Revisiting factor momentum: A one-month lag perspective

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July 1, 2025

Abstract

Recent studies have questioned the relevance of factor momentum by showing that its profitability is driven by a static tilt toward factors with positive historical means and that only a minority of individual factors exhibit significant momentum. This paper shows that replacing the traditional one-year formation window with a one-month window yields significant alpha after controlling for tilt toward positive-mean factors and doubles the number of factors with significant momentum from roughly 20% to 40%. Furthermore, we show that the positive autocorrelation between the one-month formation window and the subsequent month's return is twice as high as in the traditional one-year formation window. In the modern era of electronic trading, this autocorrelation is nearly 14 times higher. Our findings highlight that the robustness and profitability of factor momentum strategies depend critically on the formation window length.

Keywords: Factor momentum, time series momentum, factor investing

JEL classification: G11, G12, G17

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1. Introduction

Factor momentum refers to a phenomenon where the returns of factors can be predicted based on their recent returns (e.g., Ehsani & Linnainmaa, 2022). This offers an appealing opportunity for enhancing portfolio returns beyond static factor exposures. However, recent studies have questioned the profitability and robustness of factor momentum. Leippold and Yang (2021) show that factor momentum is subsumed by a quasi-static trading strategy that holds stable long or short positions in factors based on long-term average returns. Similarly, Fan et al. (2022) find that only a quarter of the individual factors they examined exhibit significant return predictability.

While the above studies focus on time-series factor momentum with a one-year formation period, we provide a perspective based on a one-month formation period. We have three main findings. First, the one-month factor momentum strategy generates statistically significant alpha at the 1% significance level, even after controlling for quasi-static exposure. In addition, almost the entire return of the one-month factor momentum strategy consists of six-factor alpha, and the strategy can even predict the returns of the quasi-static portfolio. These findings demonstrate that one-month factor momentum is a distinct phenomenon from a passive tilt toward profitable factors. Second, replacing the one-year formation window with a one-month window increases the number of return continuation factors from 19.6% to 39.1%, and the number of factors with significant six-factor alpha from 15.2% to 41.3%. These findings provide evidence that one-month factor momentum is a substantially more widespread phenomenon than its one-year counterpart.

Third, one-month factor momentum exhibits more than twice the autocorrelation with the next month's return compared to one-year factor momentum, increasing from 2.3 % to 5.6 %. In the modern era of electronic trading, the gap is even starker: the autocorrelation of one-month factor momentum rises to 8.7 %, while that of the one-year strategy drops to 0.6 %, making the difference nearly 14-fold. Moreover, once the most recent month is removed from the one-year window, the autocorrelation turns negative at –1.6 %. Ehsani and Linnainmaa (2022) argue that a factor momentum strategy is essentially a pure bet on positive autocorrelation in factor returns. Our results emphasize that this characterization applies to one-month factor momentum, but not to strategies based on longer formation windows.

We contribute to the factor momentum literature. In said literature, the papers closest to ours are likely Falck et al. (2020), who find that among different lags, factor momentum differs from stock momentum mainly when it is formed based on the most recent month's returns, and Gupta and Kelly (2018), who find that one-month factor momentum is the most profitable among different lag specifications. This paper differs from those studies by focusing specifically on the one-month formation period, examining whether one-month factor momentum survives the recent critiques by Leippold and Yang (2021) and Fan et al. (2022), and by measuring the autocorrelation between the subsequent month and different formation periods – thereby shedding light on why one-month factor momentum is more robust than its one-year counterpart. Furthermore, we demonstrate how factor momentum strategies survive in the modern era of information technology. This is relevant because the significant increase in trading volume and institutional activity implies that pre-2000 data may no longer represent the future (Chordia et al., 2014).

The remainder of this paper is organized as follows: Section 2 describes our data and methodology. Section 3 presents the empirical results. We first look at the critique of Leippold and Yang (2021) and Fan et al. (2022). Then we measure the autocorrelation between different formation periods and the subsequent month. And finally, we compare the profitability of passive and factor momentum trading strategies. Section 4 concludes this paper.

2. Data and methodology

2.1 Data

We use monthly U.S. factor return data. Our analysis begins with 153 value-weighted factors from Jensen et al. (2023).[1] These factors are formed by sorting stocks into characteristic terciles (top/middle/bottom) based on data in CRSP and Compustat.

Because we study momentum in factor returns, we exclude factors related to momentum and reversals in the same way as, for example, Arnott et al. (2023). After this, we are left with 138 factors. We use the commonly used period starting from July 1963 and ending in December 2024. However, trading strategies may use earlier data as a basis for their decisions. For example, we require the quasi-static trading strategy to have at least 10 years of data to avoid instability at the beginning of the sample period. Therefore, the quasi-static trading strategy starts trading in July 1963, but it uses data from July 1953 onward as the basis for its decisions. Similarly, to make other strategies comparable with the quasi-static strategy, we require at least 10 years of data for each factor before it can be included in the calculation of trading strategies.

[1] This dataset is available at https://jkpfactors.com/.

We compute returns as logarithmic returns, defined as $rt = ln(1 + Rt)$, where Rt is the simple percentage return. This choice is motivated by several desirable statistical properties: log returns are additive over time, typically closer to normally distributed (less skewed) than simple returns, and therefore provide more reliable Sharpe ratios, autocorrelations, and ordinary least squares -based inference for alphas (Campbell, Lo & MacKinlay, 1997). To keep economic magnitudes intuitive, we convert all results back to simple percentage returns when presenting the tables.

When analyzing the performance of individual factors and factor-based strategies, we regress their returns against the Fama–French five-factor model augmented with the momentum factor, as follows:[2]

$$r_t^f = \alpha + \sum_{i=1}^{5} \beta_i r_t^{FF5,i} + \beta_6 \mathrm{r}_t^{UMD} + \epsilon_t \tag{1}$$

where r_t^f is the monthly return of factor f, α is the regression constant, β_i is the i'th regression coefficient, $\mathrm{r}_t^{FF5,i}$ is the i'th Fama–French five-factor return (Fama & French, 2015), and r_t^{UMD} is the momentum factor return (Jegadeesh & Titman, 1993).

2.2 Factor momentum and quasi-static trading strategies

To compare the quasi-static strategy of Leippold and Yang (2021) with factor momentum strategies, we use the following formulas:

$$r_t^{t-S,\dots,t-s} = \frac{1}{F}\sum_{f=1}^{F} \mathrm{sgn}\left(\mu_{t-S,\dots,t-s}^f\right) r_{t,}^f, \quad \mu_{t-S,\dots,t-s}^f = \frac{1}{S-s}\sum_{i=s}^{S-s} r_{t-i}^f, \tag{2}$$

$$r_t^{FMOM(12-1)} = r_t^{t-12,\dots,t-1}, \quad r_t^{FMOM(12-2)} = r_t^{t-12,\dots,t-2}, \quad r_t^{FMOM(1-1)} = r_t^{t-1,\dots,t-1}, \quad r_t^{QS} = r_t^{1,\dots,t-1} \tag{3}$$

where the super- and subscripts $t-S,\dots,t-s$ mark the formation window range of i-lag returns with $i = s,\dots,S$, F is the number of factors, and $\mu_{t-S,\dots,t-s}^f$ is the formation window mean return. The only difference between these strategies is that they use a different formation period. $r_t^{FMOM(12-1)}$ goes long (short) if the average return from the past 12 months is positive (negative). $r_t^{FMOM(12-2)}$ works in the same way but bases the signal on the average return from months 12 to 2. $r_t^{FMOM(1-1)}$ presents the core strategy of this study, where the long or short position is determined solely by the return of the previous month.

[2] Data for these six factors is available at
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

r_t^{QS} uses the average return from the start of the sample up to month $t-1$. This average expands as new data become available. The holding period in all of these strategies is one month.

2.3 Return continuation in individual factors

To calculate the return continuation of individual factors, we follow Fan et al. (2022) and calculate return continuation using the following three formulas. First, we use the time series regression model of Ehsani and Linnainmaa (2022):

$$r_t^f = \alpha + \beta \operatorname{sgn}\left(\mu_{t-S,\ldots,t-s}^f\right) + \epsilon_{t,} \tag{4}$$

where r_t^f is the return of factor f in the following month. Second, for robustness, we use the same time series regression that Huang et al. (2020) used to evaluate time series momentum in individual assets:

$$r_t^f = \alpha + \beta\, \mu_{t-S,\ldots,t-s}^f + \epsilon_t \tag{5}$$

where we use the same definitions as in Equation (2). Third, as an alternative approach for return continuation, we follow Moskowitz et al. (2012) and break each factor's time-series momentum return into the autocovariance term and average squared mean returns:

$$\mathbb{E}\left[\pi_t^{TSM,f}\right] = \mathbb{E}\left[\mu_{t-S,\ldots,t-s}^f\, r_t^f\right] = \operatorname{Cov}\left(\mu_{t-S,\ldots,t-s}^f,\quad r_t^f\right) + \left(\mu_{1,\ldots,t-1}^f\right)^2, \tag{6}$$

where $\mathbb{E}\left[\pi_t^{TSM,f}\right]$ is the expected time series momentum (TSM) return, $\operatorname{Cov}\left(\mu_{t-S,\ldots,t-s}^f,\quad r_t^f\right)$ is the covariance between the formation window mean return and the next-month return, and $\mu_{1,\ldots,t-1}^f$ the mean return of the factor. The covariance term captures return continuation.

Descriptive statistics for individual factor returns can be found in Table A.1 in the Appendix.

3. Results and discussion

3.1 Factor momentum and quasi-static trading strategies

In this section, we examine whether the one-month and 12–month factor momentum returns are distinct from the quasi-static trading strategy proposed by Leippold and Yang (2021). The quasi-static strategy takes long positions in factors with positive historical average returns and short positions in those with negative average returns. To evaluate the relationship, we perform spanning regressions in both directions: regressing momentum strategies on the quasi-static strategy, and vice versa.

The first row of Table 1 reveals that one-month factor momentum delivers a statistically significant alpha at the 1% level after controlling for the quasi-static strategy. Similarly, one-month factor momentum fails to explain the returns of the quasi-static strategy.

The case is different for 12–month factor momentum. The second row of Table 1 shows that the quasi-static trading strategy subsumes 12–month factor momentum, leaving no statistically significant alpha left. Conversely, 12–month factor momentum fails to explain the returns of the quasi-static strategy. When the most recent month of returns is excluded from the formation period, the alpha is negative and non-significant. This suggests that the most recent month is a significant driver of 12–month factor momentum returns. These results are consistent with Leippold and Yang (2021), who find that the quasi-static strategy subsumes the 12–month and 12–2–month momentum strategies, but not vice versa.

Overall, our results show that mechanical exposure to profitable factors does not drive the returns of one-month factor momentum, but it remains a key source of returns for the 12–month strategy.

Table 1
Spanning tests for factor momentum

	Panel A: Regression $r_t^{FMOM} = \alpha + r_t^{QS}\beta + \epsilon_t$				Panel B: Regression $r_t^{QS} = \alpha + r_t^{FMOM}\beta + \epsilon_t$			
Formation window	Alpha (%)	t-stat	R	Adj. R^2	Alpha (%)	t-stat	R	Adj. R^2
1-1	1.96***	2.76	0.19	0.03	1.26***	6.57	0.19	0.03
12-1	0.29	0.28	0.34	0.12	1.23***	6.74	0.34	0.12
12-2	-0.12	-0.38	0.31	0.10	1.29***	7.05	0.31	0.10

Note. This table reports the results of spanning regressions. In Panel A, factor momentum strategies are regressed on the quasi-static (QS) strategy. In Panel B, the QS strategy is regressed on the factor momentum strategies. Alpha (%) refers to annualized alpha. R is the Pearson correlation coefficient between QS and FMOM returns, and the adjusted R^2 is the degrees-of-freedom–corrected version of R^2 in this univariate regression. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period covers from July 1963 to December 2024.

3.2 Factor momentum in individual factors' returns

This section investigates whether one-month factor momentum produces significant momentum and alpha across a substantial number of factors, in contrast to the traditional 12–month factor momentum. Following Fan et al. (2022), the threshold for significant momentum is that all three return-continuation tests (Equations 2–4) are significant at the 10 % level. The six-factor alpha is considered significant if it meets the 5 % level in Equation 1.

Panel A in Table 2 shows that 39.1% of the factors exhibit strong return continuation with one-month formation window, which is roughly double the size of return continuation factors with 12-month formation window (19.6%). The results for the 12-month strategy are even lower than the 22–27% reported by Fan et al. (2022), indicating a more conservative identification of continuation effects in our setting.

Panel B of Table 2 shows that one-month factor momentum produces significant alpha for 41.3% of factors, with an average alpha of 3.1%. In contrast, the traditional 12–month strategy delivers significant alpha for only 15.2% of factors, and its average alpha is more than three times lower (0.9 %). This is in line with Fan et al (2022), who report that 12–14% of the factors exhibit significant alpha.

Taken together, these findings suggest that one-month factor momentum is a substantially more widespread phenomenon than 12-month factor momentum.

Table 2
Number of factors with significant return continuation and alpha

Formation window	N	Panel A: Return-continuation		Panel B: 6-factor alpha		
		n	n (%)	n	n (%)	Mean α(%)
1-1	138	54	39.13	57	41.30	3.07
12-1	138	27	19.57	21	15.22	0.94
12-2	138	16	11.59	22	15.94	0.43

Note. This table reports the number of factors with statistically significant return continuation at the 10% level in each of Equations 2–4, as well as the number of factors with significant alpha from the FF5 + UMD model at the 5% level. N is the total number of factors, n and n(%) denote the number and percentage of statistically significant factors, and mean α(%) refers to the average annualised alpha. The sample starts in July 1963 and ends in December 2024.

3.3 Autocorrelation of factor-momentum strategies

We now examine whether the return from the previous month (the one-month factor momentum strategy) exhibits a stronger autocorrelation with the following month's return than the average return from the past 12 months (the 12–month factor momentum strategy). This also addresses the question of which of these strategies represents the true factor momentum phenomenon, as Ehsani (2022) states that the time series factor momentum strategy is a pure bet on autocorrelations in factor returns. A higher level of autocorrelation could also shed light on why one-month factor momentum withstands the critique and performs better than 12–month factor momentum. We calculate autocorrelation by measuring the correlation between the average monthly return in the formation period and the one-month holding period.

Table 3 shows that the average autocorrelation of the one-month factor momentum strategy (5.6%) is twice as high as that of the 12–month strategy (2.3%). When the most recent month is excluded from the 12-month strategy, the difference compared to the one-month strategy increases more than fivefold. In addition, the number of factors with statistically significant autocorrelation drops from 62 to 21 when the most recent month is omitted. These findings support the view that one-month factor momentum reflects the pure autocorrelation-based strategy defined by Ehsani (2022) more accurately.

In the last three columns of Table 3, we investigate whether the beginning of electronic trading has reduced the autocorrelation between factor momentum strategies and the following month's returns, as, for example, Bowles et al. (2024) have stated that this modern era of trading technology has diminished factor returns to substantially lower levels. Following Bowles et al. (2024), we set the breakpoint at the beginning of 2005 and find that the post–electronic trading era has not reduced the autocorrelation between the previous and the subsequent month. Instead, the autocorrelation has more than doubled, from 4.2% to 8.7%. In stark contrast, the 12–month trading strategy's autocorrelation with the following month is negligible. Moreover, when the most recent month is excluded, factor momentum is anything but a bet on positive autocorrelation, as the average autocorrelation turns negative at −1.6%.

Overall, our results show that one-month factor momentum consistently exhibits autocorrelation in factor returns, whereas the 12–month strategy does not, which is consistent with Falck et al. (2020) in demonstrating that one-month factor momentum is the true factor momentum.

Table 3

Factor momentum strategies' autocorrelation with the next month's returns

Formation		Full sample			Jul 1963 – Dec 2004			Jan 2005 – Dec 2024		
window	N	n	n(%)	AC(%)	n	n(%)	AC(%)	n	n(%)	AC(%)
1-1	138	62	44.93	5.63	46	33.33	4.18	56	40.58	8.66
12-1	138	32	23.19	2.30	26	18.84	1.79	10	7.25	0.64
12-2	138	21	15.22	0.92	16	11.59	0.82	4	2.90	-1.59

Note. The table reports the average autocorrelation between the formation window return and the next month's return. N is the total number of factors, n and n(%) denote the number and percentage of statistically significant factors. AC(%) is the average autocorrelation, calculated using the Fisher transformation. The threshold for statistical significance is 5 %.

3.4 Trading strategies

In this section, we investigate the profitability of factor momentum, buy-and-hold, and quasi-static trading strategies. We also investigate whether the factor momentum strategies can predict the returns of the buy-and-hold and the quasi-static portfolios.

Panel A of Table 4 shows that the one-month factor momentum strategy is more profitable than the other factor momentum strategies. Notably, the six-factor alpha of the one-month factor momentum strategy (2.6%) accounts for more than 90% of its total return (2.8%). This finding suggests that the strategy's profitability stems primarily from sources independent of exposure to common risk factors. Furthermore, one-month factor momentum remains profitable even in the post-2005 period, when online trading was already widespread. In contrast, the buy-and-hold portfolio illustrates that factor returns in general declined steeply during that period.

Panel B of Table 4 demonstrates that the one-month factor momentum strategy successfully predicts buy-and-hold portfolio returns. After a positive factor momentum signal, the buy-and-hold portfolio earns an average return of 2.1%. In contrast, after a negative signal, the return averages 0.1%. The 12–month factor momentum strategy also shows some timing ability. It yields an average return of 1.7% after a positive signal from the previous year and 0.4% after a negative signal.

Panel C of Table 4 demonstrates that one-month factor momentum can also successfully time returns of the quasi-static portfolio. Following positive (negative) momentum signals, the quasi-static strategy yields average returns of 1.9% (0.5%). The winner strategy also generates an alpha approximately five times higher than that of the loser strategy. By contrast, the twelve-month factor momentum does not detect a meaningful difference between profitable and unprofitable months. This suggests that its returns stem primarily from mechanical exposure to profitable factors and mirror the quasi-static strategy's performance characteristics.

Overall, our findings in Table 4 show that the one-month factor momentum provides a robust and independent source of return that can be effectively combined with alternative investment strategies. While we present the one-month factor momentum strategy in its simplest form, several enhancement opportunities exist that can be explored in future research.

Table 4

Profitability of the factor momentum trading strategies

Panel A: Trading strategies

Trading strategy	Full sample			Jul 1963 – Dec 2004			Jan 2005 – Dec 2024		
	Mean(%)	SR	α (%)	Mean(%)	SR	α (%)	Mean(%)	SR	α (%)
FMOM 1-1	2.77***	0.53	2.57***	3.09***	0.55	2.65***	2.11**	0.47	1.72*
FMOM 12-1	1.81***	0.35	0.78	2.05**	0.37	0.09	1.31	0.30	1.44**
FMOM 12-2	1.27*	0.24	0.29	1.40	0.25	-0.45	1.00	0.24	1.06
BH	1.32***	0.41	0.47**	1.73***	0.52	0.55**	0.47	0.17	0.31
QS	1.41***	0.93	0.87***	1.61***	0.99	0.94***	0.98***	0.80	0.69***

Panel B: Timing ability of the factor momentum strategies (full sample)

Trading strategy	N (total = 737)	Mean(%)	SD	SR	*t*-stat	α (%)
BH & FMOM 1-1 winners	419	2.14***	3.53	0.61	3.52	0.49*
BH & FMOM 1-1 losers	319	0.14	2.66	0.05	0.20	0.18
BH & FMOM 12-1 winners	493	1.72***	2.94	0.58	3.68	0.60
BH & FMOM 12-1 losers	245	0.39	3.61	0.11	0.40	0.43

Panel C: Timing ability of the factor momentum strategies (full sample)

Trading strategy	N (total = 737)	Mean(%)	SD	SR	*t*-stat	α (%)
QS & FMOM 1-1 winners	461	1.91***	1.50	1.27	7.89	1.27***
QS & FMOM 1-1 losers	277	0.54*	1.50	0.36	1.71	0.27
QS & FMOM 12-1 winners	630	1.43***	1.51	0.95	6.88	0.89***
QS & FMOM 12-1 losers	108	1.17**	1.55	0.76	2.26	0.94*

Note. This table reports the performance and timing ability of factor momentum (FMOM), buy-and-hold (BH), and quasi-static (QS) trading strategies. Panel A presents annualized returns (Mean%), Sharpe ratios (SR), and annualized alphas (α%) estimated using the Fama–French five-factor model with UMD. Panels B and C assess how effectively FMOM strategies predict BH and QS strategies, respectively. Mean returns, standard deviations (SD), Sharpe ratios, and associated t-statistics are shown for winner and loser periods. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4. Conclusion

This paper revisits factor momentum literature by testing whether factor momentum with a one-month formation period survives recent critiques — specifically, the claims that it simply reflects static exposure to high-return factors (Leippold and Yang, 2021) and is only present in a minor group of factors (Fan et al., 2022).

We find that one-month factor momentum withstands both major critiques. First, we find that one-month factor momentum continues to deliver significant abnormal returns at the 1%

significance level even after controlling for quasi-static factor exposures. Second, our results show that switching from one-year to one-month factor momentum increases the number of return continuation factors from 19.6% to 39.1%, and the number of factors with significant six-factor alpha from 15.2% to 41.3%.

Our analysis identifies one-month autocorrelation in factor returns as a significant driver of these results. This autocorrelation is both strong and consistent over time, helping to explain why the one-month factor momentum strategy performs significantly better than the traditional one-year factor momentum strategy.

Investors can leverage one-month factor momentum in multiple ways, as its returns are independent of common risk factors. It also enables investors to dynamically overweight or underweight individual factors based on recent returns, improving portfolio performance with minimal structural changes.

Our analysis is limited to the U.S. equity market, which offers the most liquid dataset. Whether the one-month factor momentum premium can be generalized to other countries remains an open question and merits further research.

Acknowledgments

We would like to thank Markus Mättö for valuable comments on this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Mikael Rönkkö gratefully acknowledges financial support from the Finnish Cultural Foundation (grant 00200962).

Data availability statement

The data that supports the findings of this study are publicly available from the Jensen, Kelly, and Pedersen Factor Library (https://jkpfactors.com) and the Kenneth R. French Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve the language and readability of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the final version of the publication.

References

Arnott, R. D., Kalesnik, V., & Linnainmaa, J. T. (2023). Factor momentum. The Review of Financial Studies, 36(8), 3034–3070. https://doi.org/10.1093/rfs/hhad006

Bowles, B., Reed, A. V., Ringgenberg, M. C., & Thornock, J. R. (2024). Anomaly time. The Journal of Finance, 79(5), 3543–3588. https://doi.org/10.1111/jofi.13372

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The econometrics of financial markets. Princeton University Press.

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? Journal of Accounting and Economics, 58(1), 41–58. https://doi.org/10.1016/j.jacceco.2014.06.001

Ehsani, S., & Linnainmaa, J. T. (2022). Factor momentum and the momentum factor. The Journal of Finance, 77(3), 1877–1925. https://doi.org/10.1111/jofi.13131

Fan, M., Li, Y., Liao, M., & Liu, J. (2022). A reexamination of factor momentum: How strong is it? Financial Review, 57(3), 585–615. https://doi.org/10.1111/fire.12300

Falck, A., Rej, A., & Thesmar, D. (2020). Is factor momentum more than stock momentum? [Working paper]. https://arxiv.org/abs/2009.04824

Gupta, T., & Kelly, B. (2019). Factor momentum everywhere. Journal of Portfolio Management, 45(5), 13–36. https://doi.org/10.3905/jpm.2019.45.5.013

Huang, D., Li, J., Wang, L., & Zhou, G. (2020). Time series momentum: Is it there? Journal of Financial Economics, 135(3), 774–794. https://doi.org/10.1016/j.jfineco.2019.07.007

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance, 48(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jensen, T. I., Kelly, B., & Pedersen, L. H. (2023). Is there a replication crisis in finance? The Journal of Finance, 78(5), 2465–2510. https://doi.org/10.1111/jofi.13249

Leippold, M., & Yang, H. (2021). The anatomy of factor momentum. [Working paper]. https://ssrn.com/abstract=3517888

https://www-sciencedirect-com.ezproxy.uef.fi:2443/science/article/pii/S0165410114000275

Appendix

Table A.1

Summary statistics

	Return				6-factor alpha	
Factor	Mean (%)	Std (%)	Sharpe	*t* -stat	Alpha (%)	*t* -stat
age	-0.39	13.39	-0.03	-0.75	1.50	1.56
aliq_at	0.39	12.97	0.03	-0.27	-2.69	-2.91
aliq_mat	-2.62	9.70	-0.27	-2.48	0.28	0.09
ami_126d	0.96	10.69	0.09	0.29	-0.15	-0.48
at_be	-0.35	11.48	-0.03	-0.69	2.88	2.09
at_gr1	1.89	11.04	0.17	0.93	-0.68	-0.99
at_me	1.04	13.14	0.08	0.12	-1.34	-1.81
at_turnover	2.87	9.63	0.30	2.01	0.79	0.51
be_gr1a	0.80	11.09	0.07	0.14	-1.43	-1.81
be_me	1.47	12.34	0.12	0.47	0.56	0.56
beta_60m	-0.86	16.67	-0.05	-1.06	-3.15	-2.85
beta_dimson_21d	-0.73	13.02	-0.06	-0.95	-2.39	-2.23
betabab_1260d	0.61	16.26	0.04	-0.33	-0.99	-1.12
betadown_252d	-1.44	16.09	-0.09	-1.34	-4.06	-3.49
bev_mev	1.23	12.81	0.10	0.27	-0.62	-1.01
bidaskhl_21d	-0.66	15.63	-0.04	-0.94	2.22	1.75
capex_abn	2.96	7.65	0.39	2.79	2.23	2.14
capx_gr1	3.40	8.88	0.38	2.72	1.03	0.84
capx_gr2	2.75	9.34	0.29	1.99	0.28	0.00
capx_gr3	1.77	9.62	0.18	1.09	-0.96	-1.23
cash_at	3.19	12.06	0.26	1.65	6.30	5.74
chcsho_12m	3.04	9.39	0.32	2.22	-0.18	-0.45
coa_gr1a	1.65	10.00	0.16	0.92	0.91	0.73
col_gr1a	-1.91	9.92	-0.19	-1.89	-3.07	-3.49
cop_at	5.13	9.34	0.55	4.08	5.46	4.89
cop_atl1	4.31	9.61	0.45	3.24	5.30	4.65
corr_1260d	0.97	10.52	0.09	0.32	-0.93	-1.20
coskew_21d	1.00	7.44	0.13	0.78	0.15	-0.12
cowc_gr1a	3.82	8.04	0.48	3.50	4.63	4.81
dbnetis_at	2.41	5.49	0.44	3.28	1.24	1.58
debt_gr3	2.07	6.31	0.33	2.36	1.16	1.23
debt_me	-0.70	12.94	-0.05	-0.93	-3.73	-4.31

dgp_dsale	1.64	7.93	0.21	1.33	1.13	0.89
div12m_me	0.37	14.73	0.03	-0.37	-2.78	-3.18
dolvol_126d	1.26	9.60	0.13	0.67	-0.02	-0.18
dolvol_var_126d	-0.37	8.26	-0.04	-0.67	-1.03	-1.80
dsale_dinv	2.83	7.93	0.36	2.54	2.08	1.78
dsale_drec	-0.46	7.03	-0.07	-0.79	-0.74	-1.06
dsale_dsga	-1.03	7.85	-0.13	-1.33	-1.12	-1.40
earnings_variability	0.80	7.21	0.11	0.60	-0.05	-0.30
ebit_bev	3.76	10.56	0.36	2.45	1.44	1.23
ebit_sale	-0.06	10.71	-0.01	-0.47	-1.44	-1.74
ebitda_mev	4.69	13.51	0.35	2.29	1.21	0.88
emp_gr1	0.38	10.41	0.04	-0.12	-2.84	-3.91
eq_dur	2.69	12.54	0.21	1.23	1.11	1.06
eqnetis_at	4.64	11.03	0.42	2.76	0.82	0.66
eqnpo_12m	2.28	12.13	0.19	1.03	-0.91	-1.25
eqnpo_me	3.83	14.92	0.26	1.40	-0.55	-0.78
eqpo_me	2.72	15.47	0.18	0.76	-0.62	-0.84
f_score	2.86	9.50	0.30	2.04	0.88	0.62
fcf_me	5.15	10.85	0.47	3.42	1.85	1.32
fnl_gr1a	3.33	5.43	0.61	4.69	2.86	4.04
gp_at	3.34	10.74	0.31	2.08	3.18	2.73
gp_atl1	2.59	11.23	0.23	1.41	2.93	2.60
inv_gr1	4.19	9.08	0.46	3.36	2.86	2.88
inv_gr1a	3.37	8.54	0.39	2.83	3.07	3.26
ival_me	3.38	11.18	0.30	1.99	2.74	2.70
ivol_capm_21d	1.99	16.86	0.12	0.30	-1.26	-1.52
ivol_capm_252d	0.51	19.54	0.03	-0.55	-3.38	-3.30
ivol_ff3_21d	1.75	16.44	0.11	0.22	-1.20	-1.50
ivol_hxz4_21d	3.08	16.57	0.19	0.83	-0.75	-1.00
kz_index	-1.06	9.23	-0.12	-1.26	-1.40	-1.53
lnoa_gr1a	3.66	9.79	0.37	2.62	0.87	0.51
lti_gr1a	0.55	5.42	0.10	0.59	-0.47	-0.89
market_equity	1.63	12.55	0.13	0.55	-0.01	-0.15
mispricing_mgmt	4.24	10.22	0.42	2.95	1.78	1.78
mispricing_perf	3.64	11.84	0.31	2.01	0.85	0.72
ncoa_gr1a	3.17	8.76	0.36	2.55	0.66	0.49
ncol_gr1a	0.05	6.89	0.01	-0.21	-0.76	-1.11
netdebt_me	2.50	12.42	0.20	1.13	5.83	5.17
netis_at	5.20	9.29	0.56	3.87	2.25	2.08
nfna_gr1a	3.54	6.08	0.58	4.41	3.34	4.13
ni_ar1	0.48	5.92	0.08	0.41	1.16	1.35
ni_be	1.95	10.42	0.19	1.09	-0.92	-1.42
ni_inc8q	-0.02	7.69	0.00	-0.31	-0.02	-0.25

ni_ivol	0.10	11.04	0.01	-0.36	0.63	0.23
ni_me	3.23	14.97	0.22	1.16	-0.22	-0.52
niq_at	2.13	11.16	0.19	1.06	-0.38	-0.65
niq_at_chg1	2.25	7.33	0.31	2.08	0.62	0.49
niq_be	3.23	10.50	0.31	2.00	-0.16	-0.42
niq_be_chg1	2.69	7.50	0.36	2.47	0.62	0.48
niq_su	3.09	6.82	0.45	3.31	1.49	1.77
nncoa_gr1a	3.58	8.86	0.40	2.90	1.06	0.91
noa_at	4.60	7.56	0.61	4.60	4.46	4.32
noa_gr1a	4.51	9.40	0.48	3.50	2.80	2.84
o_score	2.10	9.25	0.23	1.44	1.76	1.98
oaccruals_at	5.16	9.55	0.54	4.00	6.97	5.70
oaccruals_ni	3.10	7.18	0.43	3.17	3.46	3.62
ocf_at	5.36	10.20	0.53	3.86	4.96	4.40
ocf_at_chg1	2.60	7.00	0.37	2.69	2.42	2.46
ocf_me	4.38	13.71	0.32	2.06	0.12	-0.18
ocfq_saleq_std	1.24	8.55	0.15	0.80	-0.51	-0.86
op_at	3.02	10.62	0.28	1.87	2.45	1.99
op_atl1	2.20	10.88	0.20	1.19	2.16	1.76
ope_be	4.27	11.01	0.39	2.70	0.59	0.38
ope_bel1	3.01	10.19	0.30	1.97	0.63	0.44
opex_at	2.53	8.64	0.29	2.00	0.63	0.40
pi_nix	0.21	7.54	0.03	-0.07	-1.33	-1.67
ppeinv_gr1a	3.11	10.07	0.31	2.08	1.41	1.05
prc	0.23	12.61	0.02	-0.35	0.50	0.48
qmj	2.80	9.35	0.30	2.03	3.15	3.87
qmj_growth	2.00	7.47	0.27	1.84	0.97	0.86
qmj_prof	3.34	9.47	0.35	2.46	2.62	2.78
qmj_safety	1.27	10.06	0.13	0.61	2.97	2.87
rd_me	4.32	12.08	0.36	2.42	5.65	3.78
rd_sale	1.68	15.22	0.11	0.29	6.40	3.95
rd5_at	2.63	13.72	0.19	1.01	5.25	3.11
ret_60_12	1.47	10.83	0.14	0.66	-1.21	-1.48
rmax1_21d	1.48	15.28	0.10	0.18	-1.33	-1.55
rmax5_21d	2.53	17.09	0.15	0.53	-0.34	-0.63
rvol_21d	1.76	18.63	0.09	0.04	-1.71	-1.77
sale_bev	4.30	8.64	0.50	3.67	3.40	3.42
sale_emp_gr1	-0.87	7.33	-0.12	-1.21	-0.72	-1.02
sale_gr1	0.67	11.33	0.06	0.03	-1.32	-1.55
sale_gr3	-0.14	10.37	-0.01	-0.52	-2.61	-3.05
sale_me	3.81	12.53	0.30	1.96	-0.43	-0.74
saleq_gr1	-0.84	10.73	-0.08	-1.04	-2.26	-2.68
saleq_su	1.52	7.43	0.20	1.31	1.11	1.12

seas_1_1an	4.26	11.50	0.37	2.54	3.17	1.85
seas_11_15an	2.97	7.23	0.41	2.99	4.10	4.13
seas_11_15na	1.40	8.29	0.17	1.02	2.60	2.15
seas_16_20an	2.01	7.66	0.26	1.79	2.39	2.08
seas_16_20na	0.73	8.13	0.09	0.39	1.16	0.84
seas_2_5an	1.99	8.94	0.22	1.42	2.90	2.24
seas_2_5na	1.84	11.64	0.16	0.81	-0.91	-1.16
seas_6_10an	4.90	8.25	0.59	4.47	6.58	6.02
seas_6_10na	3.11	9.76	0.32	2.18	1.14	0.87
sti_gr1a	-1.30	7.92	-0.16	-1.56	-1.00	-1.22
taccruals_at	2.17	7.59	0.29	1.98	3.21	3.17
taccruals_ni	1.51	6.96	0.22	1.45	1.64	1.70
tangibility	1.48	9.00	0.16	0.95	1.75	1.23
tax_gr1a	1.82	8.83	0.21	1.29	1.30	1.19
turnover_126d	-1.23	14.82	-0.08	-1.23	-3.17	-3.21
turnover_var_126d	0.09	7.85	0.01	-0.22	-0.41	-0.83
z_score	1.55	11.22	0.14	0.66	3.34	3.03
zero_trades_126d	-1.01	14.66	-0.07	-1.12	-2.85	-2.81
zero_trades_21d	-2.36	13.66	-0.17	-1.89	-4.02	-4.12
zero_trades_252d	-0.30	14.43	-0.02	-0.73	-2.28	-2.28

Note. This table reports annualized statistics for 138 asset pricing factors from Jensen et al. (2023). Columns 2–4 show the mean return, standard deviation, and Sharpe ratio. Columns 5–6 report alphas and corresponding *t*-values from the Fama–French five-factor model plus the momentum factor.