A Reexamination of Factor Momentum: How Strong Is It? ⋆

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Abstract

Recent studies show that most financial market anomalies exhibit a momentum effect. Based on two datasets, i) an original 22-factor sample and ii) a more comprehensive 187-factor sample, we find that factor momentum effect is weak at the individual factor level. In both samples, only about 22-27% of the factors exhibit strong return continuation and dominate the factor momentum portfolio while the remaining factors do not. The factor momentum strategies do not outperform the corresponding long-only strategies in either sample. The choice of factors affects the ability of factor momentum to explain individual stock momentum.

Keywords: Time series momentum; Factor momentum; Return continuation; Factor investing.

JEL: G11, G12

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ABSTRACT

Recent studies show that most financial market anomalies exhibit a momentum effect. Based on two datasets, i) an original 22-factor sample and ii) a more comprehensive 187-factor sample, we find that factor momentum effect is weak at the individual factor level. In both samples, only about 22-27% of the factors exhibit strong return continuation and dominate the factor momentum portfolio while the remaining factors do not. The factor momentum strategies do not outperform the corresponding long-only strategies in either sample. The choice of factors affects the ability of factor momentum to explain individual stock momentum.

1. INTRODUCTION

Arnott et al. (2019) and Ehsani and Linnainmaa (2021) documented a strong and pervasive momentum effect in most financial market anomalies, called factor momentum (FMOM). A FMOM strategy is long recent top-performing factors and short poorly performing factors. Therefore, it is by nature a type of factor timing strategy.[1] Recent literature shows that FMOM has significant investment performance compared to traditional individual stock momentum (Gupta and Kelly, 2019) and that factor momentum can explain both individual stock momentum and industry momentum (Arnott et al., 2019, Ehsani and Linnainmaa, 2021). This finding seems to contradict the conventional view that timing factors are expensive and have difficulty beating a naive buy-and-hold (BAH) portfolio; see, e.g., Asness (2016a) and Asness (2016b).

This study examines the strength and profitability of factor momentum based on two datasets: i) the original set of 22 factors (EL) same as in Ehsani and Linnainmaa (2021) and ii) a more comprehensive set of 187 factors (HXZ) of Hou et al. (2015). We confirm the main findings in Arnott et al. (2019) and Ehsani and Linnainmaa (2021) that FMOM exists as a whole. We take a step further and examine the pervasiveness of factor momentum effect at the individual factor level. The motivation for conducting this research stems from a concern that a factor being statistically significant at aggregate level does not mean it is strong at individual level. For example, Huang et al. (2020) argued that the time series momentum effect is weak at the individual asset level as 47 out of 55 assets show insignificant t-statistics. Moreover, the beta coefficient

[1] See, e.g., Bender and Wang (2016), who evaluated the performance of portfolios constructed with multiple factors, Gupta and Kelly (2019), who studied the profitability of time series momentum portfolios across 65 factors, Van Gelderen et al. (2019), who assessed the performance of factor investing across mutual funds, and Chen et al. (2022), who investigated institutional investments based on 10 factors.

of pooled OLS that predicts the next month's return using the past 12-month return is likely to be biased upward.[2]

We find that only a minor group of factors (27% of EL sample and 22% of HXZ sample) show a strong momentum effect and dominate the factor momentum portfolio whereas the return persistence of the remaining factors is weak. We call those factors with strong momentum effect return continuation factors (RCFs) and the remaining factors non-RCFs. We find that RCFs can explain individual stock momentum and industry momentum while the explanatory power of non-RCFs is weak. Therefore, we conclude that factor momentum may be specific to a subset of factors but does not apply to all of them. In the EL sample, this is especially the case with the betting against beta (BAB) factor, which accounts for more than 25% of the total factor momentum profits. We argue that this is because of its unique rank weighting scheme instead of the conventional value-weighted portfolio. In the HXZ 187-factor sample, factor momentum is particularly strong in the Value-Growth group, including Long-term Reversal, Enterprise Value, and Operating Assets related anomalies but is weak in the remaining five groups. Because the two samples do not cover the same factors, we identify that the common RCFs are related to the Size and the Long-term Reversal factors.

In the profitability analysis based on both samples, we find that factor momentum, although exhibiting statistically significant positive returns, does not outperform a simple buy-and-hold strategy based on the same set of factors. For the EL sample, the average annualised return of the FMOM portfolio (4.07%) is lower than that of a BAH portfolio based on the same sample (4.26%). As is mentioned above, we further break down the larger HXZ 187 sample into six categories, namely Momentum, Value-Growth, Investment, Profitability, Intangibles, and Frictions. Our results suggest that the average returns of FMOM are greater than those of BAH in only two of the six categories (Value-Growth and Frictions) and that the differences are not statistically significant.

For both EL and HXZ samples, we construct time series FMOM portfolios following Ehsani and Linnainmaa (2021). We first present evidence supporting the thesis of Ehsani and Linnainmaa (2021) that the momentum anomaly of Jegadeesh and Titman (1993) is an aggregation of the autocorrelation of the remaining financial anomalies instead of an independent factor. However, this factor momentum effect is weak on average over the past five decades.

We find that there is a large variation in return persistence across different factors. For each factor, we use

[2] Reasons include i) not controlling for fixed effect given different factor mean returns (Hjalmarsson, 2010), and ii) size distortions caused by using past 12-month return as predictor (Ang and Bekaert, 2007, Boudoukh et al., 2008, Li and Yu, 2012, Fan et al., 2020, Guo et al., 2021, Liu and Papailias, 2021, Papailias et al., 2021).

three tests (two time series regressions and one return decomposition model) examine its return persistence. The results suggest that only those a few factors (RCFs) exhibit strong time series return persistence whereas the remaining factors (non-RCFs) do not. Among the six categories in the HXZ 187-factor sample, the Value-Growth group has the most RCFs (14 out of 32) while the Momentum group has the least (2 out of 41). We infer that this phenomenon is because the value factors are related to economic fundamentals and business cycles, and hence are mostly positive and featured with return continuation (Koijen et al., 2017). Overall, we argue that the pattern of factor momentum effect is sensitive to a subset of factors.

Based on the above findings, we decompose the entire sample into two sub-samples: the RCFs (six in the EL sample and 42 in the HXZ sample) with strong return persistence and the non-RCFs that show weak return persistence. In the EL sample, for example, the momentum profit generated by the RCFs (6.43%) is substantially greater than the profit of either the portfolio with the 14 non-RCFs (3.07%) or the entire portfolio with 20 factors (4.07%).[3] FMOM across RCFs accounts for 48.03% of the profits of the FMOM portfolio sampling all 20 factors. The six RCFs dominate the profitability of the FMOM portfolio while the 14 non-RCFs contribute much less. These findings are robust to the consideration of different formation period and holding period combinations.

We further argue that the ability of FMOM to explain individual momentum trading schemes stems from RCFs. Ehsani and Linnainmaa (2021) reported that FMOM can fully explain all the information of individual momentum trading schemes and that this ability is not sensitive to the choice of factors. However, our results from the spanning regressions suggest that only the six RCFs fully span the individual stock momentum, i.e., the standard momentum of Jegadeesh and Titman (1993), the industry momentum of Moskowitz and Grinblatt (1999) and the intermediate momentum of Novy-Marx (2013). By contrast, the 14 non-RCFs do not span individual stock momentum. This result means that not only can the portfolio return of the 14 non-RCFs not be fully explained by individual stock but also that the individual stock momentum return cannot be fully explained by the 14 non-RCFs. Our findings suggest that the choice of factors matters.

To sum up, we reexamine and validate the main finding on factor momentum proposed by Ehsani and Linnainmaa (2021). Our results confirm that the factor momentum effect generally exists and that the momentum factor of Jegadeesh and Titman (1993) is the aggregation of the autocorrelations of other finan-

[3]The two momentum factors in U.S. and global markets are excluded from the whole sample of 22 factors, which is in line with the approach in Ehsani and Linnainmaa (2021).

cial market anomalies. However, at the individual factor level, return continuation properties vary across different groups of anomalies. We also challenge Ehsani and Linnainmaa (2021) by showing that two sets of factors have different momentum effects and abilities to explain individual stock momentum, suggesting that the factor momentum effect is not pervasive. The results from investment strategies suggest that factor momentum is not an effective investment approach compared to simply longing those factors and that FMOM has less value from the perspective of practitioners.

The remainder of this paper is organised as follows. Section 2 documents our data set and portfolio construction. Section 3 examines the factor momentum effect at the individual factor level. In Section 4, we assess the FMOM performance of two different sets of factors, RCFs and non-RCFs. Finally, we summarise our findings in Section 5.

2. DATA AND PORTFOLIO CONSTRUCTION

The aim of this study is to extend the existing literature on factor momentum by further examining the findings of Ehsani and Linnainmaa (2021) and Arnott et al. (2019). We employ two data samples to analyse the factor momentum effect, i) the 22 factors (EL) as in Ehsani and Linnainmaa (2021) and ii) a much more extensive set of 187 factors (HXZ) (Hou et al., 2021).

First, following Ehsani and Linnainmaa (2021), we obtain the monthly return series of 15 U.S. and seven global equity market factors from three public sources: the AQR website, and Kenneth French's and Robert Stambaugh's data libraries. Table 1 reports the factor names, abbreviations, original studies, start dates, annualised returns, standard deviations, Sharpe ratios, and first order autocorrelation for each factor series. Of the 15 U.S. factors, 14 are available from July 1963 whereas the liquidity factor starts in January 1968. The return series of the seven global factors starts in July 1990. All series end in December 2015, which is in line with Ehsani and Linnainmaa (2021).

Table 1 shows that there is substantial dispersion in annualised returns across covered financial anomalies. The U.S. betting against beta factor earns as much as 10.64% per year whereas the global size factor earns only 1.23% per year. The table also highlights the difference in volatility across factors. The U.S. residual variance factor exhibits the highest standard deviation at 17.6% while the volatility of the global profitability factor is the lowest (4.76%). The last column of Table 1 reports the first order autocorrelation of the monthly return series for each factor where 18 are positive and at least statistically significant at the 10% level. This result means that most factors show strong autocorrelation, supporting the existence of the suggested factor momentum.

[Insert Table 1 here]

Next, to extend our investigation of factor momentum effect, we construct a much larger sample consisting of 187 factors following Hou et al. (2015). We collect monthly return series of the 187 anomalies from Hou-Xue-Zhang (HXZ) q-factors data library ranging from January 1967 to December 2020. Table 2 reports the summary statistics of the HXZ 187 factors divided into six categories, namely Momentum, Value-Growth, Investment, Profitability, Intangibles, and Frictions. We can see that there is a substantial dispersion in the average annualised returns across these six categories. The Momentum and Profitability anomalies earn as much as 6.75% and 6.52% per year on average, respectively whereas the Frictions anomalies only earn 2.74% per year on average. The mean returns of most factors are statistically significant at the 5% level ($t > 1.96$), except for the Frictions sector where only two out of ten factors are significant.

[Insert Table 2 here]

Table 2 also highlights the difference in volatility across the six categories of anomalies. The Frictions category exhibits the highest standard deviation at 15.39% as it is related to volatility based anomalies whereas that of the Investment sector is the lowest (6.67%). The last column reports the number of factors within a category that have their first order correlation being significant at the 5% level. The results show that about 66% (118/178) of the factors have significant first order autocorrelations. Value-Growth anomalies exhibit the strongest autocorrelation with 90% (29/32) of the factors being significant whereas Momentum anomalies exhibit the weakest autocorrelation (12/41).

Based on the framework of Moskowitz et al. (2012), we assess a time series factor momentum strategy using the above-mentioned two sets of factors. The strategy is long factors that have positive returns over the past 12 months and short all others. In line with Ehsani and Linnainmaa (2021), the factor momentum portfolio is equal weighted and is rebalanced at the end of each month. We use the time series factor momentum strategy for two reasons. First, Ehsani and Linnainmaa (2021) show that a time series FMOM dominates a cross-sectional FMOM and is heavily studied throughout the paper. Second, it is straightforward to examine the profitability of a time series FMOM by investigating individual factor performance. Therefore, FMOM mentioned in the rest of this paper refers to a time series factor momentum strategy.

3. HOW STRONG IS THE FACTOR MOMENTUM EFFECT?

This section examines the factor momentum effect at individual factor level based on the two above-mentioned samples: EL 22 factors and HXZ 187 factors. Specifically, we test i) whether the FMOM strategy for each of the factors generates abnormal returns that are statistically significant, ii) whether each of these factors shows strong return persistence, and iii) whether the profitability of FMOM is sourced from its time series momentum effect. Answering these questions helps us understand how strong the factor momentum effect is and motivate further studies on the topic. It also provides evidence for market practitioners who are interested in investing in factor momentum.

3.1 Abnormal returns of FMOM

In the first test, we regress the returns of FMOM strategies based on individual factors on the Fama-French five factors (FF5) plus momentum factor (UMD) as:

$$r_t^{FMOM} = \alpha + \beta_1 r_t^{UMD} + B \times R_t^{FF5} + \epsilon_t, \tag{1}$$

where r_t^{FMOM} is the return series of factor momentum constructed on an individual market factor in month t; r_t^{UMD} is the return of momentum factor (Jegadeesh and Titman, 1993); and R_t^{FF5} represents the returns of the Fama-French five factors (Fama and French, 2015). Table 3 summarises the regression results of Equation 1, in which the abnormal returns (α), coefficients of momentum factor (β_1) and their corresponding t-statistics, $t(\alpha)$ and $t(\beta_1)$, are reported.

The last column of Table 3 reports the return contribution of each factor proportional to the entire factor momentum portfolio. Although all factors are equal weighted in the factor momentum portfolio of Ehsani and Linnainmaa (2021), they make different contributions to the portfolio profits. Following Moskowitz et al. (2012) and Ehsani and Linnainmaa (2021), the portfolio return of the FMOM strategy in month t is given by:

$$r_t^{FMOM} = \frac{1}{n} \sum_{i=1}^{n} sgn(r_{t-12,t-1}^i) r_t^i, \tag{2}$$

where n is the number of available factors; $sgn(r_{t-12,t-1}^i)$ is 1 for a positive past 12-month return of the i-th factor, 0 for the zero return, and -1 for a negative $r_{t-12,t-1}^i$; and r_t^i is the return on the ith factor in month t. Following Booth and Fama (1992) and Brinson et al. (1995), the average return contribution of the ith factor (C^i) over the entire time horizon can be measured as:

$$C^i = \frac{1}{T-12}\sum_{t=13}^{T}\frac{sgn(r^i_{t-12,t-1})r^i_t}{r^{FMOM}_t}, \tag{3}$$

where T is the sample period; other notations remain the same.[4]

[Insert Table 3 here]

In Table 3, we can see that the abnormal returns of FMOM vary across factors. Most of these alphas are positive, but only three of them are statistically significant at least at the 5% level after controlling for FF5 and UMD. These are profitability (RMW), betting against beta (BAB), and global betting against beta (GBAB).[5] Notably, the abnormal returns of BAB factors, based on both the U.S. and global stock markets, outperform those of any other financial anomalies with values of 0.58% and 0.51%. These two BAB factors also have the highest return contribution to the entire FMOM portfolio (13.68% and 11.40%). This result raises our question of whether a subset of factors dominates the factor momentum portfolio.

Ehsani and Linnainmaa (2021) argued that the momentum factor of Jegadeesh and Titman (1993) is an aggregation of autocorrelation from all other financial anomalies rather than an independent risk factor. We arrive at the same conclusion from the results of Columns Four and Five in Table 3. The beta coefficients of r^{UMD}_t and their t-statistics indicate that the FMOM returns of 18 factors, except that the short-term reversal (SREV) and global size factor (GSMB) are statistically significant at least at the 10% level. Because the profits created by the autocorrelations of factors are significantly related to the returns of the momentum factor, we justify the finding that the momentum factor is an aggregation of autocorrelation from other factors.

For a more in-depth view of the abnormal returns of factor momentum, we perform factor regressions on our second dataset, the HXZ 187-factor sample. Apart from the Fama and French (2015) five-factor model (FF5), we extend our study by adding three alternative benchmark models, namely Hou et al. (2015) q-factor model (q Model), Stambaugh et al. (2012) four-factor model (SY4), and Daniel et al. (2020) three-factor model (DHS). Hou et al. (2015) q-factor model includes a market factor, a size factor, an investment factor, and a profitability factor; Stambaugh et al. (2012) four-factor model includes two mispricing factors, the management and performance factors, in addition to the market and size factors; Daniel et al. (2020) three-

[4] The first monthly return contribution of each factor is calculated in the 13th month because we employ a 12-month formation period.

[5] For the global factors, we control for the global FF5 and UMD.

factor model includes a market factor, along with two mispricing factors that capture long- and short-horizon mispricing, respectively. Evidence has shown that these competing factor models outperform the FF5 model in explaining asset returns. Therefore, we include them in our study in order to investigate whether these models add value in explaining the FMOM returns.

Table 4 reports the number of FMOM strategies that yield significant abnormal returns ($t > 1.96$) for each category using the above-mentioned four models. We can see that the number of significances varies across categories. Value-Growth and Profitability anomalies have the strongest ability to generate abnormal returns with around two-thirds of the alphas being significant at the 5% level. Factor momentum strategies of Investment and Frictions anomalies exhibit relatively weaker abnormal returns with approximately one-third of the alphas being significant.

[Insert Table 4 here]

In the larger HXZ sample, which 187 FMOM strategies are assessed simultaneously, examining the significance of abnormal returns becomes a multiple hypothesis testing procedure. If the single hypothesis testing is used as in the 22-factor sample, some of the significant abnormal returns may be caused by the Type I errors instead of strategy's inherent merit (White, 2000, Hansen, 2005, Romano et al., 2008, Harvey and Liu, 2020). To manage the potential Type I error, we apply the Superior Predictive Ability controlling the False Discovery Proportion (FDP-SPA) proposed by Hsu et al. (2014) and report the results in the last column of Table 4.[6] The results show that only 22 of the HXZ factors can produce significant abnormal returns after controlling for UMD and FF5. The number of significances is even lower when the other three models are employed. Our results indicate that time series momentum strategies based on most financial anomalies do not yield significant alphas.

3.2 Time series test of return persistence

Arnott et al. (2019) and Ehsani and Linnainmaa (2021) contend that factor momentum is a pervasive phenomenon among different factors. We question whether this is the case, as our prior findings in Table 3 show that the investigated factors make different contributions to portfolio profits. To test this hypothesis, we employ three models to determine which factors have strong return continuation. The results show that, in our original EL sample, only six factors exhibit statistically significant time series return continuation

[6] We set the target false discovery proportion at 5% and resample for 500 times. For more details of applying such a method, please refer to Hsu et al. (2014).

at the 10% level in all three tests. In the larger HXZ sample, 42 out of 187 factors show strong return continuation.

Table 5 examines the return continuation property for individual factors based on the three methods: two time series regression models and a return decomposition model. We first employ the time series regression model (Model 1) of Ehsani and Linnainmaa (2021):

$$r_t^i = \alpha + \beta sgn(r_{t-12,t-1}^i) + \epsilon_t, \tag{4}$$

where r_t^i is the return of a given factor, i, in the coming month t; $sgn(r_{t-12,t-1}^i)$ takes a value of one if the past 12-month return, $r_{t-12,t-1}^i$, is positive, and negative one otherwise. As shown in the regression results, all the beta coefficients are positive, indicating positive time series return continuation. However, only nine of them are statistically significant at the 10% level, and eight of them are significant at the 5% level.

[Insert Table 5 here]

Second, for robustness check, we adopt a similar time series regression as in Huang et al. (2020) (Model 2), as follows:

$$r_t^i = \alpha + \beta r_{t-12,t-1}^i + \epsilon_t, \tag{5}$$

where all terms remain the same as those in Equation 4. This model examines whether the period return over the past 12 months predicts the return in the coming month. The results indicate that the coefficients of nine factors are statistically significant at the 10% level and that five are at the 5% level. The results of both Model 1 and Model 2 are consistent with the findings of Ehsani and Linnainmaa (2021). We also examine the out-of-sample predictability of FMOM based on each factors, and the results suggest only four of these factors generate positive out-of-sample R^2 that are significant at the 10% level. Results of the out-of-sample R^2 analysis are presented in Appendix A.

To take our analysis a step further, we decompose the FMOM return as an alternative measure of return continuation. Following Moskowitz et al. (2012), we decompose the time series momentum return of each factor, i, into the auto-covariance term and average squared mean returns as follows:

$$E[\pi_t^{i,TSM}] = cov(r_{t-12,t-1}^i, r_t^i) + (\mu^i)^2, \tag{6}$$

where $E[\pi_t^{i,TSM}]$ is the expected time series momentum return of factor i in month t; $r_{t-12,t-1}^i$ is the period return over the 12-month formation period; r_t^i is the return in month t; $cov(r_{t-12,t-1}^i, r_t^i)$ is the covariance between past 12-month and future one-month returns; and μ^i is the unconditional expected return of factor i. The covariance term, $cov(r_{t-12,t-1}^i, r_t^i)$, represents the part of momentum profits that is attributable to return continuation. For each factor, we simply subtract the formation period mean squared return from the time series factor momentum returns to obtain the covariance term. Model 3 of Table 5 reports the mean and t-statistics of the covariance term. Nine out of 20 factors show positive returns at the 10% level of significance, and seven of them are significant at 5% level. This finding also implies that the variation in profitability and return contribution across factors partially stems from their dispersion of return continuation.

According to the results in Table 5, six out of the 20 factors show statistically significant return continuation in all three tests. They are the U.S. betting against beta, global betting against beta, long-term reversals, size, global value, and quality minus junk factors. We call them the return continuation factors (RCFs), whereas the remaining 14 factors are categorised as non-RCFs.

For the larger HXZ dataset, we perform the same analysis using Model 1-3 and report the number of significant factors for each model in Table 6. We find that the Momentum category, which contains 41 factors in total, does not have a strong time series return continuation with only three factors being statistically significant at the 5% level in Model 2. This finding is consistent with that of the EL 22 factors in which the two momentum factors do not show FMOM effect and are removed from the sample. By contrast, about half of the Value-Growth factors exhibit significant return continuation. We argue that this continuation occurs because the value factors are related to economic fundamentals and business cycles, and hence are mostly positive and featured with return continuation (Koijen et al., 2017). In the remaining four groups, the proportion of significant factors is relatively lower at around 30-40%.

[Insert Table 6 here]

Overall, among the HXZ 187 factors, 42 factors exhibit statistically significant return continuation in all three tests. Therefore, we classify them as RCFs whereas the remaining 145 factors are categorised as non-RCFs. The proportion of RCFs in the HXZ sample is 22.5%, which is comparable to that of the EL sample (27%). We further look into the RCFs at the individual factor level and find that they are clustered in Long-term Reversal, Enterprise Value, Operating Assets, and Operating Profits related factors. In the next subsection, we examine how these two different sets of factors perform when employing FMOM strategies.

3.3 FMOM and time series momentum effect

To examine whether the profitability of FMOM arises from its time series momentum effect, we conduct a performance comparison between FMOM and the time series history (TSH) strategy of Huang et al. (2020) across the 20 financial anomalies. A TSH strategy buys the asset when the past mean return is positive and sells it otherwise. Huang et al. (2020) suggested that the TSH is a simple mean model that does not rely on any time series predictability. Thus, the excess returns of FMOM minus TSH reflect the part of FMOM profits that are actually caused by time series return persistence.

Table 7 summarises the annualised returns of the FMOM and TSH strategies for each factor and their differences. Across all 20 factors, the average returns of FMOM do not significantly outperform those of TSH, except for the residual variance (difference=10.59%, t=3.17). Moreover, 11 of these factors exhibit lower FMOM performance than the corresponding TSH strategies. These results indicate that the positive returns of the FMOM strategy are not due to their time series persistence and further support our argument that the FMOM effect is weak at an individual factor level.

[Insert Table 7 here]

As the means of most factors are positive, the trading signal of TSH tends to be positive in the long-term. Simply taking the difference between FMOM and TSH may cause potential Type II errors, i.e. false negative. Therefore, to avoid such a bias and for robustness check, we build a new difference strategy (Diff) to measure profits caused by factor's time series persistence. The return of factor, i, in terms of a Diff strategy is:

$$r_t^{i,Diff} = sgn(r_{t-12,t-1}^i - \bar{r}_{1,t-1}^i)r_t^i, \tag{7}$$

where $\bar{r}_{1,t-1}^i$ represents the average return of factor i from the initial month to the most recent month. This construction measures the difference between the past 12-month return and a long-term mean. The last two columns of Table 7 report the mean of Diff strategy and the t-statistics. Nine factors exhibit significant difference at the 10% level. The result is in line with our results in the return continuation tests (Table 5) that FMOM effect is weak in most cases.

Similarly, Table 8 compares the performance of FMOM and TSH strategies based on HXZ 187 factors broken down into six categories. Across the 187 factors, the average returns of FMOM do not significantly outperform those of TSH, except for two Frictions anomalies. The results indicate that, based on the setting of Huang et al. (2020), the profits of the FMOM strategy are not due to their time series persistence, which further support our argument that the FMOM effect is weak at an individual factor level. The last two columns of Table 8 report the mean of Diff strategy and the number of factors whose mean differences are statistically significant at the 5% level. In such a more tolerant test, only 75 out of 187 anomalies exhibit statistically significant outperformance, which is consistent with our finding in the EL sample. Broken down into categories, FMOM in the Momentum group does not exhibit any outperformance, whereas about two-thirds of the factors in the Value-Growth and Profitability groups show significant differences.

[Insert Table 8 here]

Overall, this section assesses the return continuation property of each factor by evaluating the abnormal return, return contribution, and time series autocorrelation. Based on both the EL and HXZ samples, our results justify the main argument in Ehsani and Linnainmaa (2021) that factor momentum is strong when considered as a whole. However, the return continuation property for individual factors is mostly weak except for RCFs. Moreover, we find that the profits generated by the FMOM strategy are not due to its time series momentum effect, as the FMOM shows poorer performance than a historical mean model.

4. DOES THE CHOICE OF FACTORS MATTER?

In this section, we assess the performance of two different sets of factors, RCFs and non-RCFs, and their ability to explain individual stock momentum. RCFs and non-RCFs for both EL and HXZ samples are predetermined in Section 3.2. Arnott et al. (2019) and Ehsani and Linnainmaa (2021) contend that factor momentum is a pervasive phenomenon that can be captured by trading any set of factors. We show that this argument might be misleading, as RCFs dominate the entire FMOM portfolio. In both samples, an FMOM strategy based on RCFs can explain individual stock momentum, whereas one based on non-RCFs cannot. Therefore, we argue that the factor momentum effect is strong only when a subset of factors is chosen.

4.1 Performance evaluation

We first evaluate the FMOM performance of RCFs (FMOM6), non-RCFs (FMOM14), and the entire EL portfolio (FMOM20) based on a formation period of 12 months and a holding period of one month. Table 9 summarises the mean, standard deviation, Sharpe ratio, skewness, and kurtosis of the annualised returns of the three portfolios, where a buy-and-hold strategy is employed as the benchmark. We find that FMOM20 cannot beat the BAH strategy either in terms of the mean return or of the Sharpe ratio. It can also be seen that FMOM6 (mean=6.43%) outperforms FMOM20 (mean=4.07%) while FMOM14 (mean=3.07%)

underperforms FMOM20. This result indicates that FMOM6 is central to the profitability of the entire factor momentum portfolio. Furthermore, when choosing factors with strong return continuation (FMOM6), the factor momentum strategy produces superior profits than the BAH strategy. If the return continuation is weak (FMOM14), the average return of factor momentum is lower than that of the BAH strategy.

[Insert Table 9 here]

Although the strong return continuation factors lead to high profitability, they tend to cause higher volatility. The standard deviation of FMOM6 is 5.23% per year, whereas the standard deviations of FMOM14 and FMOM20 are lower at 4.48% and 4.25%, respectively. Regarding the higher moment statistics, the FMOM strategies generate lower skewness and kurtosis than the BAH strategies. Lower skewness indicates that the FMOM strategies are less attractive than the BAH (Barroso and Santa-Clara, 2015, Daniel and Moskowitz, 2016, Fan et al., 2018). Our results conclude that the profitability of factor momentum is weaker than the corresponding BAH strategy.

The key findings in the performance evaluation hold for the larger HXZ sample with 187 factors. For each of the six categories, we construct BAH and FMOM strategies and compare their performance in Table 10. Panel A summarises the mean, standard deviations, Sharpe ratios, skewness, and kurtosis of the annualised returns of the above strategies. FMOM returns in the Value-Growth and Profitability groups are the highest whereas the mean return of the Investment group is the lowest at 2.95% per annum. Panel B reports the statistical significance of FMOM minus BAH. In four out of the six categories, the average returns of FMOM are lower than those of BAH, where the underperformance is statistically significant at least at the 10% level in Momentum, Investment, and Intangible portfolios. For Value-Growth and Friction categories, the FMOM returns are slightly higher than BAH, but the differences are insignificant. These results support our main findings in the EL sample that the factor momentum does not outperform a simple BAH strategy.

[Insert Table 10 here]

To further investigate the difference between the performance of RCFs and non-RCFs, we break down the FMOM portfolios into winner and loser portfolios. Panel A of Table 11 shows the average returns with t-statistics for FMOM (winner-minus-loser), winner and loser portfolios based on the full set of 20 factors, 14 non-RCFs, and six RCFs. We also employ a buy-and-hold strategy as a benchmark in each sample. Panel B of Table 11 reports the return difference and its t-statistics for FMOM20 minus FMOM14 and FMOM20 minus FMOM6. We can see that the annualised return of FMOM14 is 3.07%, which is significantly smaller than the return of FMOM20 at the 1% level. By contrast, the return of FMOM6 (6.43%) is substantially larger than the return of FMOM20, with the t-value being statistically significant at the 1% level. When separately examining winners and losers, we see that the difference is mainly due to the winners, while the difference in losers is insignificant.

A similar pattern is observed from the results of HXZ 187 factors presented in Panel C and D of Table 11, that the differences across RCFs, non-RCFs, and the full sample are all statistically significant. The annualised return of FMOM145 is 4.26%, which is significantly smaller than the return of FMOM187 at the 1% level whereas the return of FMOM42 (5.91%) is substantially larger than the return of FMOM187 at the 1% level. Different from the results in the EL sample, we find that these differences in winners and losers are both significant at the 1% level in the HXZ sample.

[Insert Table 11 here]

We provide evidence that the number of factors in the winner portfolio is greater than that in the losers over most of the investment horizon, indicating that FMOM performance is mainly from its long-leg. Figure 1 presents time-dynamic proportion of FMOM winners over time computed as $\frac{\sum_{i=1}^{n} sgn_{win,i}}{n}$, where sgn_{win} equals one for winners and zero otherwise, and n is the number of factors. We can see that, in both Panel A and Panel B, the proportion of winners is great than 0.5 (dashed line) over most of the sample period. Specifically, number of winner factors is more than that of loser factors during 86.2% (EL) and 93.5% (HXZ) of the sample period. The aggregated average proportion of winners over time is 65.3% for the EL sample and 70.7% for the HXZ sample.

[Insert Figure 1 here]

Thus far, our conclusion that RCFs dominate the FMOM portfolio is based on a trading strategy with a 12-month formation period and one-month holding period. As a robustness check, we examine whether the outperformance of FMOM in RCFs and the underperformance of FMOM in non-RCFs are consistent by considering different formation and holding periods. Table 12 reports the differences in annualised average returns and their t-values of FMOM6 minus FMOM20, FMOM20 minus FMOM14, FMOM42 minus FMOM187, and FMOM187 minus FMOM145 with the formation and holding periods taking values of 1, 3, 6, and 12 months. As a result, we build 96 different portfolios in total, and the performance of each portfolio is detailed in Appendix B.

[Insert Table 12 here]

Panel A of Table 12 shows that the outperformance of FMOM6 is pervasive across different combinations of formation and holding periods. The average returns of FMOM6 are at least 1.10% higher than those of FMOM20 per year with almost all the t-statistics being statistically significant at the 1% level. Panel B reports that FMOM14 underperforms FMOM20 regardless of the choice of formation and holding periods. The average returns of FMOM14 are at least 0.42% lower than those of FMOM20 per year. Again, almost all of the t-statistics for the difference are statistically significant at 1%. Similarly, Panel C shows that all the average returns of difference FMOM42 are significantly higher than those of FMOM187, with all the t-statistics being greater than 3. Panel D suggests that FMOM145 significantly underperforms FMOM187 regardless of the choice of formation and holding periods. Overall, the results justify our finding that the performance differences of i) RCFs minus full sample, and ii) full sample minus non-RCFs are significantly positive and robust across formation and holding periods.

To obtain a more intuitive view, we plot the cumulative performance of different FMOM portfolios based on the EL sample in Figure 2, assuming that an amount of \$1 is invested in each portfolio in 1964.[7] Panel A compares the cumulative returns of the FMOM6, FMOM14, and FMOM20 portfolios over the sample period. Consistent with the results in Table 11, the FMOM6 portfolio earns the highest cumulative return at the end of the sample period. In 1964, a one-dollar investment in the FMOM6 portfolio would be worth over \$25 in 2015. By contrast, the same investments in FMOM20 and FMOM14 would be worth approximately \$7.50 and \$5, respectively. The cumulative performances of the three trading rules are nearly identical before 1980, but FMOM6 has taken the lead since 1980. Panel B of Figure 2 plots the cumulative returns of the winner and loser portfolios for FMOM6 and FMOM14, respectively. We can see that FMOM6 yields higher winner performance and lower loser performance than FMOM14. Therefore, both of them contribute to the superior winner-minus-loser performance of FMOM6.

[Insert Figure 2 here]

4.2 Out-of-sample test

Since the RCFs are known only at the end of the investment horizon, one might argue that the above results are subject to data snooping. To address this issue of look-ahead bias, we further introduce an Out-of-sample (OOS) method on selecting RCFs. On each month, an Out-of-sample (OOS) FMOM strategy

[7] We have also plotted the same graphs based on the HXZ sample, and the patterns are qualitatively indifferent from those of the EL sample. These results are available upon request.

selects six best-performing factors over a rolling window k ranging from 24 to 120 months with intervals of 12 months. Therefore, in month t, the OOS FMOM portfolio return equals the mean of FMOM returns across six selected factors with the highest FMOM period returns during month $t-k$ to $t-1$.

Table 13 presents the results of the OOS FMOM strategies based on different look-back windows. Panel A reports the mean of OOS FMOM strategy returns with t-statistics shown below. The FMOM strategies still yield significant out-of-sample profits as all the mean returns are statistically significant at the 1% level. Although these performances are slightly lower than the FMOM6 with the six RCFs selected in-sample, it is usual that out-of-sample performance is lower than the results using in-sample selection.

[Insert Table 13 here]

Panel B of Table 13 reports the ten factors with the highest return contributions calculated using the same method as in Equation 3. We also calculate the aggregated proportion in return contributions for these ten factors, and the number of RCFs appearing in these factors. Each column reports the results based on a given rolling window $k = \{24, 36, 48, 60, 72, 84, 96, 108, 120\}$. We find that the six RCFs identified in the in-sample results are mostly included in the top ten factors in terms of return contribution, thereby indicating that the out-of-sample results are consistent with the in-sample ones, where the six RCFs are still in the centre of the FMOM performance. The sums of return contributions of the ten factors account for 80-90% of the total OOS FMOM profits.

Interestingly, in the out-of-sample test, the two Betting Against Beta (BAB) factors are always ranked at top two regardless of the choice of rolling windows. The results in Table 3 of Section 3 also suggest that the BAB factors (Frazzini and Pedersen, 2014) account for a much larger proportion of the factor momentum profits than the remaining factors. In the FMOM20 portfolio, the U.S. and global BAB factors contribute to 13.68% and 11.40% of the total profits. In the FMOM6 portfolio, these two factors produce more than half of the profits at 28.57% and 23.41%, respectively. This result implies that the BAB factors show a much stronger factor momentum effect than other anomalies .

We argue that the extraordinary return contribution of BABs in factor momentum is related to both return continuation and weighting scheme. We apply the decomposition method of Han (2022) and find that the BAB abnormal returns are mainly sourced from its stock selection process and the use of rank weighting scheme. The methodologies and results are discussed Appendix C. We also argue that the unique rank weighting scheme of BAB factors plays an important role in its high return continuation. Across all the 22 factors in the EL sample, only the two BAB factors are constructed based on rank-weighted portfolio whereas all the remaining factors are value-weighted. A rank-weighted BAB exhibits much stronger return continuation than a value-weighted BAB strategy with the same setting.[8]

4.3 Spanning test

One of the most important findings in Ehsani and Linnainmaa (2021) is that the choice of factors does not affect the factor momentum's ability to span UMD. However, we argue that the ability of factor momentum to explain individual stock momentum stems from those RCFs. We employ the spanning test as in Ehsani and Linnainmaa (2021) on the returns of factor momentum portfolios based on RCFs and non-RCFs to examine whether these sub-samples explain the dynamics of a variety of individual stock momentum factors (IMOM). IMOM includes the standard momentum of Jegadeesh and Titman (1993), the industry momentum of Moskowitz and Grinblatt (1999), and the intermediate momentum of Novy-Marx (2013). The regression equations are:

$$\begin{aligned} r_t^{IMOM} &= \alpha + \beta_1 r_t^{FMOM} + B \times R_t^{FF5} + \epsilon_t, \qquad (a) \\ r_t^{FMOM} &= \alpha + \beta_1 r_t^{IMOM} + B \times R_t^{FF5} + \epsilon_t, \qquad (b) \end{aligned} \tag{8}$$

where r_t^{IMOM} is the return of IMOM in month t; r_t^{FMOM} is the return of FMOM based on the RCFs (FMOM6) or non-RCFs (FMOM14); and R_t^{FF5} represents the returns of the Fama-French five factors from Fama and French (2015).

Table 14 summarises the spanning regression results in which the dependent variable is the monthly return on one of the individual stock momentum factors (IMOM) or on factor momentum based on the RCFs (FMOM6) and non-RCFs (FMOM14).[9] If the dependent variable is IMOM, we estimate the first regression of Equation 8, where IMOM is one of the three individual stock momentum (standard, industry and intermediate momentum) returns, and the independent variables are the FF5 plus FMOM returns. If the dependent variable is FMOM, we estimate the second regression of Equation 8, where the independent variables are the FF5 plus one of the IMOM returns.

[Insert Table 14 here]

The regression results in Panel A of Table 14 suggest that the FMOM6 strategy spans all three individual stock momentum strategies. When the dependent variable is FMOM6, the alphas are 0.30% (t=5.95), 0.41%

[8]For details about the summary of all the portfolio construction methods and how we build value- and rank- weighted BAB portfolios, see Appendix C.

[9]We do the spanning test only for the EL 20 factor sample, as the HXZ sample contains 41 momentum factors which would cause multicollinearity problem when regressing factor momentum portfolio returns on momentum factors.

(t=7.38) and 0.34% (t=5.12) when standard, industry, and intermediate momentum is the explanatory variable, respectively. However, when the dependent variable is IMOM, none of the alphas is statistically significant. This result means that FMOM6 contains information that is not captured by any of the three individual momentum factors, whereas the dynamics of these individual stock momentum factors are fully explained by FMOM6. These results are consistent with the results in Ehsani and Linnainmaa (2021) who performed the sample analysis using the 20 factors.

Panel B of Table 14 repeats the same regressions on the returns of FMOM14 and IMOM. As indicated by the alphas when FMOM14 is the dependent variable, FMOM14 still contains information that is not present in any form of the individual stock momentum factors. However, when we reverse the analysis, the standard and intermediate momentum also span FMOM14 with alphas of 0.25% (t=1.89) and 0.21% (t=1.91). In other words, the returns of FMOM14 fail to explain part of the dynamics of standard and intermediate momentum. Therefore, we conclude that the choice of factors does affect the ability of FMOM to explain the return of individual stock momentum. These results contradict the argument in Ehsani and Linnainmaa (2021).

As a robustness check, we examine whether our findings are sensitive to the number and selection of factors in the portfolio. In Figure 3, we draw random subsets of factors for each set size and record the t-statistics of α (henceforth, $\mathrm{t}(\alpha)$) of the two models of Equation 8, where IMOM refers to the UMD factor here. Then, we plot averages of these $\mathrm{t}(\alpha)$ values as a function of the number of factors. The thick line represents the average $\mathrm{t}(\alpha)$ associated with model (a) of Equation 8; the thin line represents the average $\mathrm{t}(\alpha)$ from model (b) of Equation 8. We first form random subsets of the six RCFs and report them in Panel A of Figure 3. Then, using the same method, we report the average $\mathrm{t}(\alpha)$ for the 14 non-RCFs in Panel B.

[Insert Figure 3 here]

In Panel B of Figure 3, the thick line never exceeds 2, which means that UMD can span FMOM constructed by non-RCFs regardless of how many factors on which the strategy is based. The patterns shown by the thick lines support that the time series momentum effect across non-RCFs is much weaker than that across RCFs. By contrast, the thin line shows that although the $\mathrm{t}(\alpha)$ of the UMD continues decreasing, the value is always above two, which is statistically significant at least at the 5% level. This result means that the FMOM constructed by non-RCFs cannot span individual stock momentum. Figure 3 verifies our proposition that the six RCFs are central to the ability of FMOM in explaining individual stock momentum whereas the 14 non-RCFs are not. Our findings challenge those of Ehsani and Linnainmaa (2021), who contended that FMOM spans individual stock momentum regardless of the choice of factors.

5. CONCLUSION

We reexamine the factor momentum effect and extend the study to a more comprehensive dataset comprised of 187 factors. We justify the findings of Ehsani and Linnainmaa (2021) that the momentum factor of Jegadeesh and Titman (1993) is an aggregation of the autocorrelation of other financial factors rather than an independent financial anomaly. In general, the time series factor momentum trading strategy produces significant profits over the sample period.

However, our results suggest that the factor momentum effect is weak when individual factors are considered. Only a small group of factors (RCFs) have strong time series return continuation while the remaining factors (non-RCFs) do not. An FMOM strategy based on RCFs significantly outperforms one based on all the factors. By contrast, the annualised return of FMOM based on non-RCFs is much lower than that of FMOM in the RCFs and FMOM in all factors. A further breakdown of factors suggests that the Value-Growth group exhibits stronger factor momentum effect whereas the Momentum and Fractions groups show weak effect. Without the RCFs, FMOM loses its ability to fully span the individual stock momentum, indicating that the choice of factors matters. Our findings challenge the view that factor momentum is pervasive and that its ability to explain the dynamics of individual stock momentum is not specific to a subset of factors.

We find that the betting against beta factor of Frazzini and Pedersen (2014) makes the greatest contribution to the FMOM profits. We find that the strong momentum effect of BAB stems from its unique rank-weighting scheme whereas all the other factors use the value-weighted portfolio in our sample. This finding challenges an intuitive hypothesis that momentum in anomalies are caused by their stock selection mechanism, thereby shedding light on a future research question: is the weighting scheme in financial anomalies causing factor momentum?

Finally, although the factor momentum trading strategy generates positive returns that are statistically significant, it does not outperform a simple long-only strategy. From the perspective of market practitioners, factor momentum may not be an attractive trading strategy for investors who are seeking abnormal profits in financial markets.

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Table 1: Summary statistics of EL 22 factors.

Summary statistics of EL 22 factors. The first three columns report the factor names, abbreviations, and original studies. The fourth column reports the sample start dates, and the end date for all factors is July 2015. Columns Five to Eight report the annualised mean returns, standard deviations, Sharpe ratios, and first order autocorrelations. '*', '**', and '***' indicate that the coefficients are statistically significant at the 10%, 5% and 1% levels, respectively.

Factor	Abbrev	Original Study	Start date	Mean (%)	SD (%)	SR	AR(1)
		U.S. factors					
Size	SMB	Banz (1981)	1963-07-01	3.09	10.55	0.29	0.06
Value	HML	Barr Rosenberg and Lanstein (1984)	1963-07-01	4.25	9.73	0.44	0.17***
Profitability	RMW	Novy-Marx (2013)	1963-07-01	3.17	7.64	0.42	0.16***
Investment	CMA	Titman et al. (2004)	1963-07-01	3.66	6.97	0.53	0.13***
Momentum	UMD	Jegadeesh and Titman (1993)	1963-07-01	8.83	14.66	0.60	0.05
Accruals	AC	Sloan (1996)	1963-07-01	2.67	6.75	0.40	0.07*
Betting against beta	BAB	Frazzini and Pedersen (2014)	1963-07-01	10.64	11.56	0.92	0.13***
Cash flow to price	CP	Barr Rosenberg and Lanstein (1984)	1963-07-01	3.37	10.25	0.33	0.08*
Earnings to price	EP	Basu (1983)	1963-07-01	4.14	10.12	0.41	0.12***
Liquidity	LIQ	Pástor and Stambaugh (2003)	1968-01-01	5.18	11.81	0.44	0.08*
Long-term reversals	LREV	De Bondt and Thaler (1985)	1963-07-01	3.30	8.66	0.38	0.17***
Net share issues	NI	Loughran and Ritter (1995)	1963-07-01	3.12	8.29	0.38	0.10***
Quality minus junk	QMJ	Asness et al. (2019)	1963-07-01	4.67	7.77	0.60	0.18***
Residual variance	IVOL	Ang et al. (2006)	1963-07-01	1.49	17.60	0.08	0.12***
Short-term reversals	SREV	Jegadeesh (1990)	1963-07-01	6.02	10.85	0.56	-0.02
		Global factors					
Size	GSMB	Banz (1981)	1990-07-01	1.23	7.46	0.17	-0.01
Value	GHML	Barr Rosenberg and Lanstein (1984)	1990-07-01	4.77	7.48	0.64	0.33***
Profitability	GRMW	Novy-Marx (2013)	1990-07-01	4.38	4.76	0.92	0.19***
Investment	GCMA	Titman et al. (2004)	1990-07-01	2.28	6.32	0.36	0.36***
Momentum	GUMD	Jegadeesh and Titman (1993)	1990-07-01	9.10	12.59	0.72	0.29***
Betting against beta	GBAB	Frazzini and Pedersen (2014)	1990-11-01	10.13	9.70	1.04	0.19***
Quality minus junk	GQMJ	Asness et al. (2019)	1990-07-01	6.18	7.15	0.86	0.16***

Table 2: Summary statistics of HXZ 187 factors

Summary statistics of HXZ 187 factors broken down into six categories. The first two columns show the category names and numbers of anomalies in each category. The third and fourth columns report the annualised mean return averaged across all anomalies within each category and the number of factors that are statistically significant ($t > 1.96$) in it. Similarly, Columns Five to Eight report the average annualised standard deviation, the average annualised Sharp ratio, the average first order autocorrelation, and the number of factors that have significant ($t > 1.96$) first order autocorrelations. The sample period ranges from January 1967 to December 2020.

Category	N	Mean (%)	NoS (Mean)	SD (%)	SR	AR1	NoS (AR1)
Momentum	41	6.75	41	9.38	0.75	0.05	12
Value-Growth	32	4.24	29	11.10	0.39	0.14	29
Investment	29	3.67	28	6.67	0.56	0.08	17
Profitability	45	6.52	43	8.79	0.76	0.13	35
Intangibles	30	5.22	25	10.05	0.52	0.09	19
Frictions	10	2.74	2	15.39	0.15	0.06	6

Table 3: Abnormal returns of factor momentum strategies at individual factor level (EL 22 factors)

This table presents the relationship between factor momentum and momentum factor at individual factor level. Columns Two to Five report the regression results of Equation 1 including the intercept of regression (α) in percentage terms, the coefficient of the momentum factor (β_1) and their corresponding t-statistics, $t(\alpha)$ and $t(\beta_1)$. The last column reports the return contribution of each factor in the entire factor momentum portfolio. The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). '*', '**', and '***' indicate that the coefficients are statistically significant at 10%, 5% and 1% levels, respectively. The sample ranges from July 1964 to December 2015.

Factor	α (%)	$t(\alpha)$	β_1	$t(\beta_1)$	Return contribution (%)
SMB	0.21	(1.52)	0.22***	(3.42)	6.88
HML	0.02	(0.20)	0.30***	(7.72)	3.13
RMW	0.16*	(1.82)	0.21***	(4.01)	3.80
CMA	-0.02	(-0.24)	0.13***	(4.11)	2.90
AC	0.05	(0.62)	0.10***	(3.70)	1.10
BAB	0.58***	(3.62)	0.29***	(3.62)	13.68
CP	0.01	(0.10)	0.26***	(7.99)	3.87
EP	-0.01	(-0.07)	0.25***	(7.17)	4.24
LIQ	0.13	(0.93)	0.11**	(2.31)	3.60
LREV	0.17	(1.54)	0.14***	(3.92)	6.03
NI	-0.11	(-1.18)	0.19***	(5.81)	1.56
QMJ	0.15	(1.60)	0.21***	(8.11)	4.62
IVOL	0.04	(0.21)	0.73***	(11.45)	10.34
SREV	0.12	(0.80)	-0.02	(-0.38)	4.67
GSMB	-0.08	(-0.63)	0.09	(1.47)	1.13
GHML	0.03	(0.27)	0.30***	(4.64)	5.42
GRMW	-0.02	(-0.38)	0.06***	(2.44)	3.89
GCMA	0.03	(0.23)	0.31***	(6.25)	3.29
GBAB	0.51***	(3.26)	0.17**	(2.13)	11.40
GQMJ	0.11	(0.87)	0.22***	(6.08)	4.46

Table 4: Number of factors with significant abnormal returns at individual factor level (HXZ 187 factors)

Based on four different benchmark models, we count the number of FMOM strategies that yield significant abnormal returns ($t > 1.96$) for each category. The models are the Fama and French (2015) five-factor model (FF5), the Hou et al. (2015) q-factor model (q Model), the Stambaugh et al. (2012) four-factor model (SY4), and the Daniel et al. (2020) three-factor model (DHS). As these 187 hypotheses are tested simultaneously, we further apply the Superior Predictive Ability controlling the False Discovery Proportion (FDP-SPA) proposed by Hsu et al. (2014) to manage the potential Type I errors. The last column reports the number of significances in terms of different benchmarks after adopting the FDP-SPA. The sample period ranges from January 1967 to December 2020.

Category	Momentum	Value-Growth	Investment	Profitability	Intangibles	Frictions	All	FDP-SPA
FF5	22	19	10	34	13	4	102	22
q Model	18	25	9	28	15	3	98	22
SY4	22	16	7	30	11	3	89	14
DHS	14	24	13	31	12	4	98	12

Table 5: Return continuation tests (EL 22 factors)

This table reports the regression results of Equations 4 (Model 1) and 5 (Model 2) and the factor momentum profits that sourced from return continuation (Model 3). For Models 1 and 2, we report the slopes, the corresponding t-statistics, and R-squared. For Model 3, we present the annualised mean returns created by the covariance term of Equation 6. The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). '*', '**', and '***' indicate that the coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. The sample ranges from July 1964 to December 2015.

	Model 1			Model 2			Model 3	
Factor	β	t(β)	R^2 (%)	β	t(β)	R^2 (%)	Mean	t-value
U.S. factors								
Size	0.004***	(2.90)	1.30	0.023*	(1.80)	0.80	0.033**	(2.20)
Value	0.001	(0.87)	0.20	0.018*	(1.67)	0.60	0.008	(0.57)
Profitability	0.002*	(1.85)	0.70	0.021	(1.42)	0.90	0.020*	(1.93)
Investment	0.001	(1.47)	0.40	0.018**	(2.04)	0.60	0.016	(1.59)
Accruals	0.000	(0.45)	0.00	-0.003	(-0.23)	0.00	0.005	(0.58)
Betting against beta	0.007***	(2.83)	2.70	0.038***	(3.20)	4.20	0.073***	(3.85)
Cash-flow to price	0.002	(1.50)	0.40	0.011	(0.99)	0.20	0.014	(0.94)
Earnings to price	0.002	(1.39)	0.40	0.016	(1.49)	0.50	0.015	(0.96)
Liquidity	0.001	(1.08)	0.10	0.006	(0.54)	0.00	0.013	(0.81)
Long-term reversals	0.003***	(3.05)	1.70	0.031***	(2.72)	1.60	0.035***	(2.94)
Net share issues	0.000	(0.48)	0.00	0.027***	(2.68)	1.50	-0.001	(-0.08)
Quality minus junk	0.002**	(2.21)	0.70	0.024*	(1.74)	1.10	0.026**	(2.26)
Residual variance	0.006***	(3.48)	1.40	0.017	(1.28)	0.50	0.034	(1.59)
Short-term reversals	0.000	(0.11)	0.00	0.002	(0.12)	0.00	0.017	(1.10)
Global factors								
Size	0.001	(0.61)	0.10	0.012	(0.70)	0.20	0.006	(0.45)
Value	0.003**	(1.99)	1.80	0.032*	(1.78)	4.20	0.035**	(1.99)
Profitability	0.002***	(2.36)	1.10	0.018	(1.04)	0.50	0.033***	(3.15)
Investment	0.002	(1.59)	1.60	0.025	(0.85)	1.80	0.022	(1.19)
Betting against beta	0.006***	(2.86)	3.60	0.03**	(2.00)	2.30	0.084***	(3.95)
Quality minus junk	0.001	(0.72)	0.20	0.011	(0.54)	0.20	0.033*	(1.86)

Table 6: Number of factors with significant return continuation (HXZ 187 factors)

This table summarises the number of factors with significant return continuation for HXZ 187 factors broken down into six categories. Model 1 and Model 2 represent the regressions shown in Equations 4 and 5, and Model 3 measures the factor momentum profits that sourced from return continuation. For Models 1 and 2, the number of factors that have significant coefficients ($t > 1.96$), is reported. For Model 3, we present the number of factors whose annualised mean profits generated by the covariance term of Equation 6 are statistically significant ($t > 1.96$). The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). In the last column, we report the number of RCFs in each category if they have statistically significant return continuation in all the three models. The sample period ranges from January 1967 to December 2020.

Category	N	Model 1	Model 2	Model 3	RCF
Momentum	41	9	3	21	2
Value-Growth	32	23	15	18	14
Investment	29	14	10	18	9
Profitability	45	20	15	32	8
Intangibles	30	10	12	11	7
Frictions	10	3	2	3	2
Total	187	79	57	103	42

Table 7: Factor momentum and time series momentum effect (EL 22 factors)

This table compares the performance of FMOM and a time series history strategy of Huang et al. (2020) (TSH) as well as their differences for the 20 factors. FMOM is the time series factor momentum strategy, and TSH refers to a strategy that longs the factor if its historical mean is positive and shorts it otherwise. FMOM-TSH reports the differences whereas the Diff strategy represents our robustness check as shown in Equation 7. All the annualised means are in percentage terms. The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). '*', '**', and '***' indicate that the coefficients are statistically significant at the 10%, 5% and 1% levels, respectively. The sample ranges from July 1964 to December 2015.

Factor	FMOM	TSH	FMOM-TSH		Diff Strategy	
	Mean(%)	Mean(%)	Mean(%)	t-value	Mean(%)	t-value
All	4.07***	3.75***	0.32	(0.45)	2.83***	(4.50)
			U.S. factors			
Size	4.75***	2.93*	1.81	(0.96)	3.24**	(2.13)
Value	2.41*	4.01***	-1.60	(-0.76)	1.97	(1.42)
Profitability	3.03***	2.60**	0.43	(0.26)	2.68***	(2.36)
Investment	2.41**	3.22***	-0.81	(-0.76)	1.56	(1.45)
Accruals	1.03	2.42***	-1.39	(-1.24)	-0.27	(-0.28)
Betting against beta	11.21***	10.18***	1.03	(0.44)	8.89***	(3.93)
Cash-flow to price	2.83*	3.30**	-0.47	(-0.24)	1.32	(0.84)
Earnings to price	3.21**	4.06***	-0.85	(-0.43)	1.58	(0.99)
Liquidity	2.90*	4.64***	-1.74	(-1.01)	3.35**	(2.26)
Long-term reversals	4.63***	3.27***	1.36	(0.81)	4.19***	(3.41)
Net share issues	1.06	2.93**	-1.87	(-1.47)	2.08*	(1.67)
Quality minus junk	3.70***	4.46***	-0.76	(-0.67)	2.76**	(2.29)
Residual variance	7.40***	-3.18	10.59***	(3.17)	6.82***	(2.90)
Short-term reversals	3.10**	5.86***	-2.76	(-1.66)	-0.80	(-0.54)
			Global factors			
Size	1.09	0.00	1.09	(0.64)	1.99	(1.58)
Value	5.24***	4.10**	1.14	(0.49)	3.41	(1.6)
Profitability	3.76***	4.16***	-0.40	(-0.53)	-0.25	(-0.22)
Investment	3.18*	1.93	1.25	(1.09)	2.93	(1.58)
Betting against beta	11.02***	8.26***	2.76	(1.23)	6.81***	(2.55)
Quality minus junk	4.31***	5.87***	-1.56	(-1.24)	1.52	(0.92)

Table 8: Factor momentum and time series momentum effect (HXZ 187 factors)

This table compares the performance of FMOM and a time series history strategy of Huang et al. (2020) (TSH) based on HXZ 187 factors broken down into six categories. TSH refers to a strategy that longs the factor if its historical mean is positive and shorts it otherwise. FMOM-TSH reports the difference in mean returns whereas the Diff strategy represents our robustness check as shown in Equation 7. All the annualised mean returns are shown in percentage terms, and NoS represents the number of factors that have statistically significant mean returns with $t > 1.96$. The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). The sample period ranges from January 1967 to December 2020.

Category	FMOM		TSH		FMOM-TSH		Diff	
	Mean(%)	NoS	Mean(%)	NoS	Mean(%)	NoS	Mean(%)	NoS
All	4.63	154	4.91	149	-0.28	2	2.07	75
Momentum	4.80	35	6.66	40	-1.86	0	0.08	0
Value-Growth	5.15	28	3.73	19	1.42	0	3.56	20
Investment	2.95	24	3.47	26	-0.51	0	1.50	11
Profitability	6.03	41	6.24	40	-0.21	0	2.76	27
Intangibles	4.10	22	4.67	23	-0.57	0	2.87	15
Frictions	3.65	4	1.83	1	1.82	2	1.67	2

Table 9: Performance of factor momentum in different sets of factors (EL 22 factors)

This table reports the average annualised returns in percentage terms ($Mean$), standard deviations in percentage terms (SD), Sharpe ratios (SR), skewness, and kurtosis for the factor momentum trading scheme based on a given set of factors, where the buy-and-hold portfolio is constructed as a benchmark. Following Ehsani and Linnainmaa (2021), the two momentum factors are excluded from the sample of 22 factors. Therefore, FMOM6, FMOM14, and FMOM20 represent the time series factor momentum strategies based on 6 RCFs, 14 non-RCFs, and the whole sample, respectively. BAH6, BAH14, and BAH20 are the buy-and-hold strategies based on the same three samples, respectively. The sample period ranges from July 1964 to December 2015.

	RCFs		non-RCFs		Full sample	
	BAH6	FMOM6	BAH14	FMOM14	BAH20	FMOM20
Mean (%)	5.2	6.43	3.65	3.07	4.27	4.07
SD (%)	4.61	5.23	4.61	4.48	3.97	4.25
SR	1.24	1.23	0.79	0.69	1.08	0.96
Skewness	0.21	-0.01	0.08	0.02	0.20	0.02
Kurtosis	0.43	0.29	0.35	0.34	0.51	0.43

Table 10: Performance of factor momentum by categories (HXZ 187 factors)

This table compares the performance of FMOM and buy-and-hold (BAH) strategies based on HXZ 187 factors broken down into six categories. Panel A reports the average annualised returns ($Mean$), standard deviations (SD), Sharpe ratios (SR), skewness, and kurtosis across factors within each of the six categories. Panel B reports the $Mean$(%) and t-value of the differences between FMOM and BAH strategies. The sample period ranges from January 1967 to December 2020.

Panel A: Average performance of BAH and FMOM strategies

	Momentum		Value-Growth		Investment		Profitability		Intangibles		Frictions	
	BAH	FMOM	BAH	FMOM	BAH	FMOM	BAH	FMOM	BAH	FMOM	BAH	FMOM
Mean (%)	6.75	4.86	4.49	5.10	3.82	2.95	6.41	5.82	4.93	3.78	2.89	3.82
SD (%)	6.42	5.44	8.98	7.91	3.85	3.37	5.95	5.03	3.04	4.09	7.78	9.43
SR	1.05	0.89	0.50	0.64	0.99	0.88	1.08	1.16	1.62	0.92	0.37	0.41
Skewness	1.05	0.50	0.36	0.84	0.07	0.16	0.53	0.20	0.60	0.99	0.87	0.46
Kurtosis	7.76	6.85	5.19	9.01	0.13	2.04	3.76	5.18	2.24	9.24	8.58	9.09

Panel B: Difference (FMOM-BAH)

	Momentum	Value-Growth	Investment	Profitability	Intangibles	Frictions
Mean (%)	-1.89	0.61	-0.87	-0.59	-1.15	0.93
t-value	-4.25	0.35	-1.82	-0.89	-1.98	0.65

Table 11: Factor momentum across RCFs and non-RCFs

Panel A and C report the annualised average returns (in percentage terms) and t-statistics for the three sets of factor momentum (FMOM) portfolios, namely the whole sample, non-RCFs, and RCFs. The BAH strategies are constructed as benchmarks. Panel B and D present the spreads between the returns of different sets of FMOM portfolios based on EL 20 factors and HXZ 187 factors, respectively. The 20-factor sample begins in July 1964 and ends in December 2015, and the 187-factor sample horizon ranges from January 1967 to December 2020.

Sample	BAH	FMOM	Winners	Losers
Panel A: Annualised returns, EL 20 factors				
FMOM20	4.27	4.07	6.30	0.76
	(7.74)	(6.88)	(9.80)	(0.83)
FMOM14	3.65	3.07	5.28	1.22
	(5.73)	(4.93)	(7.41)	(1.22)
FMOM6	5.20	6.43	8.88	-0.41
	(8.82)	(8.82)	(11.13)	(-0.38)
Panel B: Difference, EL 20 factors				
FMOM20-FMOM14		0.99	1.02	-0.46
		(5.42)	(3.88)	(-1.15)
FMOM20-FMOM6		-2.36	-2.57	1.16
		(-5.33)	(-4.74)	(1.25)
Panel C: Annualised returns, HXZ 187 factors				
FMOM187	5.30	4.63	7.13	1.78
	(11.99)	(8.08)	(11.49)	(2.50)
FMOM145	5.32	4.26	6.82	2.47
	(11.33)	(7.30)	(10.43)	(3.56)
FMOM42	5.19	5.91	8.16	-0.33
	(9.34)	(9.60)	(13.41)	(-0.36)
Panel D: Difference, HXZ 187 factors				
FMOM187-FMOM145		0.38	0.32	-0.69
		(4.89)	(3.19)	(-4.71)
FMOM187-FMOM42		-1.28	-1.03	2.11
		(-4.78)	(-2.89)	(4.31)

Table 12: Differences between sets of FMOM portfolios with multiple formation and holding periods

This table reports the means and t-statistics of FMOM6 minus FMOM20, FMOM20 minus FMOM14, FMOM42 minus FMOM187, and FMOM187 minus FMOM145 using different formation and holding periods. Following Ehsani and Linnainmaa (2021), all FMOM strategies long factors with positive past 12- month returns over a formation period and short otherwise. FMOM6, FMOM14 and FMOM20 are selected based on RCFs, non-RCFs and the entire EL sample. Similarly, FMOM42, FMOM145, and FMOM187 are constructed based on 42 RCFs, 145 non-RCFs, and the entire HXZ 187 factors. The sample of Panel A and B begins in July 1964 and ends in December 2015, and the sample period in Panel C and D ranges from January 1967 to December 2020.

Panel A: FMOM6-FMOM20								
Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	1.15	1.10	1.86	2.36	2.54	2.50	4.45	5.33
3	1.51	1.71	1.65	2.50	3.28	3.68	3.75	4.93
6	1.53	1.52	1.46	2.43	5.29	4.11	3.30	4.71
12	1.44	1.58	1.83	1.91	5.25	5.27	4.64	3.55
Panel B: FMOM20-FMOM14								
Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	0.42	0.45	0.65	1.00	2.25	2.51	3.87	4.26
3	0.58	0.66	0.56	0.85	3.17	3.30	3.07	4.22
6	0.59	0.56	0.47	0.83	5.03	3.48	2.63	4.08
12	0.52	0.59	0.63	0.68	4.91	4.53	3.74	3.33
Panel C: FMOM42-FMOM187								
Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	0.82	1.11	1.22	1.28	3.14	4.13	4.75	4.78
3	0.71	0.84	0.97	1.12	4.11	4.15	4.18	4.34
6	0.48	0.61	0.77	0.96	3.37	3.48	3.56	3.74
12	0.43	0.64	0.71	0.77	3.93	4.52	3.82	3.37
Panel D: FMOM187-FMOM145								
Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	0.25	0.33	0.36	0.38	3.22	4.23	4.90	4.89
3	0.21	0.25	0.29	0.33	4.22	4.24	4.24	4.38
6	0.14	0.18	0.23	0.28	3.51	3.55	3.61	3.76
12	0.13	0.19	0.21	0.22	4.09	4.59	3.85	3.35

Table 13: Out-of-sample factor momentum

This table reports the performance of the OOS FMOM portfolio based on the EL sample. We apply different rolling windows ranging from 24 to 120 months with intervals of 12-month. Panel A presents the means and t-values of the OOS FMOM returns. Panel B reports the top ten factors that yield the highest return contributions in the OOS FMOM portfolio measured using Equation 3. Sum RC refers to the sum of return contributions for these ten factors in the OOS FMOM. No.RCF counts how many RCFs identified in the in-sample test appear in the top ten factors.

Panel A: OOS FMOM performance

	Rolling Window								
	24	36	48	60	72	84	96	108	120
Mean (%)	4.88	5.06	4.92	4.62	4.66	4.93	5.09	5.54	5.25
t-value	(4.84)	(5.14)	(5.13)	(4.84)	(4.94)	(4.99)	(5.19)	(5.58)	(5.16)

Panel B: Factor ranking in terms of return contributions

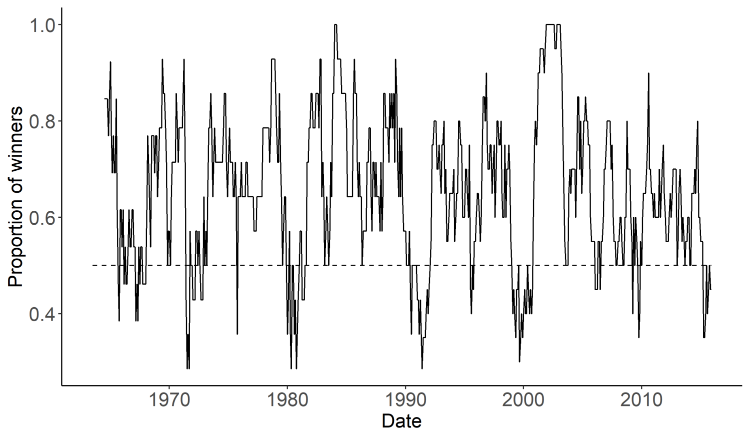
1	GBAB	GBAB	BAB	BAB	BAB	BAB	BAB	GBAB	BAB
2	BAB	BAB	GBAB	GBAB	GBAB	GBAB	GBAB	BAB	GBAB
3	GHML	GRMW	SMB	SREV	GRMW	GCMA	GHML	EP	GRMW
4	SMB	GHML	GHML	GHML	SMB	GHML	EP	GRMW	SMB
5	CMA	CMA	SREV	SMB	GHML	GRMW	SMB	SMB	GHML
6	LREV	SREV	GRMW	GRMW	SREV	GQMJ	GRMW	GHML	SREV
7	EP	EP	QMJ	QMJ	LREV	SMB	QMJ	SREV	EP
8	HML	QMJ	CP	CP	RMW	SREV	CP	IVOL	GCMA
9	GRMW	IVOL	EP	RMW	GCMA	IVOL	IVOL	GCMA	CMA
10	SREV	SMB	CMA	EP	CP	EP	SREV	HML	CP
Sum RC (%)	86.59	87.80	82.54	97.07	82.61	82.46	77.82	82.67	88.92
No. RCF	5	6	5	6	5	5	6	6	5

Table 14: Spanning regressions

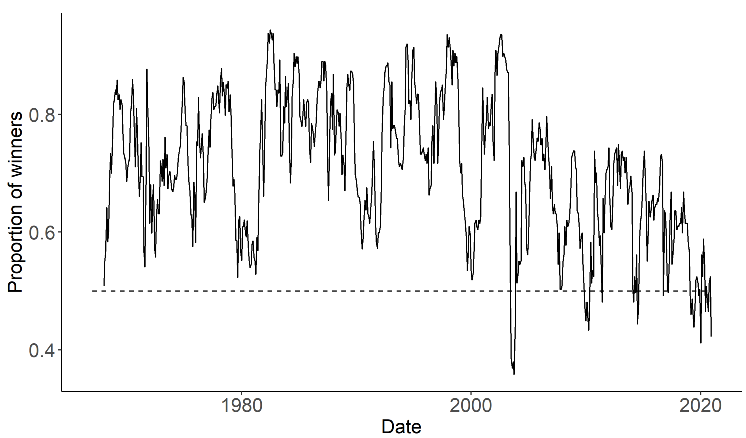
This table reports estimates from spanning regressions in which the dependent variable is the monthly return on one of the individual stock momentum factors (IMOM) or factor momentum based on RCFs (FMOM6) in Panel A and non-RCFs (FMOM14) in Panel B. If the dependent variable is IMOM, we estimate the first regression of Equation 8, where the dependent variable is one of the three individual stock momentum (standard, industry and intermediate momentum) returns, and the independent variable is the FF5 plus FMOM returns. If the dependent variable is FMOM, we estimate the second regression of Equation 8, where the dependent variable is FMOM returns, and the independent variable is the FF5 plus one of the IMOM returns. We report the intercepts (%) and the slopes for the FMOM and IMOM with t-statistics in the lines below. '*', '**', and '***' indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively. The sample begins in July 1964 and ends in December 2015.

Individual stock momentum(IMOM)	Dependent variable			
Panel A: Spanning regression of IMOM and RCFs				
	IMOM		FMOM6	
	α	FMOM6	α	IMOM
Standard momentum	0.03	1.56***	0.30***	0.19***
	(0.20)	(16.27)	(5.95)	(16.27)
Industry momentum	-0.30	1.35***	0.41***	0.15***
	(-1.57)	(10.93)	(7.38)	(10.93)
Intermediate momentum	0.06	0.96***	0.34***	0.23***
	(0.55)	(13.02)	(5.12)	(13.02)
Panel B: Spanning regression of IMOM and non-RCFs				
	IMOM		FMOM14	
	α	FMOM14	α	IMOM
Standard momentum	0.25*	2.16***	0.08*	0.19***
	(1.89)	(21.53)	(1.91)	(21.53)
Industry momentum	-0.10	1.72***	0.20***	0.09***
	(-0.56)	(12.31)	(4.25)	(12.31)
Intermediate momentum	0.21*	1.20***	0.13**	0.21***
	(1.91)	(14.45)	(2.84)	(14.45)

Figure 1: The proportion of winner signals



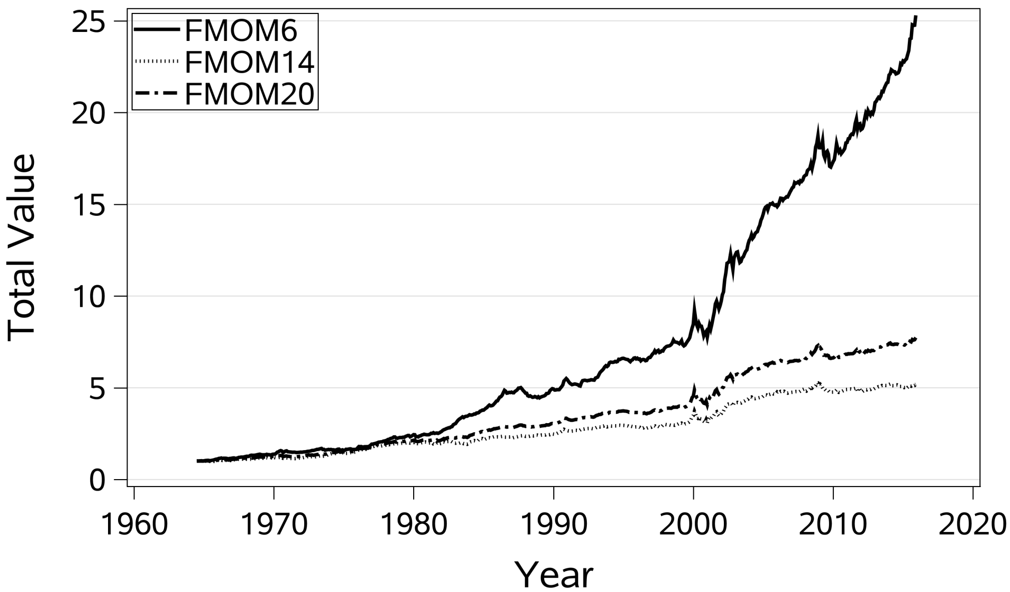
Panel A: EL sample



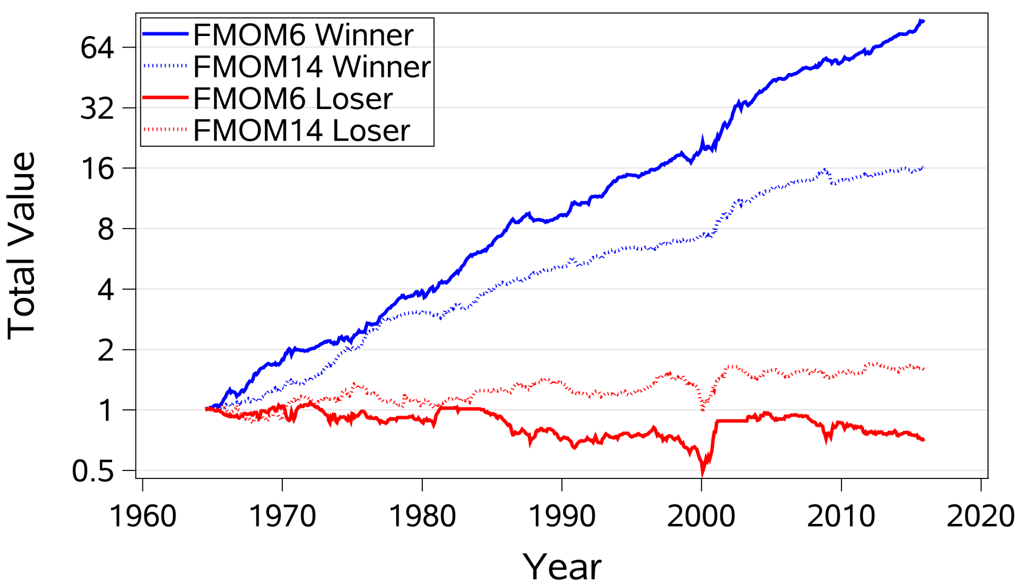
Panel B: HXZ sample

Panel A and B present the monthly proportion of winner signals based on the EL and HXZ samples, respectively. The proportion of winner signals is measured as: $\frac{\sum_{i=1}^{n} sgn_{win,i}}{n}$, where sgn_{win} equals one for winners and zero otherwise, n refers to the number of factors. The dashed line represents a standard proportion that equals 0.5. When the solid line is above the dashed one, the number of winners exceeds that of losers.

Figure 2: Cumulative performance of different factor momentum portfolios



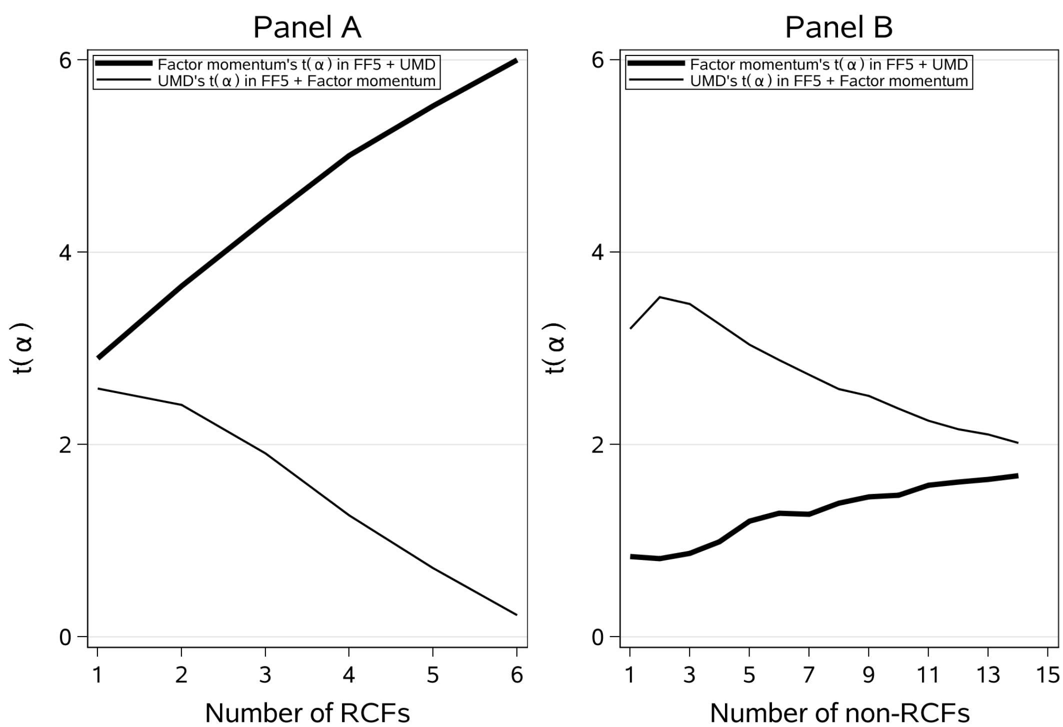
Panel A: Factor momentum strategies



Panel B: Winner and loser portfolios of FMOM6 and FMOM20

Panel A compares the cumulative returns of the FMOM6, FMOM14, and FMOM20 portfolios over the sample period. Panel B compares the cumulative returns of the winner and loser portfolios for FMOM6 and FMOM14, respectively. We assume that an equal amount of $1 is invested in each portfolio on the first trading day of July 1964.

Figure 3: Individual stock momentum versus FMOM6 and FMOM14



We form random subsets of the RCFs (Panel A) and non-RCFs (Panel B) and construct time series factor momentum strategies that trade on these factors. The number of factors ranges from 1 to 6 for RCFs and 1 to 14 for non-RCFs. The thick line represents the factor momentum strategy's averages t(α) from the Fama-French five-factor plus the UMD model; the thin line represents UMD's average t(α) from the Fama-French five-factor plus the FMOM model.

Appendix

A. Out-of-sample predictability of FMOM

To examine the out-of-sample predictability of each factor, we calculate the out-of-sample R^2 of Equation 5 (Model 2 of Table 5). Following Huang et al. (2020), we report the out-of-sample R^2 and compare it to the in-sample R^2 in Figure A.1. The in-sample R^2 for each factor is the same as the value of Column 7 in Table 5. To measure the out-of-sample R squared, R^2_{OS}, we use the method of Campbell and Thompson (2008) as:

$$R^2_{OS} = 1 - \frac{\sum_{t=K}^{T-1}(r^i_{t+1} - \hat{r}^i_{t+1})^2}{\sum_{t=K}^{T-1}(r^i_{t+1} - \bar{r}^i_{t+1})^2}, \tag{A.1}$$

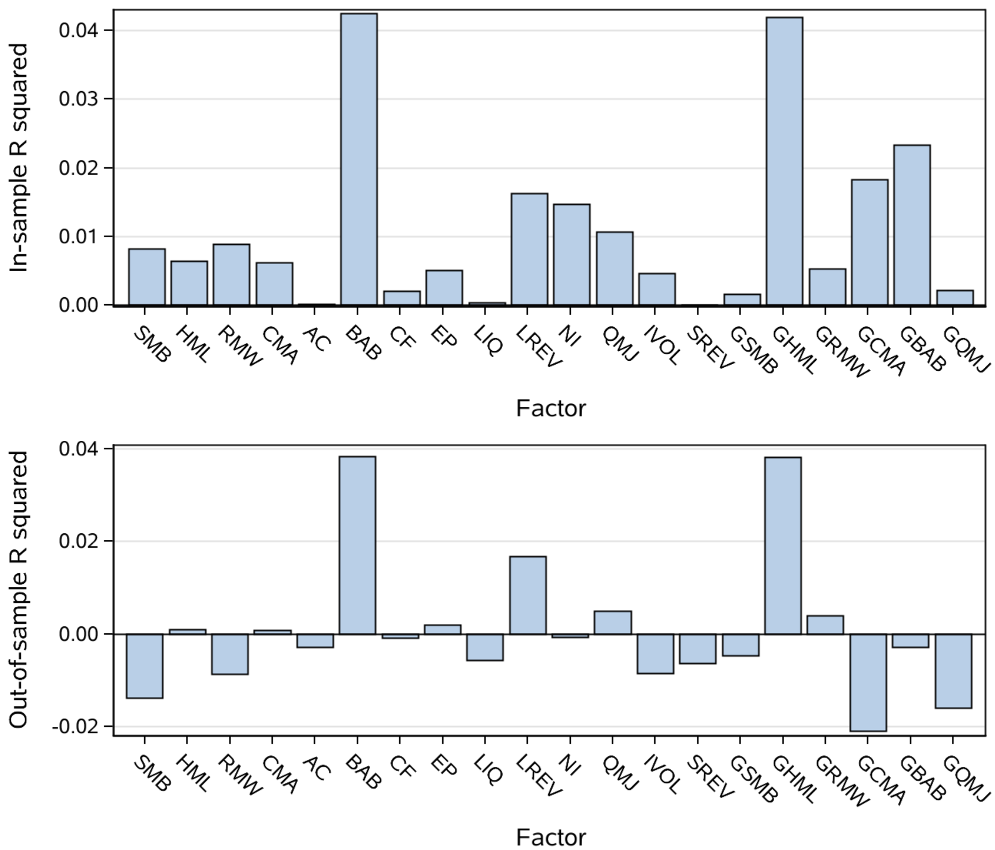
where K is the initial training sample, $\hat{r}^i_{t+1}$ is the expected return estimated as $\hat{r}^i_{t+1} = \hat{\alpha}_t + \hat{\beta}_t r^i_{t-12,t-1}$, $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the coefficients of Equation 5, and $\bar{r}^i_{t+1}$ is the sample mean of asset i with returns from the first month to the most recent month t. In line with Huang et al. (2020), we employ the first 15 years of data for in-sample training and the remaining data for out-of-sample assessment.

If $R^2_{OS} > 0$, the out-of-sample prediction of Model 2 in Table 5, $\hat{r}^i_{t+1}$, outperforms the sample mean forecast, $\bar{r}^i_{t+1}$. To assess whether the forecast of Model 2 delivers a statistically significant lower Mean Squared Forecast Error (MSFE) than sample mean, we test a null hypothesis that the MSFE of the sample mean forecast is less than or equal to that of the Model 2 forecast. This null hypothesis is equivalent to $H_0 : R^2_{OS} \leq 0$ (Huang et al., 2020).

Figure A.1 shows that the R^2_{OS} is much smaller than the in-sample R^2 on average. 12 out of 20 factors yield negative R^2_{OS}. Among the rest eight factors with positive R^2_{OS}, only four of them are statistically significant at the 10% level, namely CMA, BAB, LREV, and GHML.[10] This result implies that most of these 20 factors have no significant FMOM effect out-of-sample.

[10] As a robustness check, we further apply alternative loss functions, e.g., Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), in the Clark and West (2007) statistic. The results are consistent with outcomes when using MSFE.

Figure A.1: In-sample and out-of-sample R^2



This figure plots both the in-sample and out-of-sample R^2 for Model 2 of Table 5. The in-sample R^2 for each factor is the same as the value of Column Seven in Table 5. The out-of-sample R^2 is estimated by Equation A.1.

B. Factor momentum with different formation and holding periods

Table B.1 presents the performance of the FMOM6, FMOM14, and FMOM20 strategies with formation and holding periods ranging from one to 12 months. We also report the performance of FMOM42, FMOM145, and FMOM187 strategies in Table B.2. When the holding period is longer than a month, we use the overlapping-portfolio approach of Jegadeesh and Titman (1993) to generate the portfolio returns. Every FMOM portfolio produces statistically significant profit at the 1% level regardless of formation period-holding period combinations.

Panel A of Table B.1 shows the performance of the EL FMOM20 strategies. The portfolio with 12-month formation period and one-month holding period produces the highest average return, 4.07% per year (t-value=6.88). Panels B and C report the performance of factor momentum strategies in RCFs and non-RCFs, respectively. Similar to the FMOM20 strategy, the FMOM6 portfolio with the 12-month formation and one-month holding period creates the best annualised return, 6.43% (t-value=8.82). However, FMOM14 generates the highest profits based on the one-month formation and holding period, 3.64% per year (t-value=5.84). The results of HXZ 187 factors are reported in Table B.2, in which most of the key findings are consistent with those in the EL sample.

Table B.1: Performance of factor momentum strategies with multiple information and holding periods (EL 22 factors)

This table reports the annualised average returns and t-values of factor momentum strategies based on three different sets of factors with formation period and holding period ranging from one month to 12 months. Following Ehsani and Linnainmaa (2021), all strategies long available factors with positive returns over a formation period and short others. FMOM6, FMOM14, and FMOM20 are constructed on 6 RCFs, 14 non-RCFs, and all 20 factors, respectively.

Panel A: Factor momentum based on 20 factors

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	4.06	3.42	3.81	4.07	6.84	5.35	6.49	6.88
3	2.05	2.23	2.99	3.35	5.70	4.50	4.19	5.34
6	1.84	2.02	2.75	2.99	6.31	4.30	4.25	5.16
12	1.65	2.03	2.51	2.46	7.44	5.80	5.23	4.75

Panel B: Factor momentum based on 6 RCFs

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	5.21	4.52	5.67	6.43	6.98	5.95	7.77	8.82
3	3.56	3.94	4.64	5.85	5.68	5.13	5.01	7.32
6	3.37	3.54	4.21	5.42	7.44	5.16	4.66	6.86
12	3.08	3.62	4.34	4.37	7.75	6.64	6.07	5.57

Panel C: Factor momentum based on 14 non-RCFs

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	3.64	2.97	3.16	3.30	5.84	4.40	5.23	5.27
3	1.47	1.57	2.44	2.50	4.00	3.34	3.53	3.71
6	1.25	1.46	2.28	2.16	4.33	3.34	3.74	3.46
12	1.13	1.45	1.88	1.78	5.31	4.57	4.02	3.17

Table B.2: Performance of factor momentum strategies with multiple information and holding periods (HXZ 187 factors)

This table reports the annualised average returns and t-values of factor momentum strategies based on three different sets of factors with formation period and holding period ranging from one month to 12 months. Following Ehsani and Linnainmaa (2021), all strategies long available factors with positive returns over a formation period and short others. FMOM42, FMOM145, and FMOM187 are constructed on 42 RCFs, 145 non-RCFs, and all 187 factors, respectively.

Panel A: Factor momentum based on 187 factors

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	4.15	3.61	4.15	4.63	7.33	6.64	7.47	8.08
3	2.47	2.84	3.62	4.20	6.29	5.94	6.93	7.61
6	2.22	2.59	3.26	3.82	7.04	6.35	6.87	7.37
12	2.01	2.58	3.11	3.33	8.51	8.09	7.89	7.05

Panel B: Factor momentum based on 42 RCFs

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	4.97	4.72	5.37	5.91	8.44	7.94	9.03	9.60
3	3.18	3.68	4.59	5.32	7.63	7.08	8.17	8.94
6	2.69	3.19	4.03	4.77	8.28	7.38	7.76	8.50
12	2.45	3.22	3.82	4.10	9.81	9.22	8.86	7.95

Panel C: Factor momentum based on 145 non-RCFs

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				t-values			
1	3.90	3.29	3.78	4.26	6.71	5.93	6.70	7.30
3	2.26	2.60	3.34	3.88	5.65	5.39	6.29	6.90
6	2.08	2.41	3.03	3.54	6.42	5.83	6.33	6.71
12	1.88	2.39	2.90	3.11	7.79	7.45	7.27	6.48

C. The decomposition of the betting against beta factor

Frazzini and Pedersen (2014) defined the BAB factor as a symmetric portfolio that buys low-beta stocks, leveraged to a beta of one, and sells high-beta stocks, deleveraged to a beta of one. Han (2022) further proposed a three-step approach to decompose the return of BAB into three components: stock selection, rank weighting scheme, and the beta-parity component. Stock selection refers to the initial low-minus-high-beta portfolio in an equal-weighted scheme. Then, the rank weighting scheme assigns larger weights to the lower (higher) beta securities in the long (short) leg. Finally, the beta-parity approach rescales the long and short legs to make the portfolio market neutral.

We first construct the U.S. BAB factor by buying leveraged low-beta stocks and selling deleveraged high-beta stocks following Frazzini and Pedersen (2014). Next, to explore the source of the extraordinary momentum effect in the BAB anomaly, we conduct the three-step decomposition of Han (2022) to the factor momentum portfolio based on the U.S. BAB factor (FBAB).[11] The decomposition allows us to see which part of the BAB factor contributes to its strong momentum effect. The factor momentum return of each component (stock selection, rank weighting scheme, and beta parity) in month t is measured as:

$$r_t^{FBAB*} = sgn(r_{t-12,t-1}^{BAB}) \times r_t^{BAB*}, \tag{C.1}$$

where $sgn(r_{t-12,t-1}^{BAB})$ takes a value of one if the BAB period return over the past 12 months is positive and of negative one otherwise; r_t^{BAB*} is the return of one of the three components in the decomposition procedure.

In Table C.1, we regress each component (stock selection, rank weighting scheme, and beta parity) on the Fama-French five factors of Fama and French (2015) plus momentum factor of Jegadeesh and Titman (1993) as follows:

$$r_t^{FBAB*} = \alpha + \beta_1 r_t^{UMD} + B \times R_t^{FF5} + \epsilon_t, \tag{C.2}$$

where r_t^{UMD} is the return of momentum factor (Jegadeesh and Titman, 1993) and R_t^{FF5} represents the returns of the Fama-French five factors (Fama and French, 2015). As shown in Table C.1, the alphas of stock selection and rank weighting scheme are both significantly different from zero at the 1% level, whereas the α of beta parity is statistically insignificant. This result implies that the Fama-French five-factor model associated with the momentum factor can fully explain the information of the beta-parity component of FBAB but fails

[11] Please see Han (2022) for detailed methodologies of decomposition.

to explain the remaining two components, thereby indicating that the factor momentum effect is stronger in the stock selection and rank-based weighting processes than in the beta-parity component.

Furthermore, we argue that the extraordinary return continuation of BAB is related to its unique weighting scheme. We check the portfolio construction methods for all the factors and report them in Table C.2. Different from other factors that are value-weighted, the BAB uses a rank weighting scheme, in which higher (lower) beta stocks are given relatively larger weights in the high- (low-) beta portfolio. This scheme assigns larger weights to small firms in the long-leg and to large firms in the short-leg, as firm size is negatively related to the beta coefficient (Sullivan, 1978). By contrast, in a value-weighted scheme, large firms are given larger weights than small firms in both long and short legs. Small firms are weighted more in a portfolio using the ranking weighting scheme than a value-weighted portfolio. Prior literature such as Rouwenhorst (1998), Hong et al. (2000), and Fama and French (2012) has documented that the stock returns of small firms yield stronger autocorrelations than those of large firms. Therefore, the rank-weighted portfolio results in strong return continuation in the BAB factors.

To validate our argument, we compare the return continuation of the BAB factor based on rank, value, and equal weighting schemes using the three sets of models as in Table 5. From the results in Table C.3, we find that the rank-weighted BAB exhibits much stronger return continuation than the value-weighted BAB strategy, and the equal-weighted one sits between them. Across all three models, the coefficients or autocorrelation profit of the rank-weighted BAB are statistically significant at the 1% level, whereas the coefficients of the value-weighted BAB are much lower. We also calculate the return contributions by replacing the rank-weighted BAB with the value-weighted BAB in FMOM20 and FMOM6. The return contribution of the value-weighted U.S. FBAB decreases from 13.68% to 4.93% in FMOM20, and from 28.57% to 11.75% FMOM6. These results further support that the outstanding return contribution of the BAB factor is mainly caused by its rank-weighted portfolio construction.

Table C.1: Factor analysis: factor momentum of BAB factor

This table reports the regression results of Equation C.2. F-Selection, F-Rank, and F-Parity refer to the stock selection, rank weighted portfolio, and beta-neutral parity components of FMOM returns of BAB, respectively. FBAB is the factor momentum in BAB factor. The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). '*', '**', and '***' indicate that the coefficients are statistically significant at the 10%, 5%, and 1% levels, respectively. The sample begins in July 1964 and ends in December 2015.

Dependent	α	RMRF	SMB	HML	RMW	CMA	UMD
F-Selection	0.44***	-0.20***	-0.14	0.37***	-0.16	-0.46***	0.14
	(2.68)	(-3.32)	(-1.38)	(2.55)	(-0.77)	(-2.47)	(1.36)
F-Rank	0.20***	-0.08***	-0.05	0.13**	-0.05	-0.17**	0.05
	(2.85)	(-3.11)	(-1.11)	(2.18)	(-0.52)	(-2.17)	(0.99)
F-Parity	0.02	0.33***	0.30***	-0.26*	0.18	0.52***	0.06
	(0.10)	(3.77)	(2.70)	(-1.69)	(1.08)	(3.24)	(0.62)
FBAB	0.67***	0.06	0.11	0.23**	-0.02	-0.12	0.25***
	(4.08)	(1.17)	(1.40)	(2.18)	(-0.12)	(-0.59)	(3.45)

Table C.2: Weighting schemes of various factors

This table summarises the weighting scheme and stock selection approach for each factor in our factor momentum portfolio. The construction method of the liquidity (LIQ) factor is available at Robert Stambaugh's data library; the construction methods of the betting against beta and quality-minus-junk (U.S. and global) factors are from AQR website; the construction methods of the remaining factors are summarised from K. French Data library.

Factor	Abbrev	Weighting scheme	Construction methodology
			U.S. factors
Size	SMB	value-weighted	SMB=1/3(Small Value + Small Neutral + Small Growth) -1/3(Big Value + Big Neutral + Big Growth)
Value	HML	value weighted	HML=1/2(Small Value + Big Value)-1/2(Small Growth + Big Growth)
Profitability	RMW	value-weighted	RMW =1/2(Small Robust + Big Robust)-1/2(Small Weak + Big Weak)
Investment	CMA	value-weighted	CMA =1/2(Small Conservative + Big Conservative)-1/2(Small Aggressive + Big Aggressive)
Accruals	AC	value-weighted	AC= 30% Low Ac/B-30% High Ac/B
Betting against beta	**BAB**	**rank-weighted**	BAB=50% Low Beta-50% High Beta
Cash flow to price	CP	value-weighted	CP= 30% Low CF/P-30% High CF/P
Earnings to price	EP	value-weighted	EP= 30% Low E/P-30% High E/P
Liquidity	LIQ	value-weighted	LIQ=High Liquidity Beta Decile -Low Liquidity Beta Decile
Long-term reversals	LREV	value-weighted	LREV = 1/2(Small Low + Big Low)-1/2(Small High + Big High)
Net share issues	NI	value-weighted	NI=30% Low Net Share Issues-30% High Net Share Issues
Quality minus junk	QMJ	value-weighted	QMJ=1/2(Small quality + Big quality)-1/2(Small junk + Big junk).
Residual variance	IVOL	value-weighted	IVOL=30% Low RVar-30% High RVar
Short-term reversals	SREV	value-weighted	SREV = 1/2(Small Low + Big Low)-1/2(Small High + Big High).
			Global factors
Size	GSMB	value-weighted	Same as the U.S. size factor
Value	GHML	value-weighted	Same as the U.S. value factor
Profitability	GRMW	value-weighted	Same as the U.S. profitability factor
Investment	GCMA	value-weighted	Same as the U.S. investment factor
Betting against beta	**GBAB**	**rank-weighted**	Same as the U.S. betting against beta factor
Quality minus junk	GQMJ	value-weighted	Same as the U.S. quality minus junk factor

Table C.3: BAB factors based on rank- and value-weighting schemes

This table reports the return continuations of BAB factors based on rank-weighted, value-weighted, and equal-weighted portfolios using the three models as in Table 5. These include regressions shown in Equation 4 (Model 1), Equation 5 (Model 2), and the profits according to return continuation (Model 3). Rank-weighted refers to the original rank-based BAB portfolio introduced by Frazzini and Pedersen (2014). Value-weighted is the commonly used portfolio construction in which stock weights are determined by firm market capitalisation. The t-statistics are adjusted by the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of Newey and West (1987). '*', '**', and '***' indicate that the coefficients are statistically significant at 10%, 5%, and 1% levels, respectively.

Portfolio schemes	Model 1		Model 2		Model 3	
	β	t	β	t	Mean	t
Rank-weighted	0.007***	(2.83)	0.038***	(3.20)	0.073***	(3.85)
Value-weighted	0.004*	(1.83)	0.008	(0.57)	0.022**	(1.98)
Equal-weighted	0.007**	(2.05)	0.034***	(2.92)	0.059***	(3.84)