct-90 | -22.0 | 17.4 | 40.7 | 29.3 | 45.4 | 2.4 | 15.3 | 14.6 | 12.7 |
| Dec-19 | Mar-20 | -20.5 | -23.9 | -11.1 | 6.4 | 8.5 | -18.9 | -12.7 | -4.0 | -4.0 |
| Jun-83 | Jul-84 | -18.8 | -6.5 | -11.4 | -4.1 | -9.5 | -0.7 | -4.6 | -2.5 | 0.4 |
| Jun-98 | Aug-98 | -18.1 | 6.3 | 10.5 | 7.5 | 9.0 | 5.2 | 4.1 | 3.5 | 1.2 |
| Bear state | | MKT-rf | Winner-Loser | | | | Winner-rf | | | |
| Peak | Trough | | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel A: Maximum drawdown (annually rebalanced) | | | | | | | | | | |
| Dec-72 | Sep-74 | -53.0 | 3.8 | 4.9 | 4.0 | 26.7 | 11.2 | 8.3 | 17.1 | 22.1 |
| Oct-07 | Feb-09 | -51.5 | 40.7 | 36.7 | 42.7 | -2.4 | 20.3 | 20.9 | 26.1 | 4.5 |
| Mar-00 | Sep-02 | -50.1 | -17.7 | 78.7 | -44.0 | -47.0 | 30.0 | 92.8 | 22.4 | 16.6 |
| Nov-68 | Jun-70 | -40.2 | 16.7 | 16.9 | 28.1 | 7.9 | 3.8 | -1.7 | 1.0 | -3.7 |
| Nov-80 | Jul-82 | -33.3 | -14.9 | 9.1 | -3.2 | -38.0 | -7.9 | 8.3 | -8.2 | -26.7 |
| Aug-87 | Nov-87 | -31.0 | 7.4 | 9.7 | -4.2 | 11.1 | 1.3 | 3.2 | 0.0 | 4.2 |
| Aug-89 | Oct-90 | -22.0 | 4.1 | 36.3 | 13.1 | 30.6 | -6.1 | 12.3 | 10.6 | 7.7 |
| Dec-19 | Mar-20 | -20.5 | -5.1 | 20.3 | 8.4 | 16.8 | -4.9 | 0.3 | -4.0 | -2.1 |
| Jun-83 | Jul-84 | -18.8 | -19.1 | -26.1 | -18.9 | -20.4 | -3.1 | -12.3 | -9.7 | -3.6 |
| Jun-98 | Aug-98 | -18.1 | 6.3 | 10.5 | 7.5 | 9.0 | 5.2 | 4.1 | 3.5 | 1.2 |

## Appendix 7: Linear effects of less frequently rebalanced strategies with a 20% threshold

This table reports the contemporaneous relative changes in excess factor momentum strategy returns over and above excess market return following ex post bullish and bearish market states as described in Equation 11. The third and fourth coefficients measure the positive and negative linear effects, the fifth coefficient reports the difference (linear asymmetry) in the coefficients followed by the p-value of the Wald test in square brackets, and the last row reports the adjusted $R^2$ value of each regression. The first and second coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels. The sample starts from July 1964 and ends in December 2021.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Linear effects (quarterly rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.66** ** | 0.29 | **0.36*** | **0.46*** | **0.27*** | 0.12 | 0.16 | **0.23*** |
| | (3.46) | (1.57) | (2.00) | (2.37) | (2.43) | (1.03) | (1.42) | (2.00) |
| $\hat{\beta}_0^-$ | 0.31 | 0.29 | 0.50 | 0.51 | 0.10 | -0.05 | 0.20 | 0.22 |
| | (0.55) | (0.52) | (1.13) | (1.14) | (0.34) | (-0.19) | (0.78) | (0.85) |
| $\hat{\beta}_1^+$ | **-1.02** ** | **-1.05** ** | **-0.98** ** | **-1.02** ** | **-1.04** ** | **-1.06** ** | **-1.01** ** | **-1.03** ** |
| | (-11.26) | (-14.07) | (-16.55) | (-13.31) | (-20.13) | (-21.75) | (-25.8) | (-23.09) |
| $\hat{\beta}_1^-$ | **-1.09** ** | **-0.98** ** | **-1.11** ** | **-1.05** ** | **-1.12** ** | **-1.08** ** | **-1.12** ** | **-1.07** ** |
| | (-8.55) | (-10.73) | (-9.87) | (-7.55) | (-12.82) | (-17.15) | (-18.94) | (-15.51) |
| Linear | 0.07 | -0.07 | 0.13 | 0.04 | 0.07 | 0.03 | **0.11*** | 0.04 |
| | [0.45] | [0.43] | [0.12] | [0.69] | [0.15] | [0.6] | [0.02] | [0.44] |
| Adj. $R^2$ | 0.51 | 0.52 | 0.55 | 0.50 | 0.76 | 0.77 | 0.79 | 0.78 |

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel B: Linear effects (semi-annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | 0.31 | 0.19 | 0.20 | **0.37*** | 0.15 | 0.12 | 0.03 | 0.18 |
| | (1.70) | (1.11) | (1.15) | (2.05) | (1.36) | (1.04) | (0.27) | (1.62) |
| $\hat{\beta}_0^-$ | 0.33 | 0.42 | 0.35 | 0.14 | 0.17 | 0.11 | 0.16 | 0.07 |
| | (0.74) | (0.86) | (0.73) | (0.29) | (0.58) | (0.32) | (0.62) | (0.25) |
| $\hat{\beta}_1^+$ | **-0.91** ** | **-1.01** ** | **-1.01** ** | **-1.06** ** | **-0.99** ** | **-1.01** ** | **-1.03** ** | **-1.04** ** |
| | (-10.61) | (-13.77) | (-17.02) | (-12.99) | (-20.93) | (-23.41) | (-24.78) | (-23.85) |
| $\hat{\beta}_1^-$ | **-1.03** ** | **-1.12** ** | **-1.00** ** | **-1.07** ** | **-1.07** ** | **-1.13** ** | **-1.10** ** | **-1.09** ** |
| | (-7.81) | (-9.37) | (-8.25) | (-6.66) | (-14.49) | (-15.7) | (-18.37) | (-13.69) |
| Linear | 0.13 | 0.11 | -0.01 | 0.01 | 0.08 | **0.12*** | 0.06 | 0.05 |
| | [0.15] | [0.23] | [0.86] | [0.89] | [0.10] | [0.01] | [0.18] | [0.33] |
| Adj. $R^2$ | 0.46 | 0.52 | 0.54 | 0.51 | 0.75 | 0.77 | 0.79 | 0.78 |

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel C: Linear effects (annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.41*** | 0.02 | 0.18 | 0.12 | **0.22*** | 0.07 | -0.02 | 0.12 |
| | (2.45) | (0.12) | (1.25) | (0.77) | (2.12) | (0.64) | (-0.15) | (1.23) |
| $\hat{\beta}_0^-$ | -0.12 | 0.59 | -0.04 | -0.30 | -0.05 | 0.20 | 0.03 | -0.13 |
| | (-0.28) | (1.24) | (-0.10) | (-0.59) | (-0.16) | (0.64) | (0.12) | (-0.44) |
| $\hat{\beta}_1^+$ | **-1.05** ** | **-1.07** ** | **-1.00** ** | **-1.03** ** | **-1.06** ** | **-1.05** ** | **-1.05** ** | **-1.07** ** |
| | (-13.01) | (-14.45) | (-14.92) | (-14.01) | (-21.58) | (-24.46) | (-24.00) | (-22.14) |
| $\hat{\beta}_1^-$ | **-1.16** ** | **-1.25** ** | **-1.10** ** | **-1.11** ** | **-1.15** ** | **-1.19** ** | **-1.16** ** | **-1.13** ** |
| | (-9.14) | (-10.62) | (-9.77) | (-7.43) | (-17.28) | (-18.51) | (-20.02) | (-14.46) |
| Linear | 0.12 | **0.18*** | 0.10 | 0.07 | 0.09 | **0.14** ** | **0.11*** | 0.06 |
| | [0.15] | [0.02] | [0.17] | [0.35] | [0.05] | [0.00] | [0.02] | [0.18] |
| Adj. $R^2$ | 0.57 | 0.64 | 0.61 | 0.57 | 0.81 | 0.83 | 0.80 | 0.80 |

Appendix 8: Linear effects of less frequently rebalanced strategies with a 15% threshold

This table reports the contemporaneous relative changes in excess factor momentum strategy returns over and above excess market return following ex post bullish and bearish market states as described in Equation 11. The third and fourth coefficients measure the positive and negative linear effects, the fifth coefficient reports the difference (linear asymmetry) in the coefficients followed by the p-value of the Wald test in square brackets, and the last row reports the adjusted $R^2$ value of each regression. The first and second coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels. The sample starts from July 1964 and ends in December 2021.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Linear effects (quarterly rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.63** | 0.25 | 0.36 | **0.46*** | **0.28*** | 0.12 | 0.18 | **0.28*** |
| | (3.10) | (1.31) | (1.93) | (2.26) | (2.58) | (1.06) | (1.63) | (2.40) |
| $\hat{\beta}_0^-$ | 0.63 | 0.59 | 0.67 | 0.76 | 0.27 | 0.19 | 0.34 | 0.34 |
| | (1.3) | (1.24) | (1.72) | (1.92) | (1.07) | (0.72) | (1.49) | (1.48) |
| $\hat{\beta}_1^+$ | **-1.03** | **-1.06** | **-1.01** | **-1.05** | **-1.06** | **-1.08** | **-1.04** | **-1.06** |
| | (-10.78) | (-13.71) | (-16.33) | (-12.97) | (-20.61) | (-22.98) | (-27.67) | (-23.96) |
| $\hat{\beta}_1^-$ | **-1.03** | **-0.94** | **-1.05** | **-0.99** | **-1.07** | **-1.03** | **-1.06** | **-1.02** |
| | (-8.86) | (-10.6) | (-9.64) | (-7.68) | (-12.99) | (-15.67) | (-16.97) | (-14.82) |
| Linear | 0.00 | -0.12 | 0.04 | -0.06 | 0.00 | -0.05 | 0.02 | -0.04 |
| | [1.00] | [0.14] | [0.61] | [0.52] | [0.93] | [0.33] | [0.62] | [0.36] |
| Adj. $R^2$ | 0.50 | 0.52 | 0.55 | 0.50 | 0.76 | 0.77 | 0.79 | 0.78 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel B: Linear effects (semi-annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | 0.28 | 0.18 | 0.20 | **0.41*** | 0.17 | 0.14 | 0.06 | **0.24*** |
| | (1.42) | (1.02) | (1.08) | (2.08) | (1.50) | (1.34) | (0.51) | (2.16) |
| $\hat{\beta}_0^-$ | 0.54 | 0.61 | 0.59 | 0.40 | 0.29 | 0.26 | 0.30 | 0.19 |
| | (1.42) | (1.43) | (1.38) | (0.93) | (1.12) | (0.87) | (1.28) | (0.76) |
| $\hat{\beta}_1^+$ | **-0.92** | **-1.03** | **-1.04** | **-1.10** | **-1.01** | **-1.04** | **-1.06** | **-1.08** |
| | (-10.01) | (-13.44) | (-16.71) | (-12.68) | (-21.19) | (-25.51) | (-25.84) | (-24.97) |
| $\hat{\beta}_1^-$ | **-0.98** | **-1.05** | **-0.94** | **-1.01** | **-1.03** | **-1.07** | **-1.04** | **-1.04** |
| | (-7.98) | (-9.09) | (-8.40) | (-6.8) | (-14.22) | (-14.24) | (-16.58) | (-13.22) |
| Linear | 0.06 | 0.02 | -0.10 | -0.09 | 0.02 | 0.04 | -0.02 | -0.04 |
| | [0.46] | [0.81] | [0.22] | [0.32] | [0.70] | [0.47] | [0.66] | [0.38] |
| Adj. $R^2$ | 0.46 | 0.52 | 0.54 | 0.51 | 0.75 | 0.77 | 0.79 | 0.78 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel C: Linear effects (annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.44*** | 0.07 | 0.18 | 0.17 | **0.24*** | 0.12 | 0.01 | 0.19 |
| | (2.56) | (0.44) | (1.18) | (1.03) | (2.36) | (1.30) | (0.08) | (1.90) |
| $\hat{\beta}_0^-$ | 0.04 | 0.44 | 0.12 | -0.20 | 0.08 | 0.11 | 0.06 | -0.09 |
| | (0.10) | (1.06) | (0.34) | (-0.48) | (0.32) | (0.43) | (0.3) | (-0.38) |
| $\hat{\beta}_1^+$ | **-1.06** | **-1.08** | **-1.01** | **-1.06** | **-1.08** | **-1.06** | **-1.07** | **-1.10** |
| | (-12.37) | (-13.79) | (-13.87) | (-13.24) | (-20.76) | (-24.05) | (-22.6) | (-20.95) |
| $\hat{\beta}_1^-$ | **-1.12** | **-1.21** | **-1.06** | **-1.07** | **-1.11** | **-1.16** | **-1.13** | **-1.10** |
| | (-9.62) | (-11.18) | (-10.44) | (-7.96) | (-17.85) | (-19.27) | (-20.74) | (-15.21) |
| Linear | 0.06 | 0.13 | 0.05 | 0.02 | 0.03 | **0.09*** | 0.06 | 0.00 |
| | [0.45] | [0.08] | [0.48] | [0.84] | [0.46] | [0.03] | [0.20] | [1.00] |
| Adj. $R^2$ | 0.56 | 0.64 | 0.61 | 0.57 | 0.80 | 0.83 | 0.79 | 0.80 |

# Appendix 9: Quadratic effects of less frequently rebalanced strategies with a 20% threshold

This table reports the contemporaneous relative changes in excess factor momentum strategy returns over and above excess market return following ex post bullish and bearish market states as described in Equation 12. The third and fourth coefficients measure the positive and negative linear effects, the fifth and sixth coefficients measure corresponding quadratic effects, the seventh coefficient reports the difference (linear asymmetry) of the third and fourth coefficients followed by the p-value of the Wald test in square brackets, the eight coefficient reports the difference (quadratic asymmetry) between the fifth and sixth coefficient followed by the p-value of the Wald test in square brackets, and the last row reports the adjusted $R^2$ value of each regression. The first and second coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels. The sample starts from July 1964 and ends in December 2021.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Linear and quadratic effects (quarterly rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.80**** | **0.80**** | **0.77**** | **0.90**** | **0.43**** | **0.46**** | **0.43**** | **0.53**** |
| | (3.06) | (3.72) | (3.78) | (4.07) | (3.06) | (3.76) | (3.79) | (4.16) |
| $\hat{\beta}_0^-$ | 0.55 | 0.38 | 0.20 | 0.21 | 0.29 | 0.11 | 0.22 | 0.17 |
| | (1.20) | (0.71) | (0.47) | (0.42) | (1.21) | (0.38) | (0.88) | (0.66) |
| $\hat{\beta}_1^+$ | **-0.99**** | **-0.93**** | **-0.88**** | **-0.91**** | **-1.00**** | **-0.98**** | **-0.94**** | **-0.96**** |
| | (-13.09) | (-16.49) | (-17.47) | (-13.92) | (-21.41) | (-23.84) | (-25.81) | (-23.42) |
| $\hat{\beta}_1^-$ | **-1.21**** | **-1.03**** | **-0.95**** | **-0.89**** | **-1.22**** | **-1.17**** | **-1.13**** | **-1.04**** |
| | (-6.15) | (-6.53) | (-5.76) | (-4.60) | (-10.04) | (-13.27) | (-12.53) | (-9.36) |
| $(\beta_1^+)^2$ | -0.01 | **-0.04**** | **-0.03**** | **-0.04**** | -0.01 | **-0.03**** | **-0.02**** | **-0.02**** |
| | (-0.78) | (-4.84) | (-5.03) | (-3.98) | (-1.60) | (-4.74) | (-4.72) | (-3.81) |
| $(\beta_1^-)^2$ | -0.02 | -0.01 | 0.02 | 0.02 | -0.01 | **-0.01*** | 0.00 | 0.00 |
| | (-1.29) | (-0.54) | (1.93) | (1.34) | (-1.77) | (-1.97) | (-0.24) | (0.44) |
| Linear | **0.23*** | 0.10 | 0.07 | -0.02 | **0.22**** | **0.20**** | **0.18**** | 0.08 |
| | [0.04] | [0.32] | [0.48] | [0.86] | [0.00] | [0.00] | [0.00] | [0.17] |
| Quadratic | 0.00 | **-0.03**** | **-0.05**** | **-0.06**** | 0.00 | **-0.02**** | **-0.02**** | **-0.03**** |
| | [0.67] | [0.00] | [0.00] | [0.00] | [1.00] | [0.01] | [0.00] | [0.00] |
| Adj. $R^2$ | 0.51 | 0.54 | 0.57 | 0.52 | 0.76 | 0.79 | 0.80 | 0.79 |

Appendix 9 (continued):

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel B: Linear and quadratic effects (semi-annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | 0.34 | **0.52*** | **0.66**** | **0.81**** | **0.27*** | **0.33**** | **0.35**** | **0.46**** |
| | (1.43) | (2.48) | (3.41) | (3.63) | (2.20) | (2.86) | (3.00) | (3.77) |
| $\hat{\beta}_0^-$ | 0.05 | 0.17 | 0.23 | -0.46 | 0.15 | 0.13 | 0.14 | -0.11 |
| | (0.12) | (0.36) | (0.47) | (-0.97) | (0.54) | (0.38) | (0.52) | (-0.41) |
| $\hat{\beta}_1^+$ | **-0.90**** | **-0.93**** | **-0.91**** | **-0.96**** | **-0.96**** | **-0.96**** | **-0.96**** | **-0.97**** |
| | (-12.19) | (-15.2) | (-16.77) | (-14.5) | (-19.23) | (-22.6) | (-26.14) | (-24.16) |
| $\hat{\beta}_1^-$ | **-0.88**** | **-0.98**** | **-0.94**** | **-0.75**** | **-1.06**** | **-1.14**** | **-1.08**** | **-0.99**** |
| | (-5.54) | (-6.84) | (-5.58) | (-3.68) | (-10.83) | (-12.96) | (-13.09) | (-8.03) |
| $(\beta_1^+)^2$ | 0.00 | **-0.03*** | **-0.04**** | **-0.03**** | -0.01 | **-0.02**** | **-0.03**** | **-0.02**** |
| | (-0.16) | (-2.39) | (-5.22) | (-3.23) | (-1.24) | (-2.58) | (-4.68) | (-3.55) |
| $(\beta_1^-)^2$ | 0.02 | 0.02 | 0.01 | **0.04**** | 0.00 | 0.00 | 0.00 | 0.01 |
| | (1.83) | (1.95) | (0.78) | (3.25) | (0.24) | (-0.23) | (0.34) | (1.47) |
| Linear | -0.02 | 0.05 | 0.03 | -0.21 | 0.10 | **0.18**** | **0.13*** | 0.02 |
| | [0.89] | [0.63] | [0.75] | [0.06] | [0.11] | [0.00] | [0.03] | [0.74] |
| Quadratic | -0.02 | **-0.04**** | **-0.04**** | **-0.08**** | -0.01 | **-0.02**** | **-0.03**** | **-0.04**** |
| | [0.06] | [0.00] | [0.00] | [0.00] | [0.09] | [0.01] | [0.00] | [0.00] |
| Adj. $R^2$ | 0.46 | 0.53 | 0.56 | 0.54 | 0.75 | 0.78 | 0.80 | 0.79 |

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel C: Linear and quadratic effects (annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.66**** | 0.34 | **0.46*** | **0.39*** | **0.43**** | **0.26*** | 0.21 | **0.35**** |
| | (3.25) | (1.85) | (2.42) | (2.05) | (4.18) | (2.36) | (1.59) | (3.06) |
| $\hat{\beta}_0^-$ | -0.46 | 0.37 | -0.15 | **-0.94*** | -0.07 | 0.25 | 0.07 | -0.29 |
| | (-1.12) | (0.84) | (-0.37) | (-1.99) | (-0.26) | (0.82) | (0.3) | (-1.03) |
| $\hat{\beta}_1^+$ | **-0.99**** | **-0.99**** | **-0.93**** | **-0.97**** | **-1.01**** | **-1.00**** | **-1.00**** | **-1.02**** |
| | (-14.99) | (-16.49) | (-15.97) | (-14.87) | (-23.54) | (-26.84) | (-26.2) | (-25.61) |
| $\hat{\beta}_1^-$ | **-0.98**** | **-1.13**** | **-1.04**** | **-0.76**** | **-1.14**** | **-1.21**** | **-1.18**** | **-1.05**** |
| | (-5.91) | (-6.69) | (-7.46) | (-4.16) | (-11.02) | (-14.2) | (-14.85) | (-8.06) |
| $(\beta_1^+)^2$ | -0.02 | **-0.03*** | **-0.02*** | **-0.02*** | **-0.02**** | **-0.02**** | **-0.02**** | **-0.02*** |
| | (-1.87) | (-2.50) | (-1.98) | (-2.07) | (-2.68) | (-2.60) | (-2.77) | (-2.54) |
| $(\beta_1^-)^2$ | **0.02*** | 0.02 | 0.01 | **0.04**** | 0.00 | 0.00 | 0.00 | 0.01 |
| | (2.38) | (1.69) | (0.79) | (3.51) | (0.27) | (-0.83) | (-0.55) | (1.22) |
| Linear | -0.01 | 0.14 | 0.10 | **-0.21*** | **0.13*** | **0.21**** | **0.19**** | 0.03 |
| | [0.94] | [0.13] | [0.24] | [0.03] | [0.03] | [0.00] | [0.00] | [0.57] |
| Quadratic | **-0.04**** | **-0.04**** | **-0.03**** | **-0.07**** | **-0.02**** | **-0.01*** | **-0.02**** | **-0.03**** |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.03] | [0.01] | [0.00] |
| Adj. $R^2$ | 0.58 | 0.65 | 0.61 | 0.59 | 0.81 | 0.83 | 0.80 | 0.81 |

Appendix 10: Quadratic effects of less frequently rebalanced strategies with a 15% threshold

This table reports the contemporaneous relative changes in excess factor momentum strategy returns over and above excess market return following ex post bullish and bearish market states as described in Equation 12. The third and fourth coefficients measure the positive and negative linear effects, the fifth and sixth coefficients measure corresponding quadratic effects, the seventh coefficient reports the difference (linear asymmetry) of the third and fourth coefficients followed by the p-value of the Wald test in square brackets, the eight coefficient reports the difference (quadratic asymmetry) between the fifth and sixth coefficient followed by the p-value of the Wald test in square brackets, and the last row reports the adjusted $R^2$ value of each regression. The first and second coefficients are in % per month. The t-statistics expressed in parenthesis use Newey-West (1987) standard errors. The bolded values with asterisk **, (*) mark the significances at 1%, (5%) risk levels. The sample starts from July 1964 and ends in December 2021.

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-3 | 3-3 | 6-3 | 12-3 | 1-3 | 3-3 | 6-3 | 12-3 |
| Panel A: Linear and quadratic effects (quarterly rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.69*** | **0.68**** | **0.69**** | **0.81**** | **0.37*** | **0.38**** | **0.37**** | **0.49**** |
| | (2.54) | (3.20) | (3.39) | (3.62) | (2.53) | (3.16) | (3.30) | (3.79) |
| $\hat{\beta}_0^-$ | **0.86*** | 0.70 | 0.43 | 0.51 | **0.45*** | 0.34 | 0.36 | 0.30 |
| | (2.18) | (1.49) | (1.09) | (1.18) | (2.11) | (1.32) | (1.60) | (1.32) |
| $\hat{\beta}_1^+$ | **-1.01**** | **-0.89**** | **-0.87**** | **-0.91**** | **-1.03**** | **-0.97**** | **-0.96**** | **-0.98**** |
| | (-14.16) | (-15.78) | (-15.83) | (-12.51) | (-26.56) | (-25.89) | (-25.51) | (-22.88) |
| $\hat{\beta}_1^-$ | **-1.17**** | **-1.00**** | **-0.91**** | **-0.85**** | **-1.17**** | **-1.12**** | **-1.07**** | **-1.00**** |
| | (-6.68) | (-7.09) | (-6.20) | (-5.05) | (-10.73) | (-13.51) | (-12.94) | (-10.12) |
| $(\beta_1^+)^2$ | -0.01 | **-0.04**** | **-0.03**** | **-0.04**** | -0.01 | **-0.03**** | **-0.02**** | **-0.02**** |
| | (-0.39) | (-4.91) | (-4.65) | (-3.55) | (-0.99) | (-4.81) | (-4.30) | (-3.21) |
| $(\beta_1^-)^2$ | -0.02 | -0.01 | 0.02 | 0.02 | -0.01 | **-0.01*** | 0.00 | 0.00 |
| | (-1.50) | (-0.72) | (1.81) | (1.40) | (-1.92) | (-2.03) | (-0.32) | (0.40) |
| Linear | 0.16 | 0.11 | 0.04 | -0.05 | **0.14*** | **0.15*** | **0.11*** | 0.02 |
| | [0.15] | [0.28] | [0.69] | [0.61] | [0.03] | [0.02] | [0.05] | [0.73] |
| Quadratic | 0.01 | **-0.04**** | **-0.05**** | **-0.05**** | 0.01 | **-0.01*** | **-0.02**** | **-0.02**** |
| | [0.34] | [0.00] | [0.00] | [0.00] | [0.45] | [0.02] | [0.00] | [0.00] |
| Adj. $R^2$ | 0.51 | 0.54 | 0.56 | 0.52 | 0.76 | 0.79 | 0.80 | 0.78 |

Appendix 10 (continued):

| | Winner-Loser | | | | Winner-rf | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-6 | 3-6 | 6-6 | 12-6 | 1-6 | 3-6 | 6-6 | 12-6 |
| Panel B: Linear and quadratic effects (semi-annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | 0.24 | 0.42 | **0.56**** | **0.73**** | 0.22 | **0.27*** | **0.29*** | **0.43**** |
| | (0.95) | (1.95) | (2.93) | (3.23) | (1.72) | (2.3) | (2.47) | (3.44) |
| $\hat{\beta}_0^-$ | 0.32 | 0.42 | 0.50 | -0.11 | 0.28 | 0.28 | 0.28 | 0.04 |
| | (0.83) | (0.95) | (1.14) | (-0.25) | (1.13) | (0.96) | (1.19) | (0.16) |
| $\hat{\beta}_1^+$ | **-0.93**** | **-0.93**** | **-0.89**** | **-0.96**** | **-0.99**** | **-0.98**** | **-0.97**** | **-1.00**** |
| | (-12.38) | (-14.46) | (-14.49) | (-13.18) | (-18.63) | (-24.86) | (-24.41) | (-22.83) |
| $\hat{\beta}_1^-$ | **-0.86**** | **-0.94**** | **-0.89**** | **-0.73**** | **-1.03**** | **-1.08**** | **-1.03**** | **-0.95**** |
| | (-6.08) | (-7.23) | (-6.09) | (-4.08) | (-11.69) | (-12.99) | (-13.58) | (-8.75) |
| $(\beta_1^+)^2$ | 0.00 | **-0.02*** | **-0.04**** | **-0.03**** | 0.00 | -0.01 | **-0.02**** | **-0.02**** |
| | (0.28) | (-1.98) | (-4.76) | (-2.74) | (-0.58) | (-1.93) | (-4.07) | (-2.77) |
| $(\beta_1^-)^2$ | 0.02 | 0.01 | 0.01 | **0.04**** | 0.00 | 0.00 | 0.00 | 0.01 |
| | (1.54) | (1.54) | (0.74) | (3.40) | (0.08) | (-0.32) | (0.25) | (1.49) |
| Linear | -0.08 | 0.01 | 0.00 | **-0.24*** | 0.04 | 0.10 | 0.07 | -0.05 |
| | [0.49] | [0.95] | [0.99] | [0.03] | [0.58] | [0.11] | [0.25] | [0.43] |
| Quadratic | -0.01 | **-0.04**** | **-0.04**** | **-0.07**** | -0.01 | -0.01 | **-0.02**** | **-0.03**** |
| | [0.30] | [0.00] | [0.00] | [0.00] | [0.42] | [0.10] | [0.00] | [0.00] |
| Adj. $R^2$ | 0.46 | 0.52 | 0.56 | 0.53 | 0.75 | 0.77 | 0.80 | 0.79 |
| | Winner-Loser | | | | Winner-rf | | | |
| | 1-12 | 3-12 | 6-12 | 12-12 | 1-12 | 3-12 | 6-12 | 12-12 |
| Panel C: Linear and quadratic effects (annually rebalanced) | | | | | | | | |
| $\hat{\beta}_0^+$ | **0.63**** | 0.35 | **0.42*** | **0.39*** | **0.40**** | **0.27*** | 0.20 | **0.36**** |
| | (3.16) | (1.91) | (2.16) | (2.01) | (3.89) | (2.55) | (1.42) | (3.02) |
| $\hat{\beta}_0^-$ | -0.25 | 0.23 | 0.02 | -0.76 | 0.06 | 0.15 | 0.08 | -0.23 |
| | (-0.67) | (0.60) | (0.06) | (-1.92) | (0.27) | (0.57) | (0.44) | (-0.98) |
| $\hat{\beta}_1^+$ | **-0.98**** | **-0.97**** | **-0.91**** | **-0.97**** | **-1.01**** | **-1.00**** | **-0.99**** | **-1.03**** |
| | (-13.75) | (-15.01) | (-13.7) | (-12.66) | (-20.43) | (-24.64) | (-22.19) | (-21.49) |
| $\hat{\beta}_1^-$ | **-0.96**** | **-1.10**** | **-1.01**** | **-0.76**** | **-1.10**** | **-1.18**** | **-1.14**** | **-1.02**** |
| | (-6.62) | (-7.4) | (-8.31) | (-4.74) | (-12.15) | (-15.35) | (-15.92) | (-8.96) |
| $(\beta_1^+)^2$ | -0.02 | **-0.03*** | -0.02 | -0.02 | **-0.02*** | **-0.02*** | **-0.02*** | -0.02 |
| | (-1.66) | (-2.41) | (-1.83) | (-1.80) | (-2.18) | (-2.21) | (-2.37) | (-1.95) |
| $(\beta_1^-)^2$ | **0.02*** | 0.02 | 0.01 | **0.04**** | 0.00 | 0.00 | 0.00 | 0.01 |
| | (2.34) | (1.79) | (0.83) | (3.73) | (0.22) | (-0.66) | (-0.48) | (1.31) |
| Linear | -0.02 | 0.13 | 0.09 | **-0.21*** | 0.09 | **0.17**** | **0.15*** | -0.01 |
| | [0.82] | [0.15] | [0.29] | [0.03] | [0.12] | [0.00] | [0.01] | [0.87] |
| Quadratic | **-0.04**** | **-0.04**** | **-0.03**** | **-0.06**** | **-0.02**** | **-0.01*** | **-0.02**** | **-0.03**** |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.03] | [0.01] | [0.00] |
| Adj. $R^2$ | 0.57 | 0.65 | 0.61 | 0.59 | 0.81 | 0.83 | 0.80 | 0.80 |