Factor Momentum Everywhere*

Tarun Gupta and Bryan Kelly

Tarun Gupta is a managing director at AQR Capital Management LLC in Greenwich, CT.
tarun.gupta@aqr.com

Bryan Kelly is a vice president at AQR Capital Management LLC in Greenwich, CT and Professor of Finance at Yale School of Management in New Haven, CT. bryan.kelly@aqr.com

Abstract

In this article, the authors document robust momentum behavior in a large collection of 65 widely studied characteristic-based equity factors around the globe. They show that, in general, individual factors can be reliably timed based on their own recent performance. A time series "factor momentum" portfolio that combines timing strategies of all factors earns an annual Sharpe ratio of 0.84. Factor momentum adds significant incremental performance to investment strategies that employ traditional momentum, industry momentum, value, and other commonly studied factors. Their results demonstrate that the momentum phenomenon is driven in large part by persistence in common return factors and not solely by persistence in idiosyncratic stock performance.

Keywords: Factor momentum, time series momentum, stock price momentum

*We thank Cliff Asness, Kobi Boudoukh, Andrea Frazzini, Ronen Israel, and Toby Moskowitz for many helpful suggestions throughout this project. We thank William Fu for outstanding research assistance. AQR Capital Management is a global investment management firm, which may or may not apply similar investment techniques or methods of analysis as described herein. The views and opinions expressed are those of the authors and do not necessarily reflect the views of AQR Capital Management, its affiliates, or its employees; do not constitute an offer, solicitation of an offer, or any advice or recommendation, to purchase any securities or other financial instruments, and may not be construed as such.

Price momentum is most commonly understood as a phenomenon in which assets that recently enjoyed high (low) returns relative to others are more likely to experience high (low) returns in the future. It is customarily implemented as a cross-sectional trading strategy among individual stocks (Jegadeesh and Titman, 1993; Asness, 1994) or long-only equity portfolios (Moskowitz and Grinblatt, 1999; Lewellen, 2002). It has an impressive and robust track record of risk-adjusted performance (Asness, Frazzini, Israel, and Moskowitz, 2014; Geczy and Samonov, 2016).

Grouping stocks based on *relative* cross section performance has led many to interpret momentum as a strategy that isolates predominantly *idiosyncratic* momentum (e.g. Grundy and Martin, 2001; Chaves, 2016). In this paper, we document robust momentum behavior among the common factors that are responsible for a large fraction of the covariation among stocks. A portfolio strategy that buys the recent top-performing factors and sells poor-performing factors, i.e. that exploits "factor momentum," achieves significant investment performance above and beyond traditional stock momentum. On a standalone basis, our factor momentum strategy outperforms stock momentum, industry momentum, value, and other commonly studied investment factors in terms of Sharpe ratio. And while factor momentum and stock momentum are correlated, they are also complementary. Factor momentum earns an economically large and statistically significant alpha after controlling for stock momentum. Nor does factor momentum displace stock momentum. Because of stock momentum's especially strong hedging benefit with respect to value, we find a significant benefit to combining factor momentum, stock momentum, and value in the same portfolio.[1]

In recent decades, academic literature and industry practice have accumulated dozens of factors that help explain the comovement and average returns among individual stocks. We build and analyze a large collection of 65 such characteristic-based factors that are widely studied in the academic literature. From this data set, we establish factor momentum as a robust and pervasive phenomenon based on the following facts.

Serial correlation in returns is the basic statistical phenomenon underlying momentum and is thus the launching point for our analysis. First, we show that individual factors exhibit robust time series momentum (Moskowitz, Ooi, and Pedersen, 2012), a performance persistence phenomenon by which an asset's own recent return (in an absolute sense rather than relative to a peer group) predicts its future returns. Persistence in factor returns is strong and ubiquitous. The average monthly AR(1) coefficient across all factors is 0.11, is positive for 59 of our 65 factors, and is significantly positive in 49 cases.

[1]This is especially true when value is constructed following the "HML-Devil" refinement of Asness and Frazzini (2013).

Second, we demonstrate that individual factors can indeed be successfully timed based on their own past performance. A time series momentum trading strategy that scales exposure to a given factor in proportion with its own past one-month return generates excess performance over and above the raw factor. This individual time series momentum alpha (that is, after controlling for a passive investment in the factor) is positive for 61 of the 65 factors, and is statistically significant for 47 of them. The annualized information ratio of this strategy is 0.33 on average over all 65 factors.

Third, a combined strategy that averages one-month time series momentum of all factors earns an annual Sharpe ratio of 0.84, exceeding the performance of any individual factor's time series momentum. We refer to this combined portfolio of individual factor timing strategies as "time series factor momentum," or TSFM. It performs similarly well with longer formation windows. For example, the strategy's Sharpe ratio is 0.70 when based on previous 12-month factor performance, and remains at 0.72 with a five-year look-back window. TSFM is strongest with a one-month look-back, though we continue to find positive and significant performance with longer non-overlapping windows as well (i.e., based on momentum over 2-12 or 13-60 months prior to formation).

The TSFM strategy is largely unexplained by other well known sources of excess returns. It has two natural benchmarks for comparison. One is the equal-weighted average of the 65 raw factors, which itself has an impressive annual Sharpe ratio of 1.07. TSFM earns large and significant alphas relative to this, indicating that the performance of TSFM arises from beneficial timing, and is not simply picking up static factor performance.

The second natural benchmark is the traditional stock-level momentum strategy using the 2-12 formation strategy of Asness (1994), which we refer to as"UMD" henceforth. UMD has an annual Sharpe ratio of 0.56 in our sample. In spanning regressions, UMD partially explains the performance of TSFM, particularly when TSFM is based on a matched 2-12 formation period (i.e., excluding the most recent month). Factor momentum, however, is strongest at the one-month horizon, and this short horizon persistence is unexplained by UMD. We find that there are benefits to longer formation periods as well, though the performance of TSFM becomes more similar to UMD when the formation window is extended to include the most recent 12 months.

An important differentiating feature of TSFM is the stability of its behavior with respect to look-back window. TSFM exhibits positive momentum whether it is based on prior one-month, one-year, or even five-year performance. This contrasts starkly with stock-based momentum strategies. For both short (one month) and long (beyond two years) formation windows, stocks in fact exhibit *reversals* as opposed to momentum (De Bondt and Thaler, 1985; Jegadeesh, 1990).

TSFM is an average of time series momentum strategies on individual factors. A natural alternative strategy is to construct factor momentum relative to performance of the other factors in the cross section, as in the Jegadeesh and Titman (1993) approach. We refer to this as "cross section factor momentum," or CSFM. We find that CSFM and TSFM share a correlation above 0.90 for any formation window, and the standalone average returns and Sharpe ratios of CSFM and TSFM are very similar. However, when we regress TSFM returns on CSFM, we find positive and highly significant TSFM alphas, yet CSFM has generally negative (and significant) alphas controlling for TSFM. Their high correlation and opposing alphas reveal that TSFM and CSFM are fundamentally the same phenomenon, but that the time series approach provides a purer measure of expected factor returns than the cross-sectional method.

We also investigate the turnover and transaction costs of factor momentum. Our conclusions regarding its outperformance are unchanged when we look at Sharpe ratios net of transaction costs. The net standalone Sharpe ratios of TSFM and CSFM continue to exceed those of stock momentum, industry momentum, short-term reversal, and the Fama-French factors.

Our last empirical finding is that factor momentum is a global phenomenon. We demonstrate its robustness in international equity markets with magnitudes on par with our US findings. We find similar outperformance of TSFM over international versions of UMD, industry momentum, and CSFM.

Each of our 65 factors represents a large, diversified long-short portfolio. These portfolios are (to close approximation) devoid of idiosyncratic stock-level returns, which are washed out by the law of large numbers. Yet the TSFM strategy that buys/sells factors with high/low past returns outperforms the traditional stock momentum strategy. In other words, factor momentum captures variation in expected factor returns of roughly similar magnitude as stock-level momentum, despite being purged of idiosyncratic returns by construction. Factor momentum thus isolates persistence in the common factors, and shows that momentum is a more general phenomenon, existing alongside idiosyncratic stock return momentum.

We build upon recent work by Avramov, Cheng, Schreiber, and Shemer (2016) and Arnott, Clements, Kalesnik, and Linnainmaa (2018) analyzing momentum among factors. Those papers focus only on cross section factor momentum, and only in the US. Our findings differ from previous work in establishing that factor momentum is best understood and implemented with a time series strategy rather than a relative cross-sectional approach.

Our finding that TSFM explains the performance of stock momentum is likewise a new contribution to the literature. We also provide a more expansive view of factor momentum, studying a more comprehensive collection of US equity factors, and we are the first to document factor momentum in international equity markets.

The behavior of factor momentum is distinctly reminiscent of Moskowitz, Ooi, and Pedersen (2012), who demonstrate that asset class indices may be timed based on their recent past performance. Aggregate commodity, bond, and currency indices are rightly viewed as "factors" within those asset classes, and as such the results of Moskowitz, Ooi, and Pedersen (2012) can be understood as a manifestation of factor momentum. Taken together with the ubiquity of our equity-based findings of factor momentum in the time series, in the cross section, and around the world, we conclude that there is indeed factor momentum everywhere.

Factor Sample

We construct 65 characteristic-based factor portfolios. Our aim is to cover the expanse of factors proposed in the academic literature that studies the cross section of stock returns, subject to constraints. We cover the most well cited and robust factors, and have a high overlap with recent research on high-dimensional factor analysis.[2] We focus on factors that can be constructed beginning in the 1960s. This excludes, for example, IBES-based analyst research factors, which only become available in the late 1980s.

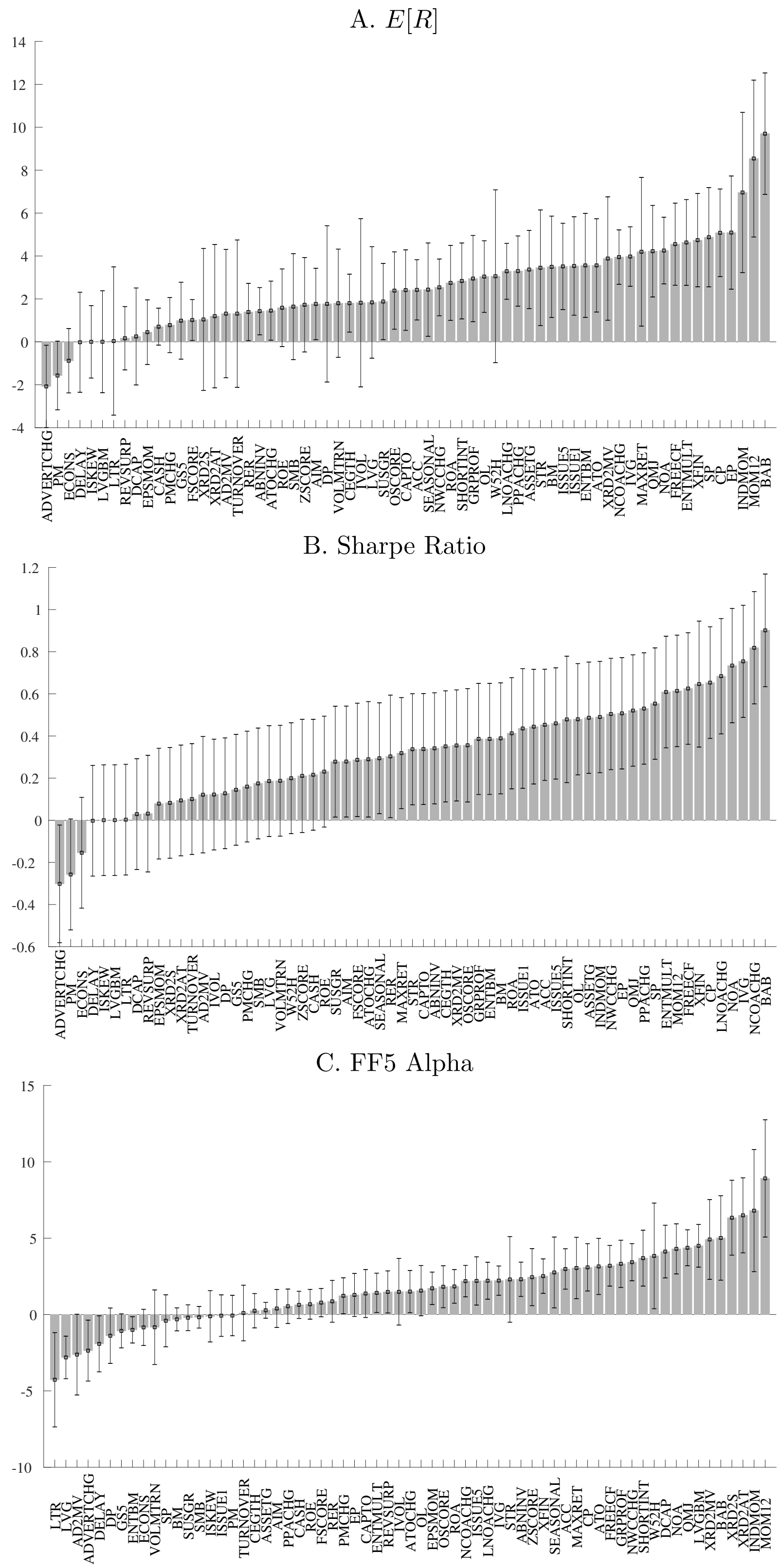
We form factors as follows. First, we cross-sectionally winsorize the top and bottom 1% of raw characteristic values each period. Next, we split the universe into large and small stocks with a cutoff equal to median NYSE market capitalization (or 80^{th} percentile of market capitalization for international stocks). Within size bins, we divide further into low/medium/high characteristic values according to a 30/40/30 percentile split. Breakpoints are taken over NYSE stocks for the US sample or all stocks in the international sample. Within these six bins, we form value-weighted portfolios, and then combine these into an ultimate long-short factor portfolio according to 0.5×("Large High" + "Small High") − 0.5×("Large Low" + "Small Low"), re-constituting portfolios each month.

Our factor list includes, among others, a variety of valuation ratios (e.g., earnings/price, book/market); factor exposures (e.g., betting against beta); size, investment, and profitabil-

[2] See Harvey, Liu, and Zhu (2016); McLean and Pontiff (2016); Kelly, Pruitt, and Su (2018); Gu, Kelly, and Xiu (2018).

Exhibit 1: Factor Sample Summary Statistics

Factor	$E[R]$	Sharpe	FF5 α
ABNINV	1.4*	0.34*	2.3*
ACC	2.4*	0.45*	3.0*
ADVERTCHG	-2.1	-0.30	-2.4
AD2MV	1.3	0.12	-2.6
AIM	1.8*	0.28*	0.4
ATO	3.6*	0.44*	3.2*
ATOCHG	1.5*	0.29*	1.5*
BAB	9.7*	0.90*	5.0*
CAPTO	2.4*	0.34*	1.4
CEGTH	1.8*	0.35*	0.2
CASH	0.7	0.22	0.6
ASSETG	3.4*	0.49*	0.3
CP	5.1*	0.65*	3.1*
DCAP	0.3	0.03	4.1*
DELAY	-0.0	-0.00	-1.9
DP	1.8	0.13	-1.4
ISSUE1	3.5*	0.44*	-0.1
ISSUE5	3.5*	0.46*	2.2*
ENTBM	3.6*	0.39*	-1.0
ENTMULT	4.6*	0.61*	1.4*
EP	5.1*	0.51*	1.3
EPSMOM	0.5	0.08	1.7*
FREECF	4.6*	0.63*	3.2*
FSCORE	1.0*	0.29*	0.8
GRPROF	2.9*	0.39*	3.3*
GS5	1.0	0.14	-1.1
BM	3.5*	0.39*	-0.3
IVG	4.0*	0.75*	2.2*
ISKEW	0.0	0.00	-0.1
IVOL	1.8	0.12	1.5
LVG	1.8	0.19	-2.8
LNOACHG	3.3*	0.68*	2.2*
LTR	0.0	0.00	-4.3
LVGBM	0.0	0.00	4.5*
MAXRET	4.2*	0.32*	3.1*
NCOACHG	3.9*	0.82*	2.2*
NOA	4.3*	0.73*	4.3*
NWCCHG	2.5*	0.50*	3.4*
ECONS	-0.9	-0.15	-0.8
OL	3.0*	0.48*	1.6
OSCORE	2.4*	0.36*	1.8*
PM	-1.6	-0.26	-0.1
PMCHG	0.8	0.16	1.2*
PPACHG	3.3*	0.53*	0.5
QMJ	4.2*	0.52*	4.4*
RER	1.4*	0.30*	0.9
STR	3.5*	0.34*	2.3
REVSURP	0.2	0.03	1.5*
ROA	2.7*	0.41*	1.8*
ROE	1.6	0.23	0.7
SEASONAL	2.4*	0.29*	2.8*
SHORTINT	2.8*	0.48*	3.7*
SMB	1.6	0.17	-0.2
SP	4.9*	0.55*	-0.4
SUSGR	1.9*	0.28*	-0.2
TURNOVER	1.3	0.10	0.1
MOM12	8.5*	0.61*	8.9*
INDMOM	7.0*	0.49*	6.8*
VOLMTRN	1.8	0.19	-0.8
W52H	3.1	0.20	3.8*
XFIN	4.7*	0.65*	2.5*
XRD2AT	1.2	0.09	6.5*
XRD2MV	3.9*	0.36*	4.9*
XRD2S	1.0	0.08	6.3*
ZSCORE	1.7	0.21	2.4*



ity metrics (e.g., market equity, sales growth, return on equity); idiosyncratic risk measures (e.g., stock volatility and skewness); and liquidity measures (e.g., Amihud illiquidity, share volume, and bid-ask spread).

Factors at a Glance

Exhibit 1 lists the variables and basic performance characteristics. We report each factor's average return, Sharpe ratio, and Fama and French (2016) five-factor alpha (returns and alphas are in percent per annum). The appendix provides additional details including a factor description and the original articles that analyzed each factor (we follow these articles as closely as possible when constructing our factor data set). We orient the long/short legs of each factor such that the predicted sign of the factor's expected return is positive (according to the paper originally proposing each factor). Note that this does not mean that all factors have positive average returns in our sample—we find that three of 65 have negative average returns when extended through 2017, and 25 are statistically indistinguishable from zero. Meanwhile, the factors with the strongest and most statistically reliable performance are the best known usual suspects, such as betting against beta, stock momentum, industry momentum, and valuation ratios (cash-flow/price, sales/price, and earnings/price).

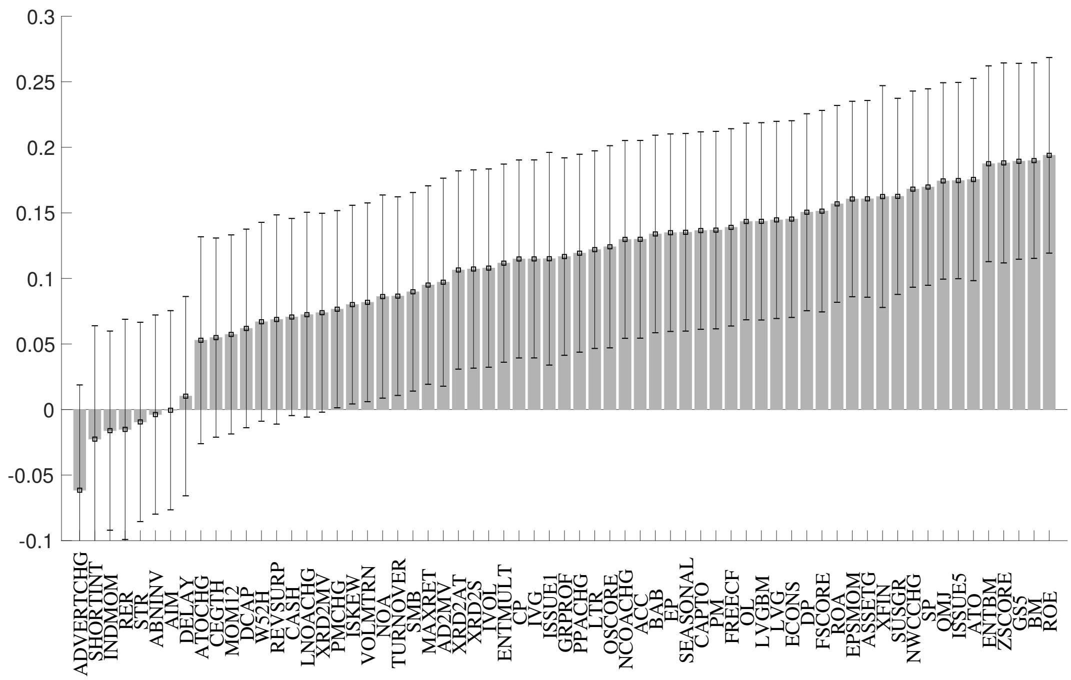
Despite the fact that all factors represent large and diversified portfolios, they nonetheless possess rather distinct return behavior. More than half of all factor pairs have a correlation below 0.25 in absolute value. Principal component (PC) analysis also supports the view that an unusually large amount of the portfolio return variation is factor-specific. It takes 19 PCs to explain 90% of the 65-factor correlation structure, 28 to explain 95% and 46 to explain 99%.

Factor Momentum

Factor Persistence

We begin our analysis by investigating the primary statistical phenomenon underlying momentum—serial correlation in returns. In Exhibit 2, we report monthly first-order autoregressive coefficients (denoted as AR(1)) for each factor portfolio along with 95% confidence intervals. When zero lies outside the confidence interval, it indicates that the estimate is statistically significant at the 5% level (or, equivalently, the t-statistic is greater than 1.96 in absolute

Exhibit 2: Factor Return Monthly AR(1) Coefficients



value).

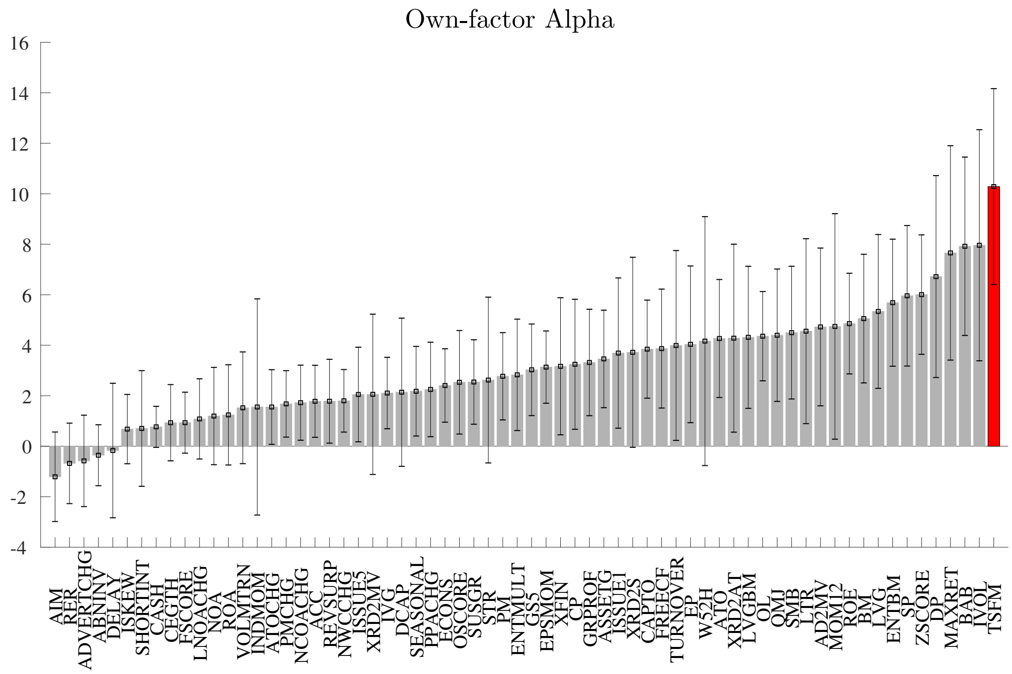
The strength and pervasiveness of one-month own-factor serial correlation is stunning. Of our 65 factors, 59 have a positive monthly AR(1) coefficient, and it is statistically significant for 49 of these. For comparison, the monthly AR(1) coefficient for the excess market return is 0.07 during our sample, which Moskowitz, Ooi, and Pedersen (2012) demonstrate is powerful enough for implementing a time series momentum strategy. The average AR(1) coefficient of our factors is 0.11, and 50 of them have a larger AR(1) coefficient than the market.[3] This is a first indication that it may be possible to time factors based on their own past performance.

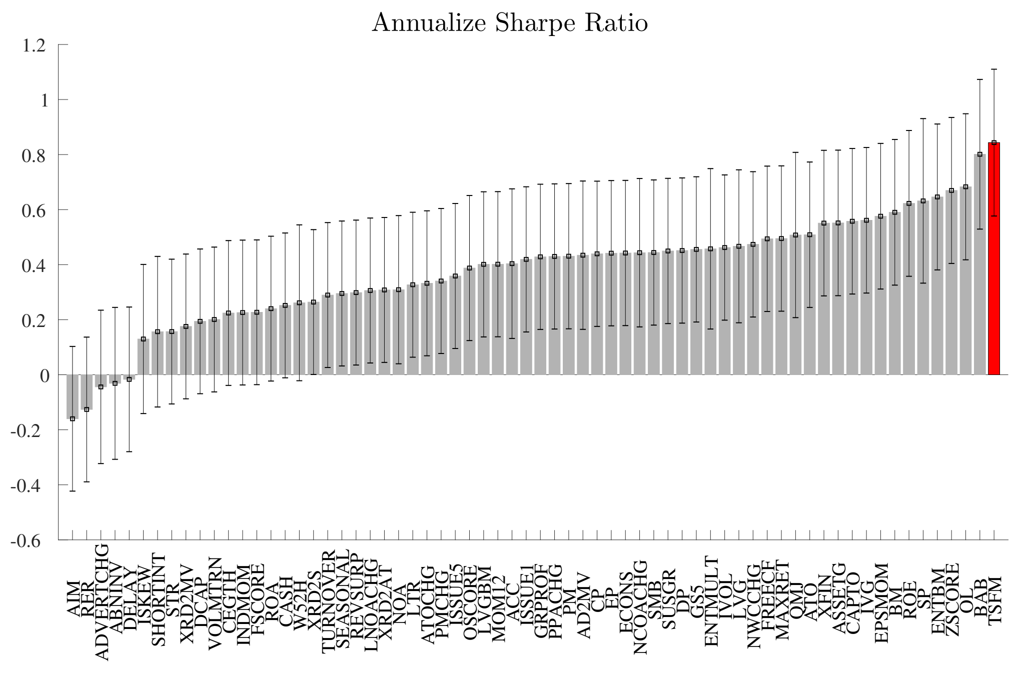
Time Series Factor Momentum

The strong autoregressive structure in factor returns suggests that it may be possible to time each factor individually based on its own recent performance. The idea of "portfolio timing" based on the portfolio's own past return underlies the time series momentum methodology of Moskowitz, Ooi, and Pedersen (2012).

[3] We believe that own-factor persistence may be even stronger than these results portray because any illiquidity imbalance in a factor will tend to create some negative serial correlation, and we are not directly accounting for that here.

Exhibit 3: Time Series Momentum for Individual Factors (One-month Formation)





We begin by exploring the benefits of portfolio timing by applying a time series momentum strategy one factor at a time. We focus on one-month holding periods, and consider various formation windows of one month up to five years. Our strategy dynamically scales one-month returns of the i^{th} factor, $f_{i,t+1}$, according to its performance over the past j months:

$$f^{TSFM}_{i,j,t+1} = s_{i,j,t} \times f_{i,t+1}, \quad s_{i,j,t} = \min\left(\max\left(\frac{1}{\sigma_{i,j,t}} \sum_{\tau=1}^{j} f_{i,t-\tau+1}, -2\right), 2\right). \tag{1}$$

Unpacking equation (1), we use the scaling term $s_{i,j,t}$ to time positions in factor i based on the factor's return over the formation period ($t-j$ to t). If formation returns are positive it buys the factor, if negative it sells the factor. We convert recent returns to z-scores by dividing by $\sigma_{i,j,t}$, which is the annualized factor volatility over the previous three years (for short formation windows, $j < 12$) or over the previous 10 years (if $j \geq 12$), and we cap z-scores at ± 2.[4]

The benefits of factor timing can be assessed in terms of alpha by regressing the scaled factor on the raw factor:

$$f^{\text{TSFM}}_{i,j,t} = \alpha_{i,j} + \beta_{i,j} f_{i,t} + e_{i,j,t}.$$

The top panel of Exhibit 3 reports the annualized percentage alphas from the time series strategy with one-month formation period for each factor, as well as 95% confidence intervals. The performance of time series momentum in individual factors is extraordinarily pervasive. It is positive for 61 out of 65 factors, and is statistically significant for 47 of these. To provide a clearer interpretation in terms of risk-return tradeoff, the bottom panel of Exhibit 3 shows Sharpe ratios for each individual factor momentum strategy. It exceeds 0.20 for 56 factors, and is statistically significant for 48 of them.

Our overall TSFM strategy combines all individual factor time series momentum strategies into a single portfolio. In particular, TSFM aggregates timed factors (with formation window j) according to

$$\text{TSFM}_{j,t} = \text{TSFM}^{\text{Long}}_{j,t} - \text{TSFM}^{\text{Short}}_{j,t}$$

where

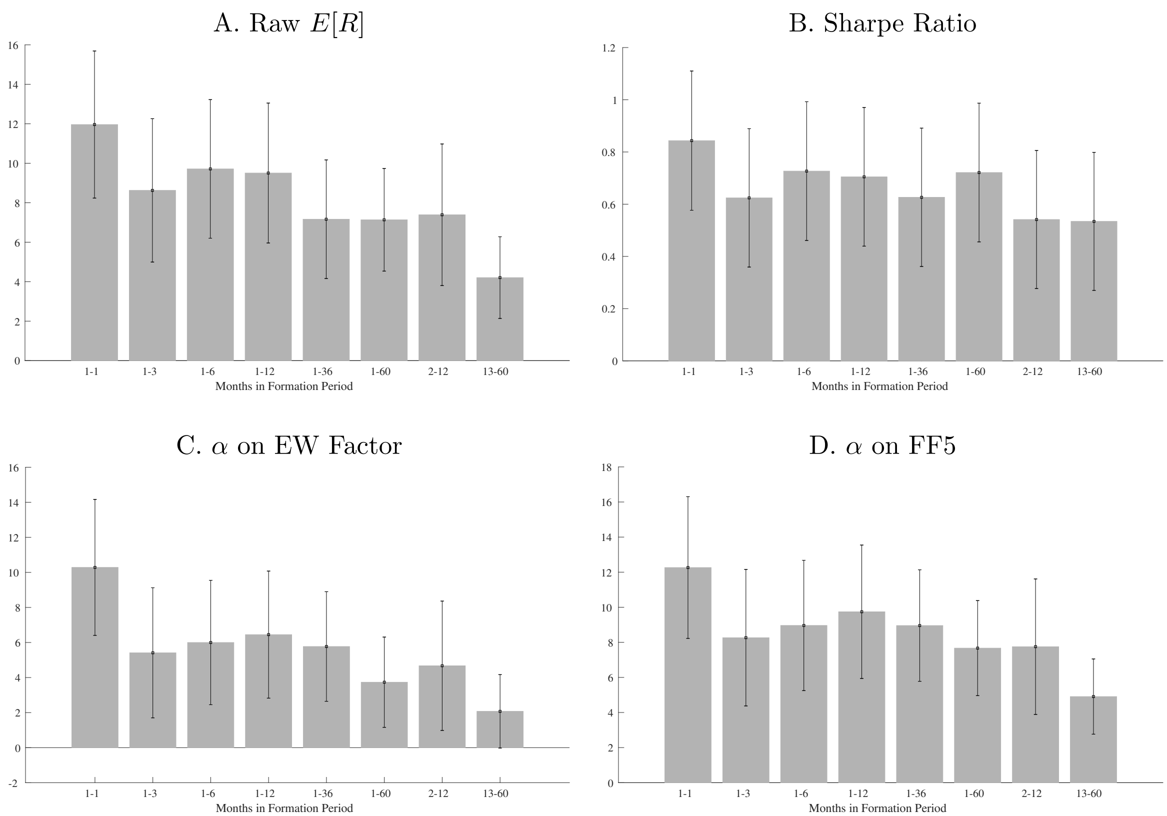
$$\text{TSFM}^{\text{Long}}_{j,t} = \frac{\sum_i 1_{\{s_{i,j,t}>0\}} f^{TSFM}_{i,j,t+1}}{\sum_i 1_{\{s_{i,j,t}>0\}} s_{i,j,t}} \quad \text{and} \quad \text{TSFM}^{\text{Short}}_{j,t} = \frac{\sum_i 1_{\{s_{i,j,t}\leq 0\}} f^{TSFM}_{i,j,t+1}}{\sum_i 1_{\{s_{i,j,t}\leq 0\}} s_{i,j,t}}.$$

That is, the long and short legs are re-scaled to form a unit leverage ($1 long and $1 short) TSFM portfolio.

TSFM earns an annualized average return of 12.0%. The last bar in the top panel reports the

[4] Our findings are robust to other estimation choices for $\sigma_{i,j,t}$, including shorter windows and exponentially weighted moving averages, and to other caps such as ± 1.

Exhibit 4: Risk-adjusted TSFM Performance



alpha from the regressing the one-month TSFM return on the equal-weighted average of raw factor returns. The equal-weighted portfolio of raw factors is itself an impressive strategy, earning an annualized Sharpe ratio of 1.07. Nevertheless, the portfolio of individual factor momentum strategies generates a highly significant 10.3% alpha (t-statistic of 4.6) after controlling for the average of untimed factors. The last bar in the bottom panel reports the annual Sharpe ratio of the combined factor momentum portfolio. It is 0.84, exceeding the Sharpe ratio of every individual factor momentum strategy.

Exhibit 4 explores how TSFM performance changes with alternative implementations. We form the momentum signal using look-back windows of one month ("1-1") up to five years ("1-60"). We also split out the 11 months excluding the most recent month ("2-12") for more direct comparability with UMD, and the four years excluding the most recent year ("13-60") to compare the role of long-term versus short-term return trends.

The upper left panel reports the raw TSFM average return for each formation period, and the upper right panel reports annualized Sharpe ratios. The 12-month TSFM strategy achieves an expected return of 9.5% and Sharpe ratio of 0.70. With a look-back as long as five years, TSFM earns 7.1% per annum with a Sharpe ratio of 0.72. Panel A shows that while one-month factor momentum is the overall performance driver, there remain large positive and significant contributions from longer (non-overlapping) 2-12 and 13-60 formation windows as well, with Sharpe ratios of 0.54 and 0.53, respectively.

When we benchmark TSFM against the equal-weighted average factor ("EW," shown in the lower left panel), or against the Fama-French five-factor model ("FF5," lower right panel), the excess performance of TSFM is little affected. For one-month formation, EW explains less than one-sixth of the TSFM average return, and at one year it explains less than one-third. The Fama-French model explains less than one-tenth of TSFM's average return for all formation windows.

Cross Section Factor Momentum

An alternative approach to forming a factor momentum strategy is to take positions in factors based on the recent performance of factors *relative* to the cross section of all factors. CSFM buys/sells factors that have recently outperformed/underperformed peers, rather than sizing factor exposures based on their own recent performance. For example, if all factors recently appreciated, TSFM will take long positions in all of them. CSFM, on the other hand, will be long only the relative outperformers and will short those with below median recent returns (despite their recent positivity).[5]

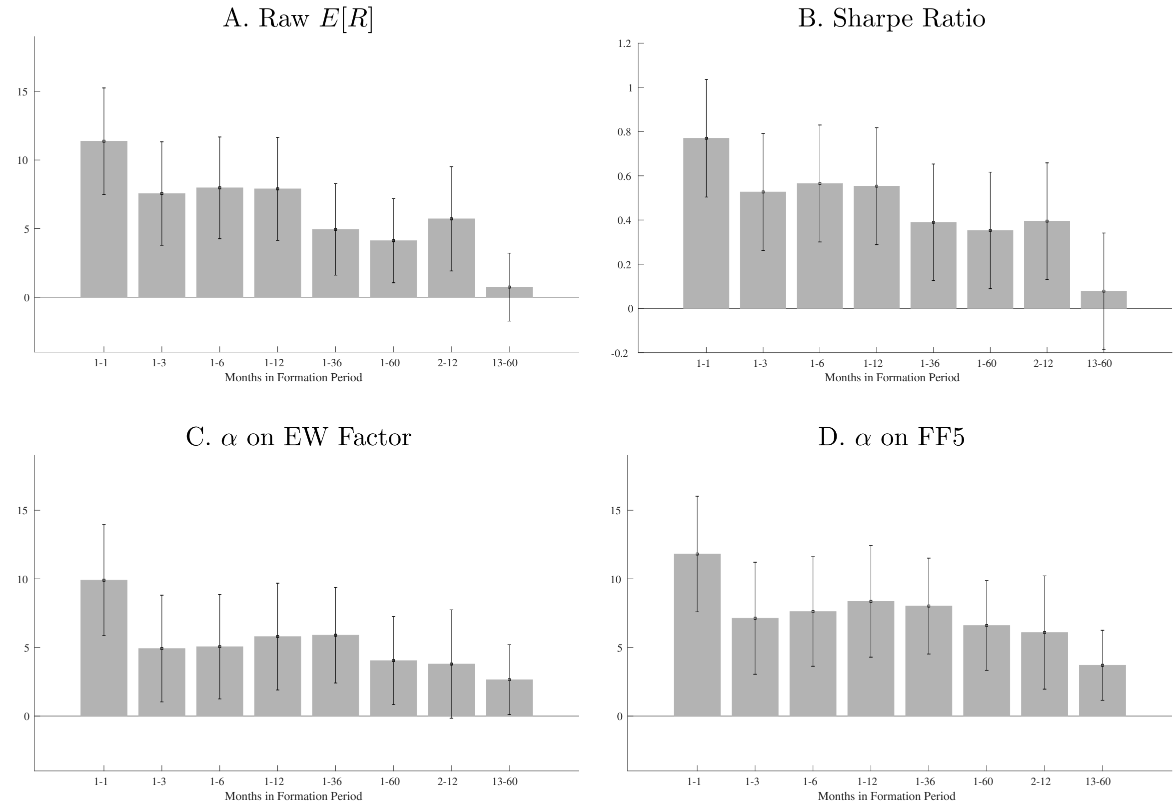
Exhibit 5 explores the performance of CSFM with various look-back windows for portfolio formation (in analogy with Exhibit 4). The results show that CSFM and TSFM have similar behavior. The Sharpe ratios of CSFM are slightly inferior to TSFM, and it has slightly smaller alphas with respect to the equal-weighted portfolio of raw factors, but their performance patterns are otherwise closely aligned.

Factor, Stock, and Industry Momentum

Next, we directly compare various incarnations of the momentum effect against each other, including factor momentum (TSFM and CSFM), stock-level momentum (UMD), short-term stock reversal (STR), and industry momentum (INDMOM, following Moskowitz and Grin-

[5]CSFM cross-sectionally de-means factors' formation-window returns, but otherwise follows the same construction as TSFM.

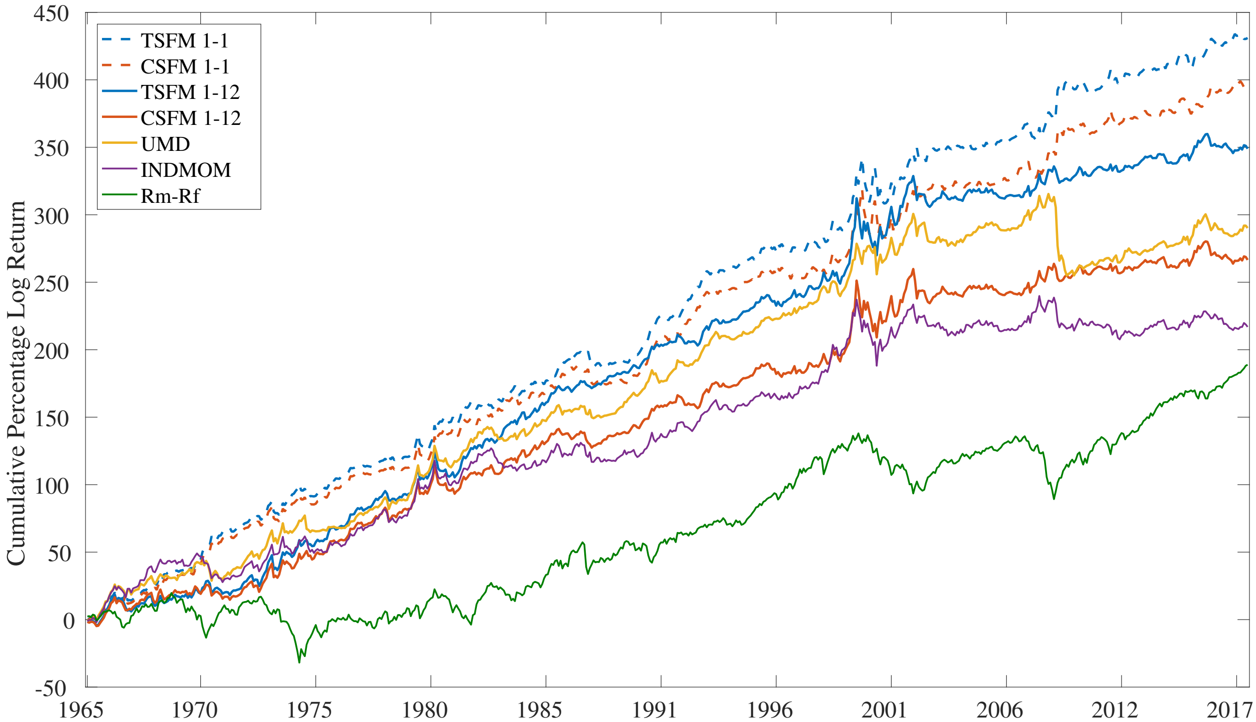
Exhibit 5: Risk-adjusted CSFM Performance



blatt, 1999; Asness, Porter, and Stevens, 2000, , for which we use a 1-12 formation strategy). In order to make a clearer comparison among average returns, we rescale all five series to have an ex post annualized volatility of 10%.

Exhibit 6 provides a preliminary visual comparison of momentum strategies. It shows the cumulative log returns for each momentum variable, including one-month and 12-month look-back windows for TSFM and CSFM, along with the excess market portfolio. Two features of this plot stand out. First is the comparatively steep slope of TSFM. This is consistent throughout the sample rather than being driven by a few good "runs." (One-month CSFM shares a similarly steep slope, but the 12-month implementation drops off substantially.) Second is the sharp drawdown of UMD, when stock momentum experienced a loss of 31% from March to May 2009 (Daniel and Moskowitz, 2016). INDMOM also experienced a drawdown of 24% over this time. In contrast, factor momentum entirely avoided the momentum crash. Over the same months, 12-month TSFM and CSFM earned 16% and 15%, respectively (one-month versions of TSFM and CSFM both earned 18%).

Exhibit 6: Cumulative Returns of Momentum Strategies



It is well known that stock momentum is concentrated in intermediate formation windows of six to 12 months. With very short look-backs (one month) or at long horizons, stocks experience reversals rather than momentum. To gain a basic understanding of comovement in strategies, particularly with respect to different formation periods, Exhibit 7 reports momentum correlations. We include UMD, which describes stock momentum from a 2-12 strategy, as well as STR which captures short-term stock reversals that arise in a 1-1 strategy. We compare each of these to TSFM and CSFM with a range of formation choices ranging from one month to 60 months, and again splitting out 2-12 and 13-60.

Exhibit 7 highlights an interesting distinction in the time series dynamics of different momentum strategies. When factor momentum is based on an intermediate window of 1-12 months, it bears a close correlation with UMD (0.76 and 0.75 for TSFM and CSFM, respectively, and similar for 2-12 factor momentum). Exhibit 7 also illustrates a close similarity between factor momentum and industry momentum.

In contrast, with a one-month window, factor momentum behaves strongly *opposite* of the stock-based STR strategy (correlation of -0.80 for both TSFM and CSFM). If factor momentum were simply capturing stock-level persistencies, then we would expect it to also

Exhibit 7: Momentum Strategy Return Correlations

Formation	CSFM			TSFM			
Window	UMD	STR	INDMOM	UMD	STR	INDMOM	CSFM & TSFM
1-1	0.10	-0.80	0.22	0.09	-0.80	0.21	0.99
1-3	0.40	-0.59	0.45	0.42	-0.60	0.47	0.99
1-6	0.57	-0.46	0.58	0.57	-0.46	0.59	0.98
1-12	0.76	-0.32	0.79	0.75	-0.35	0.77	0.98
1-36	0.64	-0.27	0.61	0.67	-0.32	0.62	0.95
1-60	0.65	-0.31	0.61	0.67	-0.35	0.60	0.91
2-12	0.77	-0.19	0.78	0.77	-0.22	0.77	0.98
13-60	0.20	-0.06	0.12	0.20	-0.12	0.05	0.85

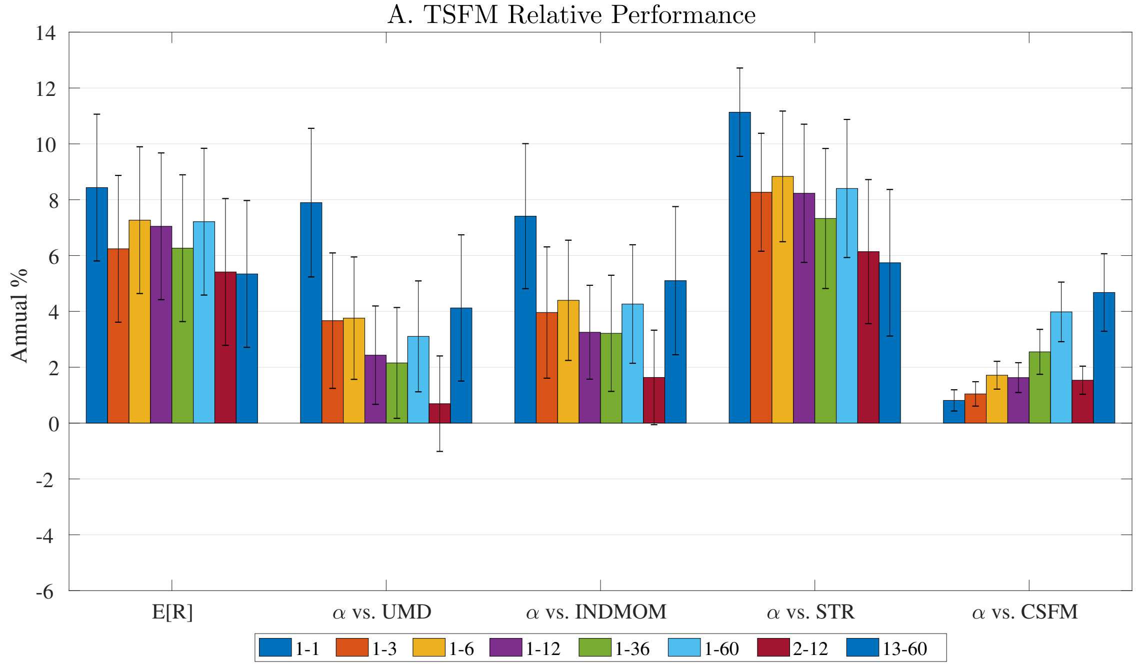
display a short-term reversal (in contrast to the findings of Exhibits 4 and 5) and would therefore expect it to be positively correlated with STR.

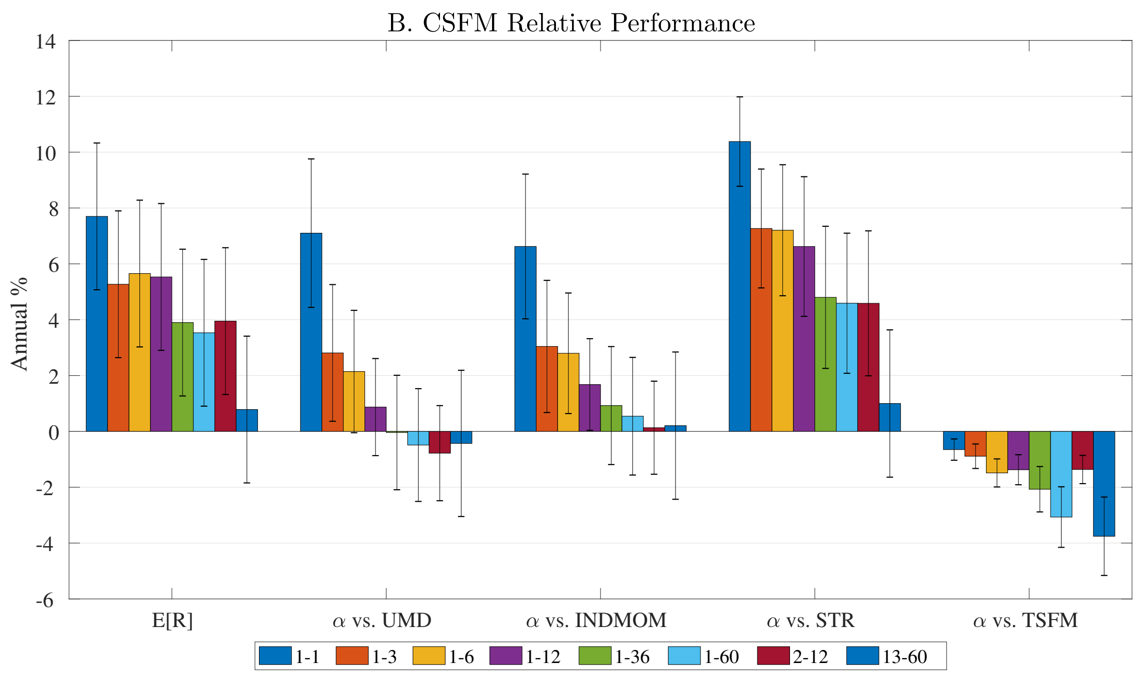
The last column shows the extremely high correlation between time series and cross section approaches to factor momentum.

Next, we regress TSFM and CSFM on momentum alternatives to understand if these strategies subsume factor momentum. Panel A of Exhibit 8 reports the average return of TSFM from various look-back windows as well as the alphas of TSFM relative to UMD, INDMOM, and STR. All estimates are accompanied by their 95% confidence intervals. A confidence interval that excludes/includes zero indicates that the estimate is statistically significant/insignificant at the 5% level. Bar colors correspond to different look-back windows for TSFM and are described in the legend (UMD, INDMOM, and STR look-back windows are held fixed).

Controlling for UMD only explains the performance of the 2-12 TSFM strategy. For all other look-back windows, TSFM has a significant alpha of at least 2% per year versus UMD. For one-month TSFM in particular, UMD has no explanatory power as the alpha and raw average returns are essentially the same. Alphas relative to INDMOM show a similar pattern as those relative to UMD, but are somewhat larger. Controlling for STR in fact raises TSFM's alpha above its raw average return, which is perhaps expected given their strong negative correlation. The right-most bars in Panel A show the alpha of TSFM relative to CSFM with matching formation window. Despite nearly perfect correlations between them, TSFM's alpha is significantly positive for all formation windows and becomes stronger at long horizons.

Exhibit 8: Comparison of Momentum Strategies





Panel B of Exhibit 8 performs the same comparison for CSFM. There are two key distinctions between Panels A and B. First, UMD and INDMOM explain more of CSFM's performance than they do TSFM's performance, and CSFM's alphas on UMD and INDMOM are insignificant for formation windows of a year or more. Second, CSFM has *negative* and significant alpha relative to TSFM. In other words, while TSFM and CSFM earn similarly high average returns and are highly correlated, TSFM harvests factor momentum compensation more efficiently than CSFM does.

In Exhibit 9, we reverse this analysis to assess the performance of UMD, INDMOM, and STR after controlling for factor momentum. We report alphas from regressions of these factors on TSFM and CSFM with various formation windows. As in Exhibit 8, bar colors correspond to different look-back windows for TSFM (holding UMD, INDMOM, and STR fixed).

The 1-12, 1-36, and 1-60 TSFM strategies can each individually explain most of the performance of UMD and INDMOM. The average annual return of UMD is 6.1%, but its alpha versus 12-month TSFM, for example, drops below 1% and its t-statistic falls below 1.0. The alpha of INDMOM is slightly negative and is likewise insignificant. CSFM is unable to explain the performance of UMD, but does capture a large portion of industry momentum. The central conclusion from this spanning analysis is that TSFM tends to outperform, and to a large extent accounts for, the returns to UMD.

Neither TSFM nor CSFM explains short-term reversal. To the contrary, controlling for factor momentum boosts the performance of STR from an unconditional average return of 3.4% per year to alphas in excess of 5%, and as high as 10.1% versus one-month TSFM. So, unlike UMD and TSFM, factor momentum and short-term reversal seem to capture distinct patterns in expected stock returns, as both have large unexplained alphas relative to each other.

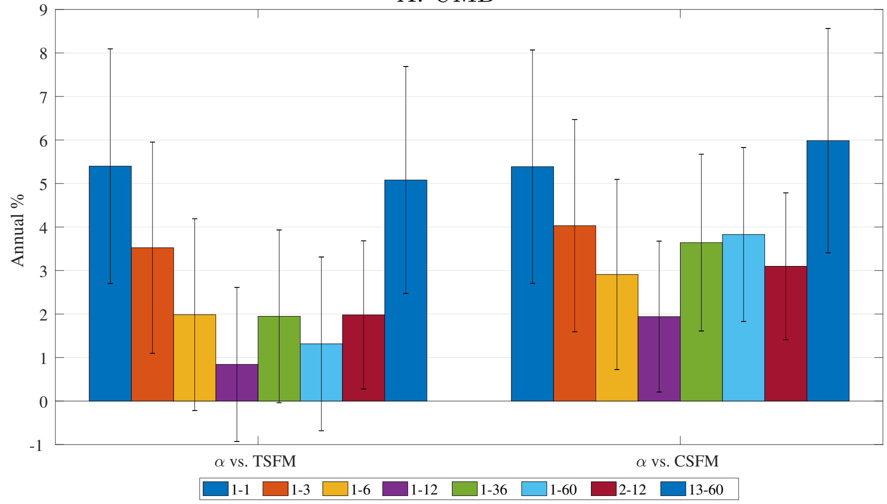
Portfolio Combinations

We next investigate the extent to which various momentum strategies play an incrementally beneficial role in a broader portfolio that includes other common investment factors. In particular, we form ex post (i.e., full sample) mean-variance efficient tangency portfolios of factors. The first column of Exhibit 10 lists the factors that we consider, which continue to be standardized to have 10% annualized volatility to put all factors on equal volatility footing. We include non-overlapping 1-1, 2-12, and 13-60 versions of TSFM and CSFM, as well as the 1-12 versions of each. We also include UMD, INDMOM, and STR. Finally we investigate combinations with the Fama-French five-factor model.

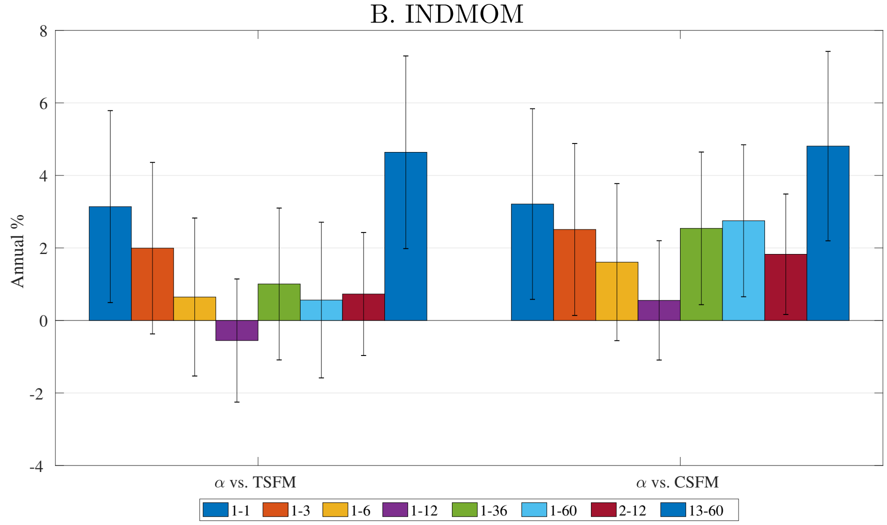
The second column reports the standalone Sharpe ratios for each factor. The remaining columns labeled 1 to 7 report tangency portfolio weights among various sets of factors.

Exhibit 9: Relative Performance of UMD, INDMOM, and STR

A. UMD



B. INDMOM



C. STR

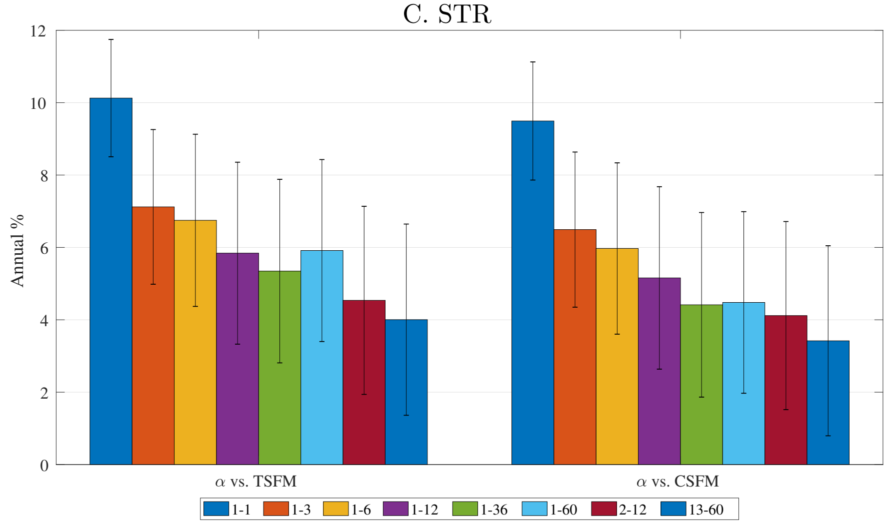


Exhibit 10: Ex Post Tangency Portfolios

	Indiv.	Tangency Portfolio Weights						
Factor	Sharpe	1	2	3	4	5	6	7
TSFM 1-1	0.84	0.47**			0.17**		0.32**	
TSFM 2-12	0.54	0.22**			0.00		-0.05*	
TSFM 13-60	0.53	0.31**			0.13**		0.07**	
TSFM 1-12	0.70			6.38**		0.15**		0.17**
CSFM 1-1	0.77		0.67**					
CSFM 2-12	0.39		0.26*					
CSFM 13-60	0.08		0.08					
CSFM 1-12	0.55			-5.38**				
UMD	0.61				0.10*	0.07	0.15**	0.06
STR	0.34						0.32**	0.13**
MKT	0.42				0.22**	0.25**	0.06**	0.19**
SMB	0.29				0.09**	0.09*	0.01	0.05
HML	0.43				0.07	0.05	0.02	0.03
RMW	0.39				0.12**	0.20**	0.05**	0.18**
CMA	0.50				0.11**	0.19**	0.04*	0.18**
Sharpe		1.07	0.83	0.98	1.65	1.32	2.62	1.42

Superscripts of * and ** signify that a weight estimate is significantly different from zero at the 5% or 1% level, respectively

Column 1 shows that the ex post efficient combination of 1-1, 2-12, and 13-60 TSFM puts the heaviest weight (0.47) on 1-1 TSFM, but also puts significantly positive weight on 2-12 and 13-60 (0.22 and 0.31, respectively). This tangency combination achieves a Sharpe ratio of 1.07. For CSFM, the tangency portfolio is dominated by a weight of 0.67 on the 1-1 component. Column 3 shows that the optimal combination of TSFM and CSFM takes a highly levered position in TSFM with a large negative offsetting position in CSFM. This result restates the fact that TSFM and CSFM are highly correlated but have oppositely signed alphas with respect to one another.

Column 4 considers the optimal combination of TSFM with UMD and the Fama-French factors. In this case, 2-12 TSFM takes an exact zero weight, and is replaced by a significantly positive weight of 0.10 on UMD. This combination earns a Sharpe ratio of 1.65 (the five Fama-French factors on their own achieve a tangency Sharpe ratio of 1.09). The same conclusion emerges if we simultaneously include UMD and STR alongside TSFM (Column 6), where all three enter the tangency portfolio with significantly positive weights. Among the Fama-French factors, MKT, CMA, and RMW are significant contributors to tangency across the

Exhibit 11: Correlation of Momentum and Value Variants

	UMD	INDMOM	TSFM 1-1	TSFM 2-12	TSFM 13-60	TSFM 1-12	CSFM 1-1	CSFM 2-12	CSFM 13-60	CSFM 1-12
UMD	-	0.84	0.09	0.77	0.20	0.75	0.10	0.77	0.20	0.76
INDMOM	-	-	0.21	0.77	0.05	0.77	0.22	0.78	0.12	0.79
HML	-0.18	-0.18	0.09	-0.04	-0.01	-0.02	0.09	-0.07	-0.26	-0.05
HML-Devil	-0.64	-0.53	0.00	-0.39	-0.2	-0.37	-0.01	-0.41	-0.36	-0.40

Exhibit 12: Ex Post Tangency Portfolios Including HML-Devil

Factor	Indiv. Sharpe	Tangency Portfolio Weights 1	2	3	4	5	6	7	8
TSFM 1-1	0.84	0.29**				0.13**		0.15**	
TSFM 2-12	0.54	0.23**				-0.04		0.10**	
TSFM 13-60	0.53	0.23**				0.12**		0.14**	
TSFM 1-12	0.70		0.59**				0.08		0.24**
UMD	0.61			0.54**		0.25**	0.23**		
INDMOM	0.49				0.54**			0.04	0.00
HML-Devil	0.30	0.25**	0.41**	0.46**	0.46**	0.24**	0.25**	0.14**	0.15**
MKT	0.42					0.17**	0.19**	0.19**	0.23**
SMB	0.29					0.06**	0.06	0.06*	0.06
RMW	0.39					0.08**	0.14**	0.13**	0.20**
CMA	0.5					-0.01	0.05	0.05	0.11**
Sharpe		1.23	0.93	1.10	0.83	1.89	1.48	1.70	1.38

Superscripts of * and ** signify that a weight estimate is significantly different from zero at the 5% or 1% level, respectively

board.

The diversification benefits from combining momentum factors with value factors become more pronounced when using the "HML-Devil" refinement of Asness and Frazzini (2013), which incorporates more timely price data in its value signal construction and significantly outperforms the traditional Fama-French HML. Exhibit 11 shows that the correlation of UMD and HML-Devil is -0.64, while UMD is only -0.18 correlated with Fama-French HML. Likewise, the correlation of 1-12 TSFM drops from -0.02 with HML to -0.37 with HML-Devil.

Motivated by the potential for stronger hedging benefits, Exhibit 12 investigates the impact of replacing HML with HML-Devil in our tangency portfolio analysis. Three observations emerge from this table. First, our central conclusions regarding factor momentum are unchanged—it remains a strong contributor to optimal multi-factor portfolios. Second, HML-Devil takes a large and statistically significant portfolio weight in all cases, in contrast with the general insignificance of Fama-French HML in Exhibit 10. Third, UMD becomes one of the most important components of the tangency portfolio thanks to the added diversification benefits of coupling UMD and HML-Devil.[6]. In summary, factor momentum and stock momentum are most effectively used in tandem when devising optimal portfolios.

Implementability

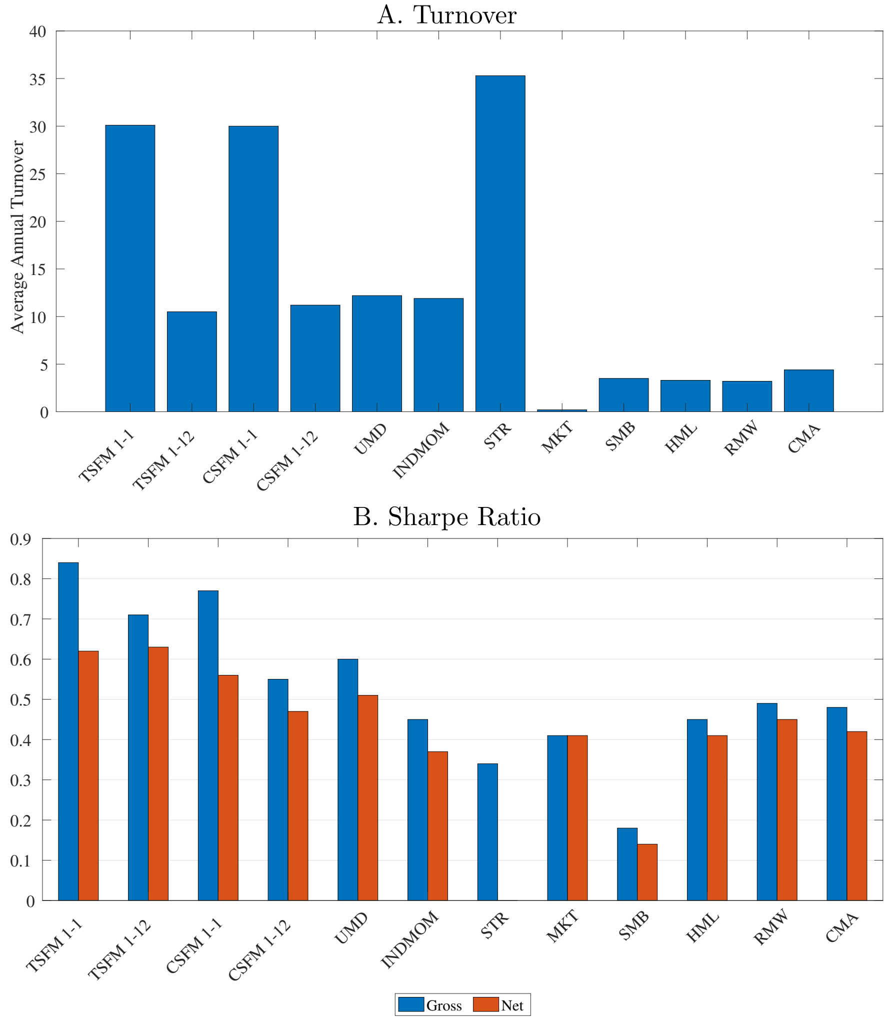
Momentum strategies are high turnover by nature, thus trading costs are a first order consideration for understanding the practical usefulness of factor momentum in portfolio decisions. Panel A of Exhibit 13 compares the average annualized turnover of factor momentum with other price trend factors.[7] In terms of formation window, STR is the natural stock-level benchmark for one-month factor momentum, while UMD and INDMOM are most natural to compare with 12-month factor momentum. In both cases we see that factor momentum turnover is comparable to, but slightly lower than, its stock-level counterpart. Panel A also shows that, like other momentum varieties, factor momentum involves substantially more trading than Fama-French factors.

Panel B of Exhibit 13 compares the performance of strategies net of transaction costs. Our calculations assume costs of 10 basis points per unit of turnover (based on the estimates of Frazzini, Israel, and Moskowitz, 2015). Red bars represent the net annualized Sharpe ratio for each strategy, along with the gross Sharpe ratio in blue for comparison. The main takeaway from the figure is that while trading costs indeed eat into the performance of factor momentum, its net performance continues to exceed that of UMD, INDMOM, STR, and the Fama-French factors. For example, the net Sharpe ratio of TSFM 1-12 is 0.63, versus 0.70 gross. But the next best net Sharpe ratio among stock-level price trend factors is 0.51 for UMD, while the best among Fama-French factors is 0.45 for RMW.

[6] Exhibit 12 highlights the benefits of combining value and momentum strategies (a point previously emphasized by Asness, Moskowitz, and Pedersen, 2013). Our factor momentum findings naturally call for an investigation into an analogous "factor value" strategy that times factors based on factor-level value signals (as discussed for example in Asness, 2016b,a; Asness, Friedman, Krail, and Liew, 2000). While an exploration of factor value, and in particular the benefits of combining it with factor momentum, is beyond the scope of this paper, it is a fascinating direction for future research.

[7] Average annualized turnover is defined as the sum of absolute changes in portfolio weights each month, averaged over all months and multiplied by 12. This describes total two-sided trading volume (both entering and exiting positions) as a fraction of gross asset value.

Exhibit 13: Turnover and Net Sharpe Ratio

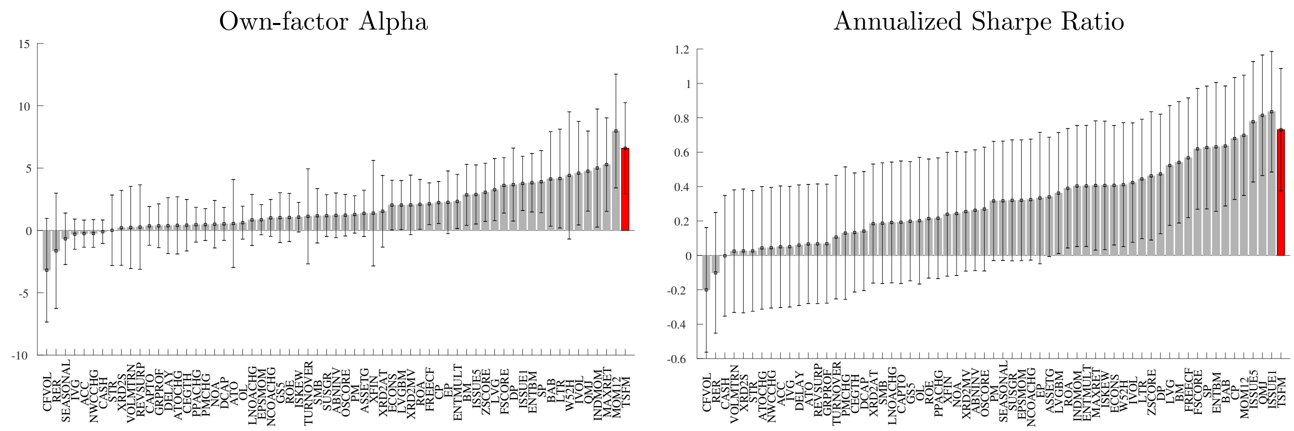


Lastly, Panel B sheds new light on the findings in Exhibit 9. It reveals that the strong performance of STR after controlling for factor momentum is illusory. Even on a standalone basis, the performance of short-term reversal is *entirely* wiped out by transaction costs.

Factor Momentum Around the World

In this section, we show that each of our main factor momentum conclusions from the US sample are strongly corroborated in international equity markets. We study three international samples. The Europe sample includes Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, UK, Greece, Ireland, Italy, Netherlands, Norway, Portu-

Exhibit 14: Time Series Momentum for Individual Factors (Global ex. US, One-month Formation Window)



gal, Sweden, and Israel. The Pacific sample includes Australia, Hong Kong, Japan, New Zealand, and Singapore. The broadest international sample we consider is global (ex. US), and combines Europe, Pacific, and Canada. Due to data limitations, we study only 62 of the original 65 factors in the international sample.[8]

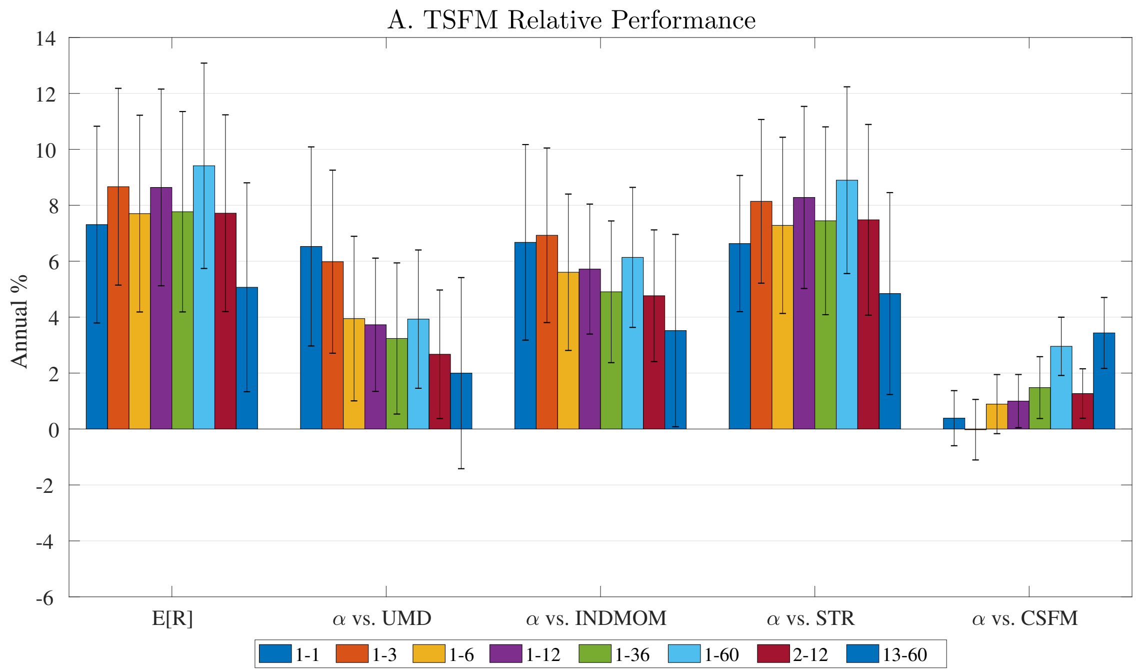
First, individual factor returns are highly persistent. The average AR(1) coefficient is 0.10 (versus 0.11 in the US), is positive for 51 of 62 factors, and is significant for 30 of these. Exhibit 14 shows that the success of individual factor time series momentum strategies (one-month formation) work as well for international factors as they do for the US. The alpha of momentum-timed factors versus raw factors is positive for 55 of 61 factors and is significant for 22 of these (versus 61 of 65 positive in US, and 47 of those significant). The TSFM portfolio that aggregates individual time series factor momentum strategies has a Sharpe ratio of 0.73 (versus 0.84 in the US) and earns an alpha of 6.6% per year after controlling for the equal-weighted portfolio of raw (untimed) factors.

Second, international factor momentum demonstrates extraordinarily stable performance regardless of formation window (shown in the left-most bars of Exhibit 15). Both TSFM and CSFM earn essentially the same average return whether they use a short look-back of one-month, all the way through a long look-back of five years. As in the US sample, this is a remarkable divergence from stock-level continuation patterns, where a one-month window gives rise to reversal while a one-year window captures momentum.

Third, international factor momentum demonstrates large and significant excess performance

[8] Excluded are ADVERTCHG, AD2MV, and AIM.

Exhibit 15: Comparison of Momentum Strategies (Global ex. US)



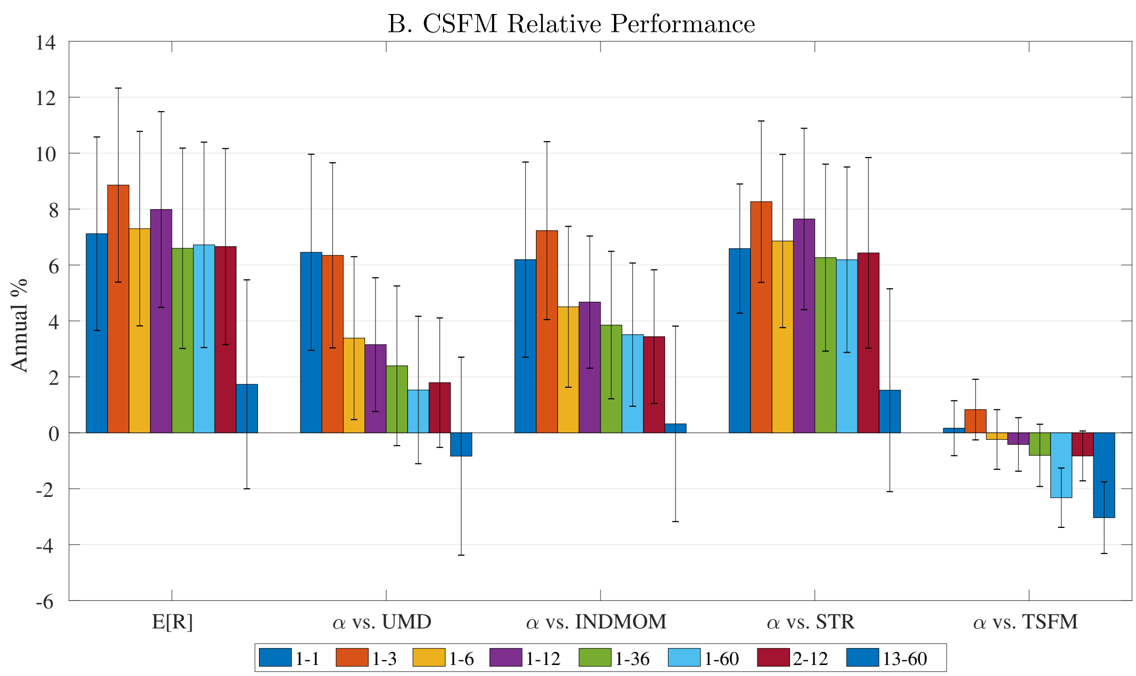


Exhibit 16: Relative Performance of UMD, INDMOM, and STR (Global ex. US)

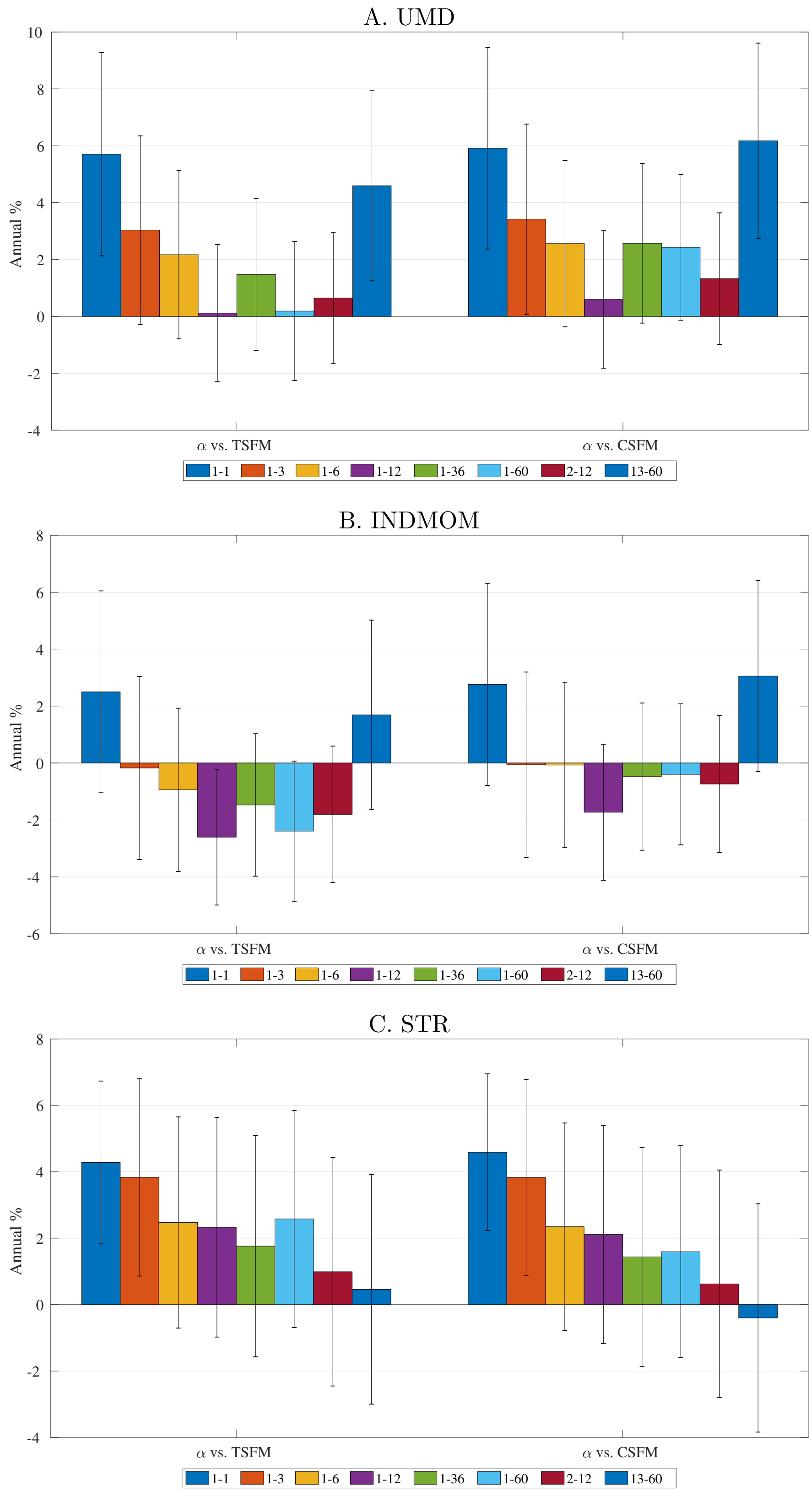


Exhibit 17: Ex Post Tangency Portfolios (Global ex. US)

	Indiv.	Tangency Portfolio Weights						
Factor	Sharpe	1	2	3	4	5	6	7
TSFM 1-1	0.73	0.51**			0.18**		0.32**	
TSFM 2-12	0.77	0.44**			0.16		0.08	
TSFM 13-60	0.51	0.05			0.07		0.04	
TSFM 1-12	0.86			1.71*		0.18**		0.19*
CSFM 1-1	0.71		0.62**					
CSFM 2-12	0.67		0.49**					
CSFM 13-60	0.17		-0.11					
CSFM 1-12	0.80			-0.71				
UMD	0.67				0.00	0.09	0.07	0.09
STR	-0.07						0.28**	0.02
MKT	0.58				0.32**	0.34**	0.14**	0.33**
SMB	0.09				0.01	0.02	-0.01	0.01
HML	0.27				-0.03	-0.03	0.00	-0.03
RMW	0.51				0.17**	0.21**	0.05*	0.20**
CMA	0.42				0.12*	0.19**	0.05	0.19**
Sharpe		1.18	1.09	0.88	1.89	1.51	2.37	1.51

after controlling for other varieties of international momentum including UMD, INDMOM, and STR (Exhibit 15). The TSFM alpha versus UMD is significantly positive for all formation windows except 13-60.

Fourth, TSFM and CSFM are more than 0.95 correlated for all formation windows. Yet TSFM tends to possess positive alpha relative to CSFM, and CSFM earns negative alpha versus TSFM, indicating that, as in the US sample, TSFM more efficiently captures the benefits of factor momentum.

Fifth, the performance of UMD and INDMOM is explained by factor momentum. Exhibit 16 shows that UMD's alpha is essentially zero and INDMOM has a negative alpha after controlling for either TSFM or CSFM.

Sixth, international tangency portfolio analysis in Exhibit 17 highlights the additivity of factor momentum to the broader set of investment factors.[9] The conclusions from Exhibit 17 are qualitatively similar to the US analysis in Exhibit 10. US and international TSFM 1-1

[9]All momentum variables are based on international equities. However, because our data begins earlier than Ken French's international five-factor data, we use the US Fama-French factors.

share a correlation of 0.62, and the US and international 1-12 versions are 0.64 correlated. The ex post tangency portfolio that combines US and international TSFM 1-1 earns an annual Sharpe ratio of 0.83, while individually they each earn 0.73.

In further (unreported) robustness analyses, we find that the majority of the performance of the factor momentum strategy arises from dynamically adjusting factor weights over time, rather than from taking static long/short bets on factors that have higher/lower average returns unconditionally. We also find that the performance of factor momentum is not dependent on using dozens of fine-grained factors. Instead, with a set of only six broad "theme" factors,[10] we reproduce the same basic factor momentum phenomenon found in the 65 factor data set.

Conclusion

We document robust persistence in the returns of equity factor portfolios. This persistence is exploitable with a time series momentum trading strategy that scales factor exposures up and down in proportion to their recent performance. Factor timing in this manner produces economically and statistically large excess performance relative to untimed factors. We aggregate individual factor timing strategies into a combined "time series factor momentum" strategy that dominates all individual timing strategies. TSFM is complementary with stock momentum, as both enter optimized multi-factor portfolios with significant positive weights (particularly when combined with HML-Devil).

An interesting aspect of factor momentum is its stability with respect to the definition of "recent" performance. Whether the look-back window is as short as one month or as long as five years, our strategy identifies large positive momentum among factors. This contrasts sharply with stock momentum, which exhibits reversal with respect to recent one-month performance, momentum at intermediate horizons of around one year, and again reversal for windows beyond two years.

Factor momentum is a truly global phenomenon. It manifests equally strongly outside US, both in a large global (ex. US) sample and finer Europe and Pacific region subsamples.

Taken alongside the evidence of time series momentum in commodity, bond, and currency factors (Moskowitz, Ooi, and Pedersen, 2012), our findings of momentum among equity

[10]The six theme factors are valuation, momentum, earnings quality, sustainable growth, management and risk. Each theme aggregates a set of closely related subfactors—for example, valuation includes book-to-market, earnings-to-price, and dividend yield.

factors—in the time series, in the cross section, and around the world—support the conclusion that factor momentum is a pervasive phenomenon in financial markets.

References

Arnott, R. D., M. Clements, V. Kalesnik, and J. T. Linnainmaa (2018): "Factor momentum," *SSRN Working Paper*.

Asness, C. (1994): "Variables That Explain Stock Returns," *Ph.D. Thesis, University of Chicago*.

Asness, C., and A. Frazzini (2013): "The devil in HML's details," *Journal of Portfolio Management*, 39(4), 49.

Asness, C., A. Frazzini, R. Israel, and T. Moskowitz (2014): "Fact, Fiction, and Momentum Investing," *Journal of Portfolio Management*, 40(5), 75.

Asness, C. S. (2016a): "My factor philippic," *SSRN Working Paper*.

——— (2016b): "The Siren Song of Factor Timing aka "Smart Beta Timing" aka "Style Timing"," *Journal of Portfolio Management*, Special Issue, 1–6.

Asness, C. S., J. A. Friedman, R. J. Krail, and J. M. Liew (2000): "Style timing: Value versus growth," *Journal of Portfolio Management*, 26(3), 50–60.

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

Asness, C. S., R. B. Porter, and R. L. Stevens (2000): "Predicting stock returns using industry-relative firm characteristics," *SSRN Working Paper*.

Avramov, D., S. Cheng, A. Schreiber, and K. Shemer (2016): "Scaling up market anomalies," *Working Paper*.

Chaves, D. B. (2016): "Idiosyncratic momentum: U.S. and international evidence," *The Journal of Investing*, 25(2), 64–76.

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

De Bondt, W. F., and R. Thaler (1985): "Does the stock market overreact?," *The Journal of finance*, 40(3), 793–805.

Fama, E. F., and K. R. French (2016): "Dissecting anomalies with a five-factor model," *The Review of Financial Studies*, 29(1), 69–103.

Frazzini, A., R. Israel, and T. Moskowitz (2015): "Trading costs of asset pricing anomalies," *AQR Working Paper*.

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

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

Gu, S., B. T. Kelly, and D. Xiu (2018): "Empirical Asset Pricing Via Machine Learning," *Yale Working Paper*.

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

Jegadeesh, N. (1990): "Evidence of predictable behavior of security returns," *The Journal of finance*, 45(3), 881–898.

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

Kelly, B., S. Pruitt, and Y. Su (2018): "Characteristics are covariances: A unified model of risk and return," Discussion paper, National Bureau of Economic Research.

Lewellen, J. (2002): "Momentum and autocorrelation in stock returns," *The Review of Financial Studies*, 15(2), 533–564.

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

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

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012): "Time series momentum," *Journal of financial economics*, 104(2), 228–250.

Appendix

Factor List

Abbrev.	Description	Authors	Journal	Year
ABNINV	Abnormal capital investment	Titman, Wei, and Xie	JFQA	2004
ACC	Accurals	Sloan	AR	1998
AD2MV	Advertisement expense divided by market value	Chan, Lakonishok, and Sougiannis	JF	2001
ADVERTCHG	Change in expenditures on advertising	Chemmanur and Yan	JFE	2009
AIM	Amihud illiquidity measure	Amihud	JFM	2002
ASSETG	Year-on-year percentage change in total assets	Cooper, Gulen, and Schill	JF	2008
ATO	Asset turnover	Soliman	AR	2008
ATOCHG	Change in asset turnover	Soliman	AR	2008
BAB	Market beta	Frazzini and Pedersen	JFE	2014
BM	Book to market	Stattman	CMBA	1980
CAPTO	Capital turnover	Haugen and Baker	JFE	1996
CASH	Cash holding	Palazzo	JFE	2012
CEGTH	Capital expenditure growth	Anderson and Garcia-Feijoo	JF	2006
CP	Cash flow to price	Lakonishok, Shliefer, and Vishny	JF	1994
DCAP	Debt capacity	Hahn and Lee	JF	2009
DELAY	Delay in a stock price's response to information	Hou and Moskowitz	RFS	2005
DP	Dividend yield	Litzenberger and Ramaswamy	JF	1982
ECONS	Earnings consistency	Alwathainani	BAR	2009
ENTBM	Enterprise component of book to market	Penman, Richardson, and Tuna	JAR	2007
ENTMULT	Enterprise multiple	Loughran and Wellman	JFQA	2011
EP	Earnings to price	Basu	JFE	1983
EPSMOM	Momentum in earnings per share	Ball and Brown	JAR	1968
FREECF	Cash flow to book value of equity	Freyberger, Neuhierl, Weber	WP	2017
FSCORE	F-score	Piotroski	JAR	2000
GRPROF	Gross profitability	Novy-Marx	JFE	2013
GS5	Sales growth	Lakonishok, Shliefer, and Vishny	JF	1994
INDMOM	Industry momentum	Moskowitz and Grinblatt	JF	1999
ISKEW	Idiosyncratic skewness	Boyer, Mitton and Vorkink	RFS	2007
ISSUE1	Log growth of adjusted shares over 12 month	Pontiff and Woodgate	JF	2008
ISSUE5	Log growth of adjusted shares over 60 months	Pontiff and Woodgate	JF	2008
IVG	Inventory growth	Belo and Lin	RFS	2012
IVOL	Idiosyncratic volatility	Ang, Hodrick, Xing, and Zhang	JF	2006
LNOACHG	Growth in long-term net operating assets	Fairfield, Whisenant, and Yohn	AR	2003
LTR	Long-term return reversal	De Bondt and Thaler	JF	1984
LVG	Leverage	Bhandari	JF	1988
LVGBM	Leverage component of book to market	Penman, Richardson, and Tuna	JAR	2007
MAXRET	Extreme stock returns	Bali, Cakici and Whitelaw	JFE	2011
MOM12	Momentum	Jegadeesh and Titman	JF	1993
NCOACHG	Noncurrent operating assets changes	Soliman	AR	2008

NOA	Net operating assets	Hirshleifer, Hou, Teoh, and Zhang	JAE	2004
NWCCHG	Net working capital changes	Soliman	AR	2008
OL	Operating leverage	Novy-Marx	ROF	2010
OSCORE	O-score	Griffin and Lemmon	JF	2002
PM	Profit margin	Soliman	AR	2008
PMCHG	Change in profit margin	Soliman	AR	2008
PPACHG	Changes in property, plant, and equipment divided by assets	Lyandres, Sun, and Zhang	RFS	2007
QMJ	Profitability	Soliman	AR	2008
RER	Real estate holdings divided by property, plant, and equipment	Tuzel	RFS	2010
REVSURP	Revenue surprises	Jegadeesh and Livnat	JAE	2005
ROA	Return on assets	Cooper, Gulen, and Schill	JF	2008
ROE	Return on equity	Haugen and Baker	JFE	1996
SEASONAL	Return seasonalities	Heston and Sadka	JFE	2008
SHORTINT	Short interest	Asquith, Pathak, and Ritter	JFE	2005
SMB	Market equity	Banz	JFE	1981
SP	Sales to price	Lewellen	CFR	2015
STR	Short-term reversal	Jegadeesh	JF	1990
SUSGR	Sustainable growth	Lockwood and Prombutr	JFR	2016
TURNOVER	Share volume	Pontiff and Maclean	JFM	1998
VOLMTRN	Volume trend	Haugen and Baker	JFE	1996
W52H	52-week high	George and Hwang	JF	2004
XFIN	External financing	Bradshaw, Richardson, and Sloan	JAE	2006
XRD2AT	R&D expenditure divided by total assets	Li	RFS	2011
XRD2MV	R&D expenditure divided by market value	Chan, Lakonishok, and Sougiannis	JF	2001
XRD2S	R&D expenditure divided by sales	Chan, Lakonishok, and Sougiannis	JF	2001
ZSCORE	Z-score	Dichev	JF	1998