

Revisiting Equity Factor Investing

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Abstract

In this paper, we examine why factor investing has not gained traction among asset owners in Japan by analyzing the performance of equity factor strategies. Our results suggest that inadequate assessment of transaction costs, changes over time in the magnitude and time-series properties of factor premiums, and evaluation methods that place undue emphasis on short-term investment performance may help explain the gap between investors' expectations for factor investing and the realized investment performance.



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1 Introduction

Factor investing is an investment approach that seeks to capture the risk premiums associated with factors, which are common drivers of asset returns. Factor strategies in asset classes, such as stocks and bonds, are widely used in practice as a standard form of active

management. Ang [2014] went a step further by proposing an approach in which asset owners made their own decisions about factor allocation. One implementation approach, known as "smart beta," began attracting attention around 2012. In 2014, the GPIF introduced smart beta as a "third box" distinct from traditional index investing and active management.¹

Since then, however, use of the term "smart beta" appears to have declined markedly. Moreover, because the GPIF has not continued to adopt similarly positioned strategies, factor investing does not appear to have become established as a standard investment strategy for asset owners, at least in Japan.

This paper reexamines equity factor strategies. The multifactor models that underpin factor investing remain widely used in academic research and continue to be useful. Rather than conducting an empirical asset-pricing analysis using these models, we ask why factor investing has not gained traction among asset owners, focusing on how the performance of strategies derived from these models is evaluated. We hypothesize that performance since the emergence of smart beta has fallen short of investors' expectations and examine four possible explanations.

First, we examine the transaction costs. Because equity factor strategies typically hold large numbers of securities, the transaction costs incurred during rebalancing may have a non-negligible effect on performance. Yet academic studies of factor models rarely incorporate portfolio-construction costs explicitly, leaving their practical implications underexplored. If investors made implementation decisions primarily on the basis of historical simulations that did not adequately account for transaction costs, realized post-implementation returns would likely fall correspondingly short. We estimate security-level transaction costs and assess their effect on factor-strategy performance.

Second, we examine whether return levels changed after smart beta gained prominence. McLean and Pontiff [2016] found that the premiums associated with factors identified in academic research tended to decline after the relevant study was published. Harvey et al. [2016] highlighted the effects of data snooping on reported factors. If the rise of smart beta attracted capital to particular factors and thereby compressed their premiums, or if some reported effects were spurious, realized strategy performance would likely disappoint investors. We divided the sample at the end of 2012 and compared returns across the two subperiods.

Third, we examine strategies that dynamically allocate across factors. During the smart beta boom, many factor strategies were proposed, including approaches that did not invest in a single factor but instead selected, at each point in time, the factor expected to generate the highest return. We use factor momentum as an example of dynamic factor selection and

¹ Okada [2014] provided a detailed account of smart-beta adoption by pension funds in Japan and abroad.

consider how such strategies may have affected assessments of factor investing.

Finally, we examine both the length of the historical data window used to make factor-investing decisions and the length of the investment horizon used to evaluate a strategy after implementation. Standard multifactor models are rooted in static frameworks, such as arbitrage pricing theory (APT), and academic empirical studies often use methods designed for such frameworks. Much of this research therefore seeks to identify multifactor models that hold on average over long samples. In practice, however, asset owners may select funds or decide whether to retain them on the basis of only a few years of performance, creating a substantial mismatch with the models' assumptions. We use simulations based on historical data to examine how the length of the evaluation window affects investors' assessments of factor investing.

2 Data

Following Novy-Marx and Velikov [2016], a comprehensive study of factors in the U.S. equity market, we analyze the 16 factors shown in Figure 1.² For each signal listed in Figure 1, we construct market-capitalization-weighted quintile portfolios of stocks listed on the former Tokyo Stock Exchange and Osaka Securities Exchange, excluding Foreign Securities Division listings, ETFs, and TOKYO PRO Market listings. We define the factor-strategy return as the difference between the returns on the portfolios with the highest and lowest signal values. Figure 1 provides further details on portfolio construction. Rebalancing frequency follows each factor's definition. Following Kubota and Takehara [2007], annually rebalanced portfolios are rebalanced at the end of August; monthly portfolios are rebalanced at each month-end.

At each month-end, we estimate transaction costs for each security from daily returns over the preceding 250 trading days, following Lesmond et al. [1999] and Hasbrouck [2009]. Both methods are standard when transaction-level data are unavailable, but because they use different approaches, they produce different estimates. We therefore use their average as the estimated transaction cost. Net returns equal the gross returns of the quintile portfolios minus the sum, across securities, of the products of monthly changes in portfolio weights and estimated transaction costs. Market data, including stock prices and trading volume, and the Fama-French-Carhart (FFC) four-factor series are obtained from Financial Data Solutions; financial-statement data are obtained from Quick Astra Manager. Because financial data before 1980 contain many missing values, the sample runs from the end of August 1981 through the end of December 2022. For strategies that use the TSE Sector Index to form

² Based on evidence regarding adoption by domestic institutional investors, we also include volatility-based strategies. To maximize the available sample length, we exclude strategies that require quarterly reports or calculate their signals annually using fiscal-year-end financial statements.

quintile portfolios, the sample begins in 1982 to match the index's coverage. We evaluate factor-strategy performance using the return spreads of the quintile portfolios and alphas estimated with the FFC model.

3 Analysis

3.1 Factor Strategies and Transaction Costs

Panel A of Figure 1 reports average factor-strategy returns over the full sample and alphas estimated using the FFC model. $\bar{r}^g$ denotes the average gross return, α^g denotes the alpha from a time-series regression of the gross-return series r^g on the FFC factors, $\bar{r}^n$ denotes the average net return, and α^n denotes the alpha from a time-series regression of the net-return series r^n on the FFC factors.³

We first examine the effect of transaction costs. Annually rebalanced strategies have a turnover of 10% or less and transaction costs below 0.1% per year, so their net returns do not decline materially. Monthly strategies, by contrast, incur substantially higher transaction costs. In particular, for strategies with turnover above 50%, transaction costs reduce returns by nearly 1 percentage point per year.

Among annually rebalanced portfolios, the average gross returns $\bar{r}^g$ of the strategies based on market capitalization (*Size*) and the book-to-price ratio (*Bpr*) are significantly positive at the 1% level. No other strategy produces a statistically significant gross return $\bar{r}^g$ or gross alpha α^g . Net returns $\bar{r}^n$ are also significantly positive for *Size* and *Bpr*, and *Size*'s net alpha α^n remains significant even after the FFC model controls for size and value effects. The earnings-to-price strategy (*Epr*) also performs relatively well, although its results are not statistically significant. Strategies based on the return-on-equity (*Roe*), the investment-to-assets ratio (*Ivst*), total asset growth (*Ag*), changes in shares outstanding (*Ni*), and the accruals-to-assets ratio (*Acc*) perform weakly.

Transaction costs have a clear effect on monthly strategies. Strategies based on the most recent stock-return data (*Str*, *Irr*, and *Ssn*) have high turnover: their gross returns are significantly positive, but their net returns become sharply negative. Consistent with the weak performance of stock and industry momentum in the Japanese market, both the net returns and alphas of *Mom* and *Imm* are negative. The volatility-based strategies (*Ivol* and *Tvol*) incur relatively low transaction costs among monthly strategies and exhibit positive post-cost alphas of approximately 10%.

These results show that transaction costs cannot be ignored in factor strategies and can materially affect the performance of strategies that rebalance frequently. Because our analysis does not model techniques for reducing rebalancing costs, it may understate net

³ We also use the generalized-alpha method of Novy-Marx and Velikov [2016], which accounts for transaction costs, and obtain results broadly consistent with those reported here.

returns. Nevertheless, investors who adopted newly proposed factor strategies during the rise of smart beta without fully accounting for transaction costs may have been disappointed when realized performance fell short of back-test expectations.

3.2 Changes in Risk Premiums

We next consider whether the multifactor model that best describes the stock market changed at some point and altered the levels of individual factor premiums and their implications for strategy performance. A detailed empirical investigation of the multifactor model is beyond the scope of this paper, which focuses on evaluating factor-strategy performance. However, the recent weakness of major factors, such as value, has attracted considerable attention among practitioners. We therefore examine whether similar changes are evident in the factor strategies studied here.

To reflect the period when smart beta gained prominence, we divide the sample into observations through December 2012 and those from January 2013 onward. We test the difference in each factor's average return between the two subperiods and use Hotelling's T-squared test to assess whether the vector of mean returns changed jointly. For factor-adjusted alpha, we estimate a full-sample regression with an indicator equal to 1 from 2013 onward and 0 otherwise; the intercept and indicator coefficient capture the pre-2013 alpha and its subsequent change, respectively. Because Section 3.1 shows that transaction costs are material, we use net returns in this analysis.

Panel B of Figure 1 summarizes the results. *Size* and *Bpr* perform strongly over the full sample. *Size* delivers significantly positive returns in both subperiods, and we fail to reject the null hypothesis of equal mean returns across the two periods. For *Bpr*, however, the highly significant positive return in the first subperiod turns negative in the second. The difference in mean returns is -0.75%, and the null hypothesis is rejected at the 10% level. *Epr* exhibits a similar pattern, indicating a change in performance for some factors. For the factor portfolios jointly, however, the Hotelling test yields a p -value of 0.86. Thus, we fail to reject the null hypothesis of a constant mean vector and find no evidence of an aggregate shift in factor-strategy performance.

For alpha, we focus on the coefficient on the post-2012 indicator (a_2). Among annually rebalanced factors, a_2 for *Epr* is -0.73, indicating a decline in alpha, whereas a_2 for *lvst* is 0.55, implying a shift from negative to positive alpha. For monthly factors, none of the a_2 coefficients differs significantly from zero; thus, we find no evidence that alpha levels changed after smart beta gained prominence.

Thus, performance shifts are evident for several major factors, including *Bpr*, *Epr*, and *lvst*. However, the Hotelling test provides no evidence of a change in the joint structure of factor returns.

3.3 Dynamic Factor Selection Based on Factor Momentum

We analyze factor momentum as a strategy for dynamic factor selection. Gupta and Kelly

[2019] argued that momentum effects observed among individual stocks also arose among factors and showed that factor-momentum strategies could exploit strong absolute or relative factor performance over a specified lookback period. The time-series factor momentum strategy (*TSFM*) adjusts the portfolio weight assigned to factor i at the end of month t according to the factor's performance over the preceding j months. We first define the adjustment coefficient as

$$s_{i,j,t} = \min \left(\max \left(\frac{1}{\sigma_{i,j,t}} \sum_{\tau=1}^j r_{i,t-\tau+1}, -2 \right), 2 \right)$$

where $r_{i,t}$ is the monthly gross return on factor i in month t , and $\sigma_{i,t}$ is the standard deviation of the factor's returns over the preceding 36 months. Using this coefficient, we define the factor strategy's long and short components as

$$TSFM_{j,t+1}^{Long} = \frac{\sum_i 1_{\{s_{i,j,t} > 0\}} s_{i,j,t} \times r_{i,j,t+1}}{\sum_i 1_{\{s_{i,j,t} > 0\}} s_{i,j,t}}, TSFM_{j,t+1}^{Short} = \frac{\sum_i 1_{\{s_{i,j,t} \leq 0\}} s_{i,j,t} \times r_{i,j,t+1}}{\sum_i 1_{\{s_{i,j,t} \leq 0\}} s_{i,j,t}},$$

and calculate the strategy's return for month $t + 1$ as $TSFM_{j,t+1} = TSFM_{j,t+1}^{Long} - TSFM_{j,t+1}^{Short}$. The cross-sectional factor momentum strategy (*CSFM*) ranks the 13 factors by their returns over the preceding j months, takes equal-weighted long positions in factors above the median, and takes equal-weighted short positions in factors below the median.

Figure 2 reports gross and net returns and alphas for *TSFM* and *CSFM*. We use lookback periods of $j = 1, 3, 6$, and 12 months. As in Section 3.2, we divide the sample into observations through December 2012 and those from January 2013 onward. Sections 3.1 and 3.2 show that the Figure 1 strategies with turnover above 100% experience substantial post-cost return reductions; we therefore report results for the remaining 13 factors.

We first examine the results through December 2012.

Across all lookback periods, *TSFM* and *CSFM* generate strong gross returns and alphas. Both $\bar{r}^g$ and α^g are positive and statistically significant at the 5% level, except when $j = 12$. Gross alphas α^g exceed those of single-factor strategies, indicating that flexible factor selection improves performance. Performance is particularly strong when $j = 3$ or $j = 6$. Deducting transaction costs lowers $\bar{r}^n$ by approximately 0.30 percentage points and eliminates any statistical significance, although all net returns remain positive. These results suggest that a factor-momentum strategy proposed at the end of 2012, especially one whose back-test ignored transaction costs, would have appeared highly attractive to investors.

From 2013 onward, however, performance deteriorates markedly even before costs. In most cases, $\bar{r}^g$ falls below 0.1%, while $TSFM_{12}$ and $CSFM_{12}$ turn negative. Alphas are generally higher than raw returns, but none of these estimates is statistically significant. After costs, most momentum-strategy returns are near zero or negative.

Figure 2 dynamically combines the returns of precomputed factor strategies. Transaction costs are deducted within each factor strategy, but costs incurred when switching among

factors are not. The results therefore assume that each factor strategy is available as an investable product that can be bought and sold without transaction costs. An investor constructing the underlying factor portfolios directly would incur not only the costs of implementing each factor strategy but also additional costs when portfolio holdings change as the selected factor changes.

A definitive assessment of factor momentum, and of dynamic factor selection more generally, requires further research. In 2012, however, many asset managers were competing to offer factor strategies, and a dynamic selection process would likely have favored factors with strong recent performance. If so, subsequent outcomes may have been materially affected by the pronounced change in factor-momentum return characteristics around that time.

3.4 Performance-Based Factor Selection

In institutional investment practice, recent performance often receives substantial weight, and decisions to retain or terminate a strategy may be based on only its first few years of live performance. We use bootstrap simulations to examine how the length of the evaluation window affects assessments of factor strategies.

As in the previous section, we consider 13 factors and use returns net of transaction costs to generate 10,000 block-bootstrap samples with six-month blocks. We use the first 3 or 10 years of each simulated series as the reference period and the subsequent 3, 10, or 29 years as the investment period. Although investment decisions are typically based on reference-period performance, for simplicity, we select the factor with the highest Sharpe ratio during the reference period and hold it throughout the investment period. We then calculate the selected strategy's average return in both periods. Figure 3 presents the empirical density of average returns for each period, summary statistics, and the Kullback-Leibler (KL) distance between the two distributions.

With a three-year reference period, the distribution of average returns is centered above zero. Negative values are rare, whereas values of 2% or more occur frequently, producing a long right tail. The high skewness and kurtosis reported in the lower panel confirm a pronounced right tail. Because the mean greatly exceeds the full-sample results in Figure 1, selecting the best-performing factor over the most recent three years may favor strategies whose apparent success reflects chance rather than persistently high expected returns. This selection process can therefore produce biased investment decisions. Extending the reference period to 10 years moderates the skew, but the reference-period mean still substantially exceeds the factor's long-run mean, and skewness remains high. Thus, even a 10-year evaluation window, which is long by practical standards, does not eliminate the distribution's positive skew.

We next examine average returns during the investment period. As the investment horizon lengthens, skewness approaches zero and kurtosis declines, eliminating the positive skew

observed in the reference period. Although the mean is positive in every case, suggesting positive expected returns, many factors may have been selected because of fortuitously strong reference-period performance; realized investment-period returns are therefore substantially lower than their reference-period counterparts. The mean improves slightly as the investment period lengthens, but the gap from the reference period remains large. Thus, factors selected solely for strong past performance are highly likely to deliver substantially lower subsequent returns than those used to justify the investment. Moreover, because return dispersion is high over short investment periods, even a factor with a genuinely high expected return may not realize its advantage over a short horizon.

The density for a three-year reference period and a 29-year investment period also appears bimodal. A plausible explanation is that a short three-year selection window does not reliably identify factors with genuinely high expected returns. The investment-period distribution therefore mixes factors with and without high expected returns, producing the apparent bimodality.

The KL divergence supports these findings. With a three-year reference period, the divergence is large and does not decline as the investment horizon lengthens. Extending the reference period increases the probability of selecting factors with genuinely high expected returns and therefore mitigates this pattern. Nevertheless, the reference-period distribution is the distribution of a selection statistic computed across 13 factors, whereas the investment-period distribution is a mixture of factor-specific return distributions. Because the two distributions are fundamentally different, the latter does not converge to the former even as the investment horizon lengthens. Decisions based on short-term performance therefore create excessive expectations for factor-strategy returns, while subsequent realized returns are highly likely to differ materially from the in-sample performance used to make the decision. These results indicate that the windows commonly used in practice for both investment decisions and subsequent performance evaluations are too short. Although practical constraints make this partly unavoidable, current practices systematically create the scope for disappointment both when strategies are selected and when their realized performance is evaluated.

4 Conclusion

We examined why factor investing had not become standard practice among asset owners by evaluating the performance of equity factor strategies. The analysis yielded four conclusions.

First, few factor strategies in the Japanese equity market remain effective over long horizons after transaction costs, and strategies that succeed in markets such as the United States cannot simply be transplanted to Japan. Reliance on back-tests that inadequately model transaction costs may therefore have overstated the expected performance. Second,

although we found no market-wide structural break, several individual factor returns changed around 2012, so investors who entered at that time might have experienced disappointing subsequent performance. Third, the return characteristics of factor momentum also changed, potentially weakening strategies that dynamically select factors. Fourth, selecting factors on the basis of only a few recent years creates a substantial gap between the in-sample return distribution and the distribution realized after investment. Under prevailing investment practices, short evaluation horizons might also lead investors to underestimate long-run strategy performance. Future research should improve the measurement of transaction costs, develop and test cost-reduction techniques, broaden the set of factors examined to reflect the characteristics of the Japanese market, and refine forecasting and risk-management methods for changing factor structures and dynamic factor selection. More detailed analyses are also needed to determine appropriate sample lengths for factor selection and performance evaluation.

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Figure 1: Factor Strategy Performance and Trading Costs

Panel A									Panel B				
Definition		Trading Costs			Sep. 1981–Dec. 2022				$\bar{r}^n$		$r^n = a_1 + a_2 \times I_{t \geq 2013} + b \cdot F^n + \epsilon$		
Signal	Spread	Turnover	Cost (bps)	$\bar{r}^g$	α^g	$\bar{r}^n$	α^n	1981–2012	2013–2022	Diff.	a_1	a_2	
<u>Annual Rebalancing</u>													
<i>Size</i>	Market Capitalization	L-H	1.45	3.87	0.63 (0.01)	0.31 (0.00)	0.59 (0.02)	0.27 (0.00)	0.61 (0.06)	0.55 (0.03)	0.09 (0.83)	0.26 (0.04)	-0.11 (0.51)
<i>Bpr</i>	Book-to-Price Ratio	H-L	3.11	4.87	0.71 (0.00)	0.12 (0.20)	0.66 (0.01)	0.07 (0.48)	0.89 (0.00)	-0.05 (0.92)	-0.75 (0.10)	0.07 (0.54)	-0.06 (0.78)
<i>Epr</i>	Earnings-to-Price Ratio	H-L	4.81	6.59	0.32 (0.08)	0.26 (0.17)	0.25 (0.16)	0.19 (0.31)	0.46 (0.02)	-0.41 (0.18)	-0.66 (0.07)	0.37 (0.12)	-0.73 (0.02)
<i>ROE</i>	Return on Equity	H-L	4.15	5.67	-0.13 (0.52)	0.23 (0.12)	-0.18 (0.34)	0.17 (0.25)	-0.23 (0.36)	-0.05 (0.80)	0.29 (0.38)	0.24 (0.22)	-0.27 (0.33)
<i>Gp</i>	Gross Profit-to-Assets Ratio	H-L	1.09	1.24	0.04 (0.86)	0.25 (0.29)	0.03 (0.90)	0.23 (0.32)	-0.10 (0.74)	0.44 (0.17)	0.58 (0.17)	0.13 (0.69)	0.39 (0.32)
<i>Ivst</i>	Investment-to-Assets Ratio	L-H	5.68	7.42	0.12 (0.41)	-0.02 (0.87)	0.05 (0.74)	-0.10 (0.47)	0.01 (0.96)	0.18 (0.33)	-0.02 (0.95)	-0.21 (0.22)	0.55 (0.04)
<i>Ag</i>	Total Asset Growth	L-H	6.08	7.90	0.18 (0.31)	-0.04 (0.76)	0.10 (0.57)	-0.13 (0.38)	0.08 (0.71)	0.16 (0.52)	0.08 (0.80)	-0.23 (0.21)	0.51 (0.07)
<i>Ni</i>	Change in Shares Outstanding	L-H	6.74	9.35	0.12 (0.34)	0.05 (0.65)	0.03 (0.84)	-0.04 (0.71)	0.01 (0.94)	0.07 (0.67)	-0.02 (0.93)	-0.09 (0.50)	0.37 (0.05)
<i>Acc</i>	Accruals-to-Assets Ratio	L-H	6.23	8.23	-0.01 (0.93)	0.00 (0.98)	-0.09 (0.42)	-0.09 (0.44)	-0.13 (0.37)	0.02 (0.90)	0.10 (0.68)	-0.17 (0.23)	0.30 (0.19)
<u>Monthly Rebalancing</u>													
<i>Ivol</i>	FF3 Idiosyncratic Volatility (1 Year, Daily)	L-H	9.52	15.20	0.44 (0.21)	0.56 (0.02)	0.29 (0.41)	0.41 (0.09)	0.35 (0.42)	0.09 (0.84)	-0.31 (0.60)	0.29 (0.38)	0.54 (0.15)
<i>Tvol</i>	Return Volatility (1 Year, Daily)	L-H	11.81	17.81	0.48 (0.21)	0.64 (0.02)	0.30 (0.43)	0.46 (0.10)	0.41 (0.40)	-0.03 (0.96)	-0.45 (0.49)	0.33 (0.37)	0.55 (0.25)
<i>Mom</i>	Price Momentum (12m, Excl. Most Recent Month)	H-L	31.93	42.93	0.03 (0.93)	0.09 (0.33)	-0.40 (0.22)	-0.34 (0.00)	-0.43 (0.30)	-0.30 (0.35)	0.29 (0.58)	-0.34 (0.00)	0.13 (0.41)
<i>Imm</i>	Industry Momentum (12m, Excl. Most Recent Month)	H-L	38.47	47.74	0.12 (0.66)	0.03 (0.91)	-0.36 (0.19)	-0.45 (0.06)	-0.38 (0.29)	-0.31 (0.10)	0.14 (0.75)	-0.55 (0.09)	0.32 (0.45)
<i>Str</i>	Prior-Month Return	L-H	84.61	112.31	0.58 (0.01)	0.56 (0.02)	-0.54 (0.02)	-0.56 (0.02)	-0.69 (0.01)	-0.08 (0.78)	0.56 (0.21)	-0.63 (0.05)	0.33 (0.46)
<i>Irr</i>	Prior-Month Return Less Sector Return	L-H	86.79	121.62	0.98 (0.00)	0.95 (0.00)	-0.24 (0.13)	-0.27 (0.12)	-0.22 (0.26)	-0.30 (0.19)	0.08 (0.82)	-0.20 (0.38)	-0.28 (0.38)
<i>Ssn</i>	Five-Year Same-Month Average Return	H-L	86.28	115.10	0.37 (0.08)	0.47 (0.01)	-0.78 (0.00)	-0.68 (0.00)	-0.75 (0.00)	-0.90 (0.00)	0.09 (0.80)	-0.60 (0.01)	-0.28 (0.48)

Note: The table reports factor-strategy returns and alphas from September 1981 through December 2022 using stocks listed on the former Tokyo and Osaka stock exchanges, excluding Foreign Securities Division listings, ETFs, and TOKYO PRO Market listings.

$\bar{r}^g$ denotes the average gross portfolio return; α^g denotes the alpha from a time-series regression of r^g on the FFC factors; $\bar{r}^n$ denotes the average net portfolio return; and α^n denotes the alpha from a time-series regression of r^n on the net FFC factor returns. The coefficients a_1, a_2 come from a time-series regression of net return r^n on net FFC factor returns F^n and an indicator $I_{t \geq 2013}$ equal to 1 from 2013 onward. Except for Cost, all values are monthly percentages. Parentheses contain p -values. Standard errors are Newey-West adjusted for heteroskedasticity and serial correlation.

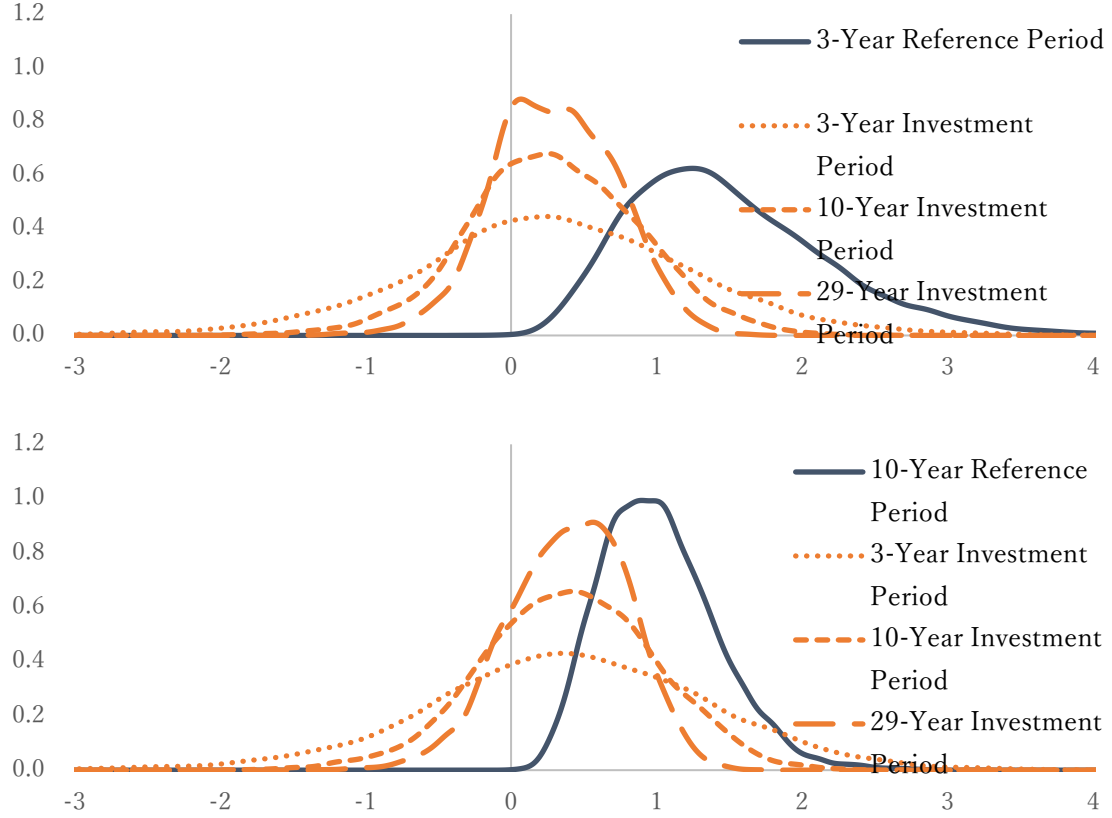
Source: Author's calculations.

Figure 2: Performance of Factor-Momentum Strategies

	1981–2012				2013–2022			
	$\bar{r}^g$	α^g	$\bar{r}^n$	α^n	$\bar{r}^g$	α^g	$\bar{r}^n$	α^n
TSM_1	0.64 (0.02)	0.66 (0.05)	0.33 (0.22)	0.34 (0.32)	0.03 (0.93)	0.13 (0.67)	-0.11 (0.70)	0.00 (0.99)
TSM_3	0.84 (0.01)	0.78 (0.05)	0.52 (0.11)	0.46 (0.24)	0.06 (0.73)	0.18 (0.45)	-0.07 (0.70)	0.04 (0.87)
TSM_6	0.88 (0.01)	0.89 (0.01)	0.57 (0.08)	0.58 (0.08)	0.06 (0.77)	0.11 (0.59)	-0.08 (0.69)	-0.03 (0.87)
TSM_{12}	0.59 (0.05)	0.62 (0.01)	0.27 (0.37)	0.29 (0.21)	-0.11 (0.67)	-0.04 (0.87)	-0.26 (0.34)	-0.19 (0.44)
CSM_1	0.57 (0.03)	0.61 (0.03)	0.26 (0.32)	0.29 (0.31)	-0.10 (0.71)	-0.01 (0.97)	-0.24 (0.36)	-0.16 (0.62)
CSM_3	0.68 (0.01)	0.65 (0.03)	0.37 (0.16)	0.33 (0.28)	0.02 (0.94)	0.15 (0.52)	-0.13 (0.57)	0.01 (0.98)
CSM_6	0.59 (0.04)	0.61 (0.02)	0.28 (0.33)	0.29 (0.27)	0.15 (0.41)	0.20 (0.31)	0.01 (0.97)	0.06 (0.77)
CSM_{12}	0.44 (0.12)	0.46 (0.05)	0.13 (0.66)	0.14 (0.56)	0.10 (0.71)	0.21 (0.46)	-0.04 (0.88)	0.07 (0.81)

Note: The sample runs from September 1981 through December 2022. Using the 13 factors in Figure 1 other than Str , Irr , and Ssn , we construct time-series factor momentum (TSM_j) and cross-sectional factor momentum (CSM_j) strategies at each month-end based on returns over the preceding j months. The definitions of $\bar{r}^g$, α^g , $\bar{r}^n$, and α^n are the same as in Figure 1. All values are monthly percentages. Parentheses contain p -values. Standard errors are Newey-West adjusted for heteroskedasticity and serial correlation.

Figure 3: Monthly Return Statistics for the Reference and Subsequent Investment Periods



Reference Period	3 yr				10 yr			
	Investment Period				Investment Period			
	3 yr	10 yr	29 yr		3 yr	10 yr	29 yr	
Mean	1.51	0.29	0.30	0.30	1.02	0.40	0.40	0.39
SD	0.71	0.98	0.60	0.42	0.40	0.99	0.60	0.41
Skewness	0.95	-0.08	-0.01	-0.07	0.65	-0.18	-0.10	-0.29
Kurtosis	1.45	0.73	0.31	-0.05	0.66	0.65	0.14	-0.02
KL Distance	--	3.59	4.65	6.14	--	2.98	2.73	3.26

Note: Using the 13 factors in Figure 1 other than *Str*, *Irr*, and *Ssn*, we drew 10,000 block-bootstrap samples from monthly returns from September 1981 through December 2022, using six-month blocks. The first 3 or 10 years of each simulated series form the reference period; the subsequent 3, 10, or 29 years form the investment period. We select the factor with the highest Sharpe ratio during the reference period and calculate its average return in both periods. The table reports summary statistics for the 10,000 average-return observations and the Kullback-Leibler (KL) distance between the reference-period and investment-period distributions.