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Short-Term Trend: *A Jewel Hidden in Daily Returns*

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KEY FINDINGS

- The authors examine the performance of time-series momentum using daily rather than monthly returns with standard lookback periods of 1, 3, and 12 months and a rebalancing period of one month.
- They introduce a shorter duration momentum strategy with weekly rebalancing frequency.
- The authors show that the short-term momentum strategy is a strong diversifier to the longer-term strategies but that the benefit is heavily dependent on the quality of trade execution.

ABSTRACT: *This article examines the performance of time-series momentum strategies using daily returns for 78 futures markets across four major asset classes between January 1985 and December 2017. The authors find that the 252-day, 63-day, and 21-day momentum strategies perform similarly to the previously documented 12-month, 3-month, and 1-month strategies, respectively. The performance is stronger with volatility-based position sizing, robust to implementation considerations such as a one-day gap between signal generation and execution, and persistent across asset classes and subperiods. The authors introduce a shorter duration momentum strategy with a weekly rebalancing frequency, which cannot be replicated using monthly returns. The authors find that the short-term strategy is a strong diversifier to the longer-term strategies, but the benefit may be reduced, or even completely offset, if the quality of trade execution is poor. The authors also find that the positive contribution of short-term momentum is driven by its superior diversifying characteristics rather than by the rebalancing frequency effect.*

TOPICS: ***Factor-based models, performance measurement, portfolio construction, style investing****

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Time-series momentum as documented by Moskowitz, Ooi, and Pedersen (2012) takes a long exposure in a security if its cumulative lagged 12-month return is positive and a short exposure if the return is negative, while holding positions for a month and rebalancing the portfolio monthly. This type of strategy is often denoted *12-1 momentum.* Hurst, Ooi, and Pedersen (2017) extended previous research to show that 3-1 and 1-1 time-series momentum strategies that rely on three-month and one-month lagged returns with monthly rebalancing, respectively, positively contribute to the original strategy within an equally weighted portfolio.

The purpose of this article is to examine whether using daily returns to generate signals and rebalance intramonth can further improve the aggregate performance of time-series momentum strategies and whether that improvement can be captured by investors after transaction costs. The contribution of this article is threefold. First, we show that the 252-21 daily time-series momentum strategy[1] behaves similarly to the 12-1 monthly strategy of Moskowitz, Ooi, and Pedersen (2012) and provides strong performance across asset classes while exhibiting relatively low pairwise correlations across asset classes and yielding better performance when exposure in each market is adjusted to the 40% target volatility recommended by Moskowitz, Ooi, and Pedersen (2012). The performance of the daily strategy is close to that of the monthly strategy for each asset class, except for equities, in which the daily strategy yields a Sharpe ratio of 0.60, which is inferior to the 0.80 Sharpe ratio of the monthly strategy. The difference is driven by a few intramonth events, such as the market crash in October 1987. There is significant diversification across asset classes, with pairwise correlations ranging from 0.06 to 0.22. The performance of 252-21 daily time-series momentum is robust across subperiods, with consistently low average pairwise correlations across asset-specific strategies ranging from 0.04 to 0.20. Volatility adjusting of exposures consistently enhances performance for each asset class by improving Sharpe ratios by at least 0.23. This finding is consistent with that of Kim, Tse, and Wald (2016), who reported that the abnormal returns of time-series momentum are largely driven by scaling returns by volatility.[2]

Second, we consider 63-21 and 21-21 daily time-series momentum strategies[3] that resemble the 3-1 and 1-1 monthly time-series momentum strategies of Hurst, Ooi, and Pedersen (2017) and introduce the 21-5 daily short-term momentum strategy.[4] Unlike the other three strategies, the short-term momentum strategy cannot be approximated using monthly returns. We find that the performance of the four time-series momentum strategies is strong in each asset class, except that the 21-21 strategy produces a marginally negative Sharpe ratio in equities. We also find that volatility-adjusting exposure improves Sharpe ratios and that there is a fair amount of diversification, with pairwise correlations ranging from 0.21 between the 252-21 and 21-5 strategies to 0.61 between the 21-21 and 21-5 strategies. The 63-21 and 21-21 daily strategies perform similarly to the 3-1 and 1-1 monthly strategies, except for underperformance in equities that is driven by the same intramonth events, as in the case of the 252-21 strategy. Overall, the differences in performance are more significant relative to the 252-21 strategy because the calendar effect is more pronounced for shorter time frames. We also evaluate robustness to implementation considerations by examining the performance of the daily strategies after introducing a one-day gap between signal generation and execution. We find that the impact on performance is small; therefore, the daily strategies are potentially more implementable than the traditional monthly strategies of Hurst, Ooi, and Pedersen (2017).

Finally, we examine the portfolio contribution of short-term momentum. Because of its attractive Sharpe ratio and moderate correlations to the other three strategies, short-term momentum can potentially serve as a strong diversifier. However, it is not clear whether the improvement in performance is robust to trading costs that are likely to be higher because of more frequent rebalancing. We start with the Hurst, Ooi, and Pedersen (2017) benchmark of an equally weighted portfolio of 252-21, 63-21, and 21-21 daily strategies. We evaluate the portfolio contribution of short-term momentum by considering two balanced portfolios that include short-term momentum. The first balanced approach replaces the 21-21 strategy with the 21-5 short-term momentum strategy. The second splits the original allocation to the 21-21 strategy equally between the 21-5 and 21-21 strategies.

Although the standard portfolio of Hurst, Ooi, and Pedersen (2017) delivers a solid Sharpe ratio of 1.10,

[1] Because there are approximately 21 trading days in a month and 252 trading days in a 12-month period, we approximate a 12-1 monthly momentum strategy with a 252-21 daily momentum strategy. The 252-21 strategy uses a cumulative lagged return over 252 days to generate a signal and holds the position for 21 days, at which point it generates the next signal.

[2] Kim, Tse, and Wald (2016) reported that once volatility scaling is removed, the alpha of time-series momentum drops from 1.27% to 0.41% and delivers a cumulative return that is similar to that of a naive buy-and-hold strategy.

[3] Because there are approximately 21 trading days in a month and 63 trading days in a three-month period, we approximate 3-1 and 1-1 monthly momentum strategies with 63-21 and 21-21 daily momentum strategies, respectively.

[4] We choose the holding period of five days to match a weekly rebalancing frequency.

the balanced portfolios yield Sharpe ratios of 1.28 and 1.21, which are superior in economic terms and statistically significant at the 1% level. The correlations of all three portfolios to the S&P 500 Total Return Index are roughly equivalent. This result indicates that short-term momentum can improve the performance of time-series momentum portfolios as standalone investments and serve as diversifiers to stock portfolios.

We repeat the analysis after excluding commodities from the short-term momentum strategy, primarily because they are less liquid than the financial asset classes of equities, fixed income, and foreign exchange (FX). Moreover, Haynes and Roberts (2015) reported that nonelectronic and manual trading are significantly more common in commodities such as agricultural, energy, and metals futures contracts than in financials. By contrast, automated trading that is essential to successful shorter-term strategies is more prevalent in financials than in commodities. We find that excluding commodities has very marginal impact on performance and thus focus on short-term momentum that excludes commodities.

Although including short-term momentum in well-diversified portfolios of time-series momentum strategies improves performance gross of fees, it is important to consider the impact of transaction costs. In our analysis, we consider two sets of assumptions: the conservative estimate of Hurst, Ooi, and Pedersen (2017)[5] and an optimistic estimate that represents 50% of that original cost estimate. It is reasonable to assume less conservative costs because managers tend to heavily invest in optimal execution by relying on co-located servers and sophisticated proprietary execution algorithms. Frazzini, Israel, and Moskowitz (2018) confirmed this assumption and reported that previous studies have substantially overstated transaction costs.

Under the conservative estimate of transaction costs, short-term momentum fails to improve the net-of-fee performance of the original portfolio of Hurst, Ooi, and Pedersen (2017). However, by imposing a less conservative cost assumption that represents 50% of the original estimate, the portfolio contribution of short-term momentum is significant at the 10% significance level for the first balanced approach and at the 5% significance level for the second balanced approach. The improvement in the Sharpe ratio from 0.92 to 0.98–1.01 is also meaningful in economic terms.

Thus, we conclude that although short-term momentum has the potential to improve the net-of-fees performance of time-series momentum portfolios, the degree of improvement is highly dependent on the quality of execution.

We further investigate why short-term momentum improves the performance of well-diversified portfolios of time-series momentum. Because Hurst, Ooi and Pedersen (2013) reported that daily and weekly rebalancing frequencies are superior to monthly frequencies for 1-month, 3-month, and 12-month strategies before considering transaction costs, we investigate whether the positive contribution of short-term momentum is driven by the rebalancing frequency effect or its diversifying characteristics. We find that, although the rebalancing effect is meaningful before transaction costs, it becomes insignificant after costs are considered. By contrast, short-term momentum tends to consistently deliver positive returns during the worst periods for the 12-month momentum. Therefore, we conclude that the positive contribution of short-term momentum is driven by its superior diversifying characteristics rather than by the rebalancing frequency effect. Our findings are reminiscent of those of Israelov and Katz (2011), who reported that long-term investors who tend to change their portfolios slowly can benefit from incorporating short-term information (signals) to time their trades, even after accounting for transaction costs.

The remainder of the article is divided into five sections. In the first section, we describe the data. In the second section, we examine the standard 12-month time-series momentum strategy and its daily extension. In the third section, we investigate the three-month and one-month strategies described by Hurst, Ooi, and Pedersen (2017) and introduce short-term time-series momentum. In the fourth section, we explore the portfolio contribution of the short-term momentum strategy. The fifth section concludes.

DATA

In this article, the empirical results are derived using daily return data from Commodities Systems

[5] See Exhibit D1 in the online appendix for details. We assume that the assets under management (AUM) are large enough to ignore rounding issues associated with fractional contract sizes obtained when targeting 40%, as done by Moskowitz, Ooi, and Pedersen (2012). This is consistent with the common practice of hedge fund managers imposing minimum AUM requirements.

for 78 futures markets across four major asset classes between January 1984 and December 2017. Our dataset contains more markets than work by Moskowitz, Ooi, and Pedersen (2012), who examined 58 markets, and Hurst, Ooi, and Pedersen (2017), who investigated 67 markets, although Hurst, Ooi, and Pedersen (2017) used a longer time period. We start our analysis in 1984 because futures markets were largely limited to commodities before 1984.

Exhibit A1 in the online appendix reports the name, CSI symbol, exchange, Bloomberg symbol, start date, annualized excess return, and annualized standard deviation of the futures contracts considered in the study. The dataset includes 28 commodity markets, 20 equity markets, 19 fixed-income markets, and 11 FX markets. The euro performance is proxied with the German mark for the pre-euro period.

The S&P 500 total return (TR) index returns are obtained from Bloomberg.

STANDARD 12-MONTH TIME-SERIES MOMENTUM

This section evaluates the performance of a momentum strategy that resembles the 12-month time-series momentum examined by Moskowitz, Ooi, and Pedersen (2012) but relies on daily rather than monthly returns to generate signals. Because there are approximately 252 trading days in a calendar year and approximately 21 trading days in a month, we use 252 days to mimic the 12-month lookback period and 21 days to represent a one-month holding period. Thus, the 12-1 monthly time-series momentum of Moskowitz, Ooi, and Pedersen (2012) is replicated using 252-21 daily time-series momentum. Specifically, we compare two approaches. One approach relies on an equal dollar allocation across markets. The second approach, suggested by Moskowitz, Ooi, and Pedersen (2012), adjusts the position size in each market to a volatility target of 40% per annum.

For the strategy with an equal dollar allocation to each market, the performance of time-series momentum is equal to

$$TSMOM_{t,t+1} = \frac{1}{N_t}\sum_{i=1}^{N_t} sign(r^i_{t-l,t})\, r^i_{t,t+1} \tag{1}$$

where N_t represents the number of markets at time t, l is the lookback parameter of the strategy, $r^i_{t-l,t}$ is the cumulative lagged-return of security i between $t-l$ and t,[6] and $r^i_{t,t+1}$ is the return of security i between t and $t+1$.

The performance of the strategy with volatility adjusting is described as follows:

$$TSMOMV_{t,t+1} = \frac{1}{N_t}\sum_{i=1}^{N_t} sign(r^i_{t-l,t})\frac{40\%}{\sigma^i_t}\, r^i_{t,t+1} \tag{2}$$

where σ^i_t is the exponentially weighted volatility estimate of Moskowitz, Ooi, and Pedersen (2012). Exponential weighting captures the autoregressive property of volatility by giving more weight to more recent observations in constructing volatility forecasts and is similar to the autoregressive conditional heteroskedasticity model introduced by Engle (1982).

Although the aforementioned formulas describe monthly strategies, their daily performance can be calculated using fixed weights applied within each month. Similarly, results of the daily strategies can be calculated using the same methodology by replacing a single calendar month in the formulas with a trading month that consists of 21 trading days. Because we ignore the collateral portion of futures contracts' return, the performance of time-series momentum strategies is comparable to excess returns. See Asness, Moskowitz, and Pedersen (2013) for a detailed discussion regarding excess returns of futures contracts.

Performance of Time-Series Momentum

Exhibit 1 reports the performance and pairwise correlations of a time-series momentum strategy TSMOMD. The strategy goes long if the cumulative return in a market over the last 252 days is positive and short if the return is negative. The strategy applies an equal dollar allocation to each market with rebalancing

[6] Although cross-sectional momentum in equities is commonly measured using the lagged 12-month cumulative return, ignoring the most recent month's return to avoid short-term reversals potentially related to the liquidity and microstructure issues discussed by Jegadeesh (1990) and Lo and MacKinaly (1990), Asness, Moskowitz, and Pedersen (2013) showed that excluding the most recent month is not needed in other asset classes and that momentum returns are even stronger outside of equities when the last month's return is not excluded. In the time-series momentum literature (e.g., Moskowitz, Ooi, and Pedersen 2012 and Hurst, Ooi, and Pedersen 2017), the most recent month's performance is not excluded.

EXHIBIT 1
Performance of TSMOMD 252-21

	Commodities	Equities	Fixed Income	FX
Panel A: Performance				
Annualized Excess Return	5.24%	4.30%	1.35%	2.61%
Annualized Standard Deviation	9.36%	12.46%	2.13%	6.09%
Sharpe Ratio	0.56	0.35	0.63	0.43
Panel B: Pairwise Correlations				
Commodities	1	0.16	0.08	0.25
Equities		1	0.15	0.21
Fixed Income			1	0.12
FX				1

EXHIBIT 2
Performance of TSMOMDV 252-21

	Commodities	Equities	Fixed Income	FX
Panel A: Performance				
Annualized Excess Return	10.84%	13.38%	18.64%	14.41%
Annualized Standard Deviation	12.68%	22.23%	19.23%	21.83%
Sharpe Ratio	0.86	0.60	0.97	0.66
Panel B: Pairwise Correlations				
Commodities	1	0.11	0.06	0.22
Equities		1	0.13	0.16
Fixed Income			1	0.11
FX				1

performed after 21 trading days. Thus, the strategy generates signals every 21 days. Panel A presents the annualized excess return, annualized standard deviation, and Sharpe ratio for each asset class (commodities, equities, fixed income, and FX). Panel B reports the pairwise correlations of the time-series momentum strategies across the four asset classes.

The performance is robust across asset classes. The Sharpe ratios range between 0.35 for equities and 0.63 for fixed income. This result is consistent with those of Moskowitz, Ooi, and Pedersen (2012) and Hurst, Ooi, and Pedersen (2017), who reported attractive performance of time-series momentum across 58 and 67 markets, respectively. Because our dataset contains more markets than previous studies, our article presents additional evidence in support of time-series momentum as a pervasive characteristic of financial markets driven by either behavioral factors, as shown by Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999), or related to a hedging premium, as discussed by Moskowitz, Ooi, and Pedersen (2012) and Molyboga, He, and Qian (2018).

There is also a substantial degree of diversification; pairwise correlations range between 0.08 and 0.25,[7] indicating that there are meaningful differences in trends across asset classes.[8]

Although diversification is valuable from the standalone performance perspective of time-series momentum strategy, it is important to consider its portfolio contribution to traditional portfolios of stocks and bonds. Moskowitz, Ooi, and Pedersen (2012) reported that there is a common factor that affects time-series momentum strategies across asset classes. Fung and Hsieh (1997), Moskowitz, Ooi, and Pedersen (2012), and Hurst, Ooi, and Pedersen (2017) showed that the time-series momentum strategy performs particularly well during extreme up or down moves of the stock market. The superior performance during periods of market stress is scarce and, therefore, important for most investors who have high exposure to stocks. Although the portfolio contribution of time-series momentum to global portfolios is beyond the scope of this article, we consider correlations of the momentum strategies to the stock market.

The Impact of Volatility Targeting on Performance

Exhibit 2 reports the performance and pairwise correlations of a time-series momentum strategy with a targeted volatility exposure TSMOMDV. As before, the strategy goes long if the cumulative return in a market over the last 252 days is positive and short if the return is negative. In contrast to the previous static scaling,

[7] The lowest value of 0.08 corresponds to the correlation between time-series momentum in commodities and fixed income, whereas the highest value of 0.25 is associated with the correlation between time-series momentum in commodities and FX.

[8] The pairwise correlations of underlying asset returns range from −0.43, the correlation between equities and fixed income, to 0.58, the correlation between commodities and FX; their absolute values range from 0.18 to 0.58, indicating that the degree of co-movement across underlying assets is greater than that of the time-series momentum strategies.

the strategy adjusts position size to target 40% volatility in each market, following Moskowitz, Ooi, and Pedersen (2012), and rebalances after 21 trading days. Panel A presents the annualized excess return, annualized standard deviation, and Sharpe ratio for each asset class (commodities, equities, fixed income, and FX). Panel B reports the pairwise correlations of the time-series momentum strategies across the four asset classes.

We find that adjusting exposures for volatility improves the performance of time-series momentum without increasing pairwise correlations. The Sharpe ratios increase for each asset class and range between 0.60 for equities and 0.97 for fixed income. The improvement in the Sharpe ratio is the lowest for FX, for which the Sharpe ratio increases from 0.43 to 0.66, or by approximately 0.23. The improvement in the Sharpe ratio is the highest for fixed income, for which the Sharpe ratio increases from 0.63 to 0.97, or by approximately 0.34. Although the magnitude of improvement varies across asset classes, the improvement is roughly 50% in all four asset classes. The degree of diversification is relatively unchanged, with the pairwise correlations ranging from 0.06 to 0.22. Thus, the improvements in Sharpe ratios are driven by better time-series diversification accomplished by risk targeting. This finding is consistent with those of Moreira and Muir (2017) and Kim, Tse, and Wald (2016).

Having established that time-series momentum yields robust performance across asset classes with a significant degree of diversification and that adjusting positions for volatility improves performance, we turn to subperiod analysis.

Subperiod Analysis

Exhibit 3 reports the subperiod Sharpe ratios by asset class and average pairwise correlations for the two time-series momentum strategies, TSMOMD and TSMOMDV. Both strategies go long if the cumulative return in a market over the last 252 days is positive and short if the return is negative. TSMOMD applies an equal dollar allocation across markets, whereas TSMOMDV adjusts position sizes to target 40% volatility in each market, following Moskowitz, Ooi, and Pedersen (2012). Rebalancing is performed after 21 trading days. The asset classes include commodities, equities, fixed income, and FX. The subperiods are 1985–1989, 1990–1994, 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2017. Panel A presents the subperiod performance of TSMOMD. Panel B reports the subperiod performance of TSMOMDV.

EXHIBIT 3

Subperiod Performance of 252-21 TSMOMD and TSMOMDV

	Commodities	Equities	Fixed Income	FX	Avg Corr
Panel A: TSMOMD					
1985–1989	0.49	–0.09	0.89	0.77	0.05
1990–1994	0.73	0.22	0.52	0.27	0.04
1995–1999	1.26	1.06	0.81	0.66	0.06
2000–2004	0.84	0.55	0.53	1.13	0.09
2005–2009	0.23	0.49	0.39	–0.21	0.20
2010–2014	0.18	0.16	1.06	0.03	0.08
2015–2017	0.57	0.18	–0.18	0.38	0.11
Panel B: TSMOMDV					
1985–1989	0.87	0.47	1.00	1.22	0.05
1990–1994	1.19	0.16	1.30	0.58	0.02
1995–1999	1.54	1.27	0.88	0.84	0.07
2000–2004	0.92	0.77	1.07	1.27	0.09
2005–2009	0.53	0.76	0.64	–0.04	0.13
2010–2014	0.40	0.24	1.38	–0.03	0.08
2015–2017	0.65	0.64	0.34	0.53	0.09

The strategies perform consistently well across time periods, with only 3 out of 28 instances of negative performance for TSMOMD and 2 out of 28 instances of marginally negative performance for TSMOMDV. TSMOMDV outperforms TSMOMD in 26 out of 28 instances, providing additional evidence of the positive impact of volatility targeting on the performance of time-series momentum. Pairwise correlations are consistently low and range between 0.02 and 0.20 across the subperiods.

Monthly versus Daily Signals

Because the short-term strategy introduced in the next section relies on daily returns, we investigate whether data frequency has an impact on the performance of standard time-series momentum strategies. Specifically, we compare the performance of 252-21 daily time-series momentum to that of 12-1 monthly time-series momentum. Exhibit 4 reports the Sharpe ratio of the daily 252-21 time-series momentum strategy, the Sharpe ratio of the monthly 12-1 time-series momentum

Exhibit 4

Comparison of Monthly and Daily Time-Series Momentum

	Commodities	Equities	Fixed Income	FX
Panel A: TSMOM				
Daily	0.56	0.35	0.63	0.43
Monthly	0.52	0.36	0.69	0.35
Difference	0.04	–0.01	–0.05	0.08
Panel B: TSMOMDV				
Daily	0.86	0.60	0.97	0.66
Monthly	0.85	0.80	0.99	0.67
Difference	0.00	–0.20	–0.02	–0.01

strategy, and their difference for commodities, equities, fixed income, and FX. Panel A reports results for the time-series momentum strategies with an equal dollar allocation across markets. Panel B reports results for the time-series momentum strategies in which the position size is adjusted to target 40% volatility in each market, following Moskowitz, Ooi, and Pedersen (2012).

The monthly and daily strategies perform similarly, except in the case of equities for the time-series momentum strategy with volatility-adjusted positions, in which the daily strategy underperforms the monthly strategy with a difference of 0.2 in the Sharpe ratios. This difference is largely driven by a few isolated events. The most notable occurred around the crisis of 1987, when the stock market plunged by more than 20% on October 19 and recovered almost 15% over the next two days.[9] This highly volatile, mean-reverting behavior potentially leads to large discrepancies in the performance of the daily and monthly time-series momentum strategies. The difference is larger for the strategy with targeted volatility because the dollar exposure of the daily trading strategy was reduced in response to the elevated volatility levels.

Because the difference in performance is significant for TSMOMV in equities, we further investigate dispersion across the strategies. Although the correlation between the performance of the monthly and daily TSMOM strategy in equities is equal to 0.97, the correlation value is much lower value for TSMOMV at 0.88. Section B in the online appendix includes a more

[9] The numbers are based on the S&P 500 Total Return Index.

Exhibit 5

Performance of TSMOMD and TSMOMDV

	All	Commodities	Equities	Fixed Income	FX
Panel A: TSMOMD					
252–21	0.68	0.56	0.35	0.63	0.43
63–21	0.45	0.42	0.13	0.49	0.42
21–21	0.23	0.21	0.00	0.48	0.23
21–5	0.41	0.25	0.23	0.59	0.28
Panel B: TSMOMDV					
252–21	1.27	0.86	0.60	0.97	0.66
63–21	0.87	0.60	0.25	0.83	0.52
21–21	0.54	0.38	–0.03	0.71	0.29
21–5	0.83	0.48	0.27	0.92	0.37

comprehensive comparison of daily and monthly implementations of time-series momentum.

THREE-MONTH, ONE-MONTH, AND SHORT-TERM TIME-SERIES MOMENTUM

In this section, we replicate the 3-1 and 1-1 monthly time-series momentum strategies of Hurst, Ooi, and Pedersen (2017) using daily returns and introduce a short-term time-series momentum strategy. As in the previous section, we use 21-21 and 63-21 daily time-series momentum strategies to mimic the 1-1 and 3-1 monthly time-series momentum strategies of Hurst, Ooi, and Pedersen (2017). For each strategy, we investigate the impact of position sizing. The short-term strategy relies on a lookback window of 21 days and a holding period of five days. Thus, we denote it as 21-5. In contrast to the other three strategies, the short-term strategy cannot be implemented using monthly returns.

Performance of the Three-Month, One-Month, and Short-Term Momentum Strategies

Exhibit 5 reports the Sharpe ratios of the two time-series momentum strategies, TSMOMD and TSMOMDV, by asset class and across all asset classes using four sets of parameters: 252-21, 63-21, 21-21, and 21-5. Panel A presents the performance of TSMOMD, and Panel B reports the performance of TSMOMDV.

With the exception of a flat performance of the 21-21 strategies in equities, the performance of both strategies is robust across parameter sets. Moreover, in all cases except for the 21-21 strategy in equities, adjusting exposure for volatility following Moskowitz, Ooi, and Pedersen (2012) produces higher Sharpe ratios. The performance of the 21-5 short-term momentum is consistently superior to that of the 21-21 strategy for each asset class, regardless of the choice of position sizing.

Diversification across Time-Series Momentum Strategies

Exhibit 6 reports the pairwise correlations and pairwise annualized alphas of the two time-series momentum strategies, TSMOMD and TSMOMDV, with respect to four sets of parameters: 252-21, 63-21, 21-21, and 21-5. Panel A presents the pairwise correlations of the TSMOMD strategies. Panel B presents the pairwise correlations of the TSMOMDV strategies. Pairwise correlations are positive and range between 0.54 and 0.61 for adjacent sets of parameters and 0.21 and 0.23 for the 252-21 longer-term strategy and the 21-5 short-term strategy. The highest correlation of 0.60–0.61 is between the 21-21 one-month momentum strategy and the 21-5 short-term momentum strategy.

Panels C and D show pairwise annualized alphas and *t*-statistics of alphas for each strategy regressed against each of the other three strategies for TSMOMD and TSMOMDV, respectively. The 252-21 strategy delivers alphas that are large in economic and statistical terms with respect to any of the other three strategies, regardless of the positing sizing method. This result is consistent with the primary focus of the original study by Moskowitz, Ooi, and Pedersen (2012) on 12-month time-series momentum. By contrast, the 21-21 strategy exhibits no statistically significant alpha with respect to any of the other three strategies, regardless of the position sizing method. Strikingly, the short-term momentum strategy is the only strategy that yields a statistically significant alpha with respect to the 252-21 strategy. We further investigate what drives that positive alpha in the next section.

The moderate correlations between the short-term strategy and the longer-term time-series momentum strategies demonstrate a diversification benefit of time-series momentum that extends the previously reported findings of Hurst, Ooi, and Pedersen (2017). This finding is important because a higher degree of diversification can potentially lead to superior portfolio performance.

Exhibit 6

Comparison of Daily Strategies TSMOMD and TSMOMDV

	252–21	63–21	21–21	21–5
Panel A: Correlations of TSMOMD				
252–21	1.00	0.54	0.34	0.21
63–21		1.00	0.59	0.40
21–21			1.00	0.60
21–5				1.00
Panel B: Correlations of TSMOMDV				
252–21	1.00	0.55	0.36	0.23
63–21		1.00	0.59	0.40
21–21			1.00	0.61
21–5				1.00
Panel C: Alphas of TSMOMD				
252–21		2.16%***	2.99%***	2.95%***
		[3.01]	[3.73]	[3.54]
63–21	0.43%		1.59%**	1.45%*
	[0.60]		[2.30]	[1.84]
21–21	–0.02%	–0.20%		–0.08%
	[–0.02]	[–0.30]		[–0.13]
21–5	1.30%	1.10%	1.32%**	
	[1.57]	[1.43]	[1.96]	
Panel D: Alphas of TSMOMDV				
252–21		9.00%***	12.23%***	12.27%***
		[5.54]	[6.75]	[6.48]
63–21	1.92%		6.41%***	6.21%***
	[1.16]		[3.99]	[3.42]
21–21	0.87%	0.34%		0.36%
	[0.48]	[0.21]		[0.24]
21–5	6.11%***	5.48%***	5.70%***	
	[3.19]	[3.05]	[3.68]	

*Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.*

We explicitly examine portfolio implications after comparing the performance of monthly and daily signals of individual strategies.

Section B of the online appendix provides additional information regarding differences in the performance of daily and monthly implementations of one-month and three-month strategies. We find that relying on daily returns to implement the standard 1-, 3-, and 12-month momentum strategies of Hurst, Ooi, and Pedersen (2017) has no additional benefit. Yet daily returns are critical for implementing the short-term momentum strategy.

In Exhibit C1 of the online appendix, we also evaluate robustness to implementation considerations by examining the performance of the daily strategies after introducing a one-day gap between signal generation and execution. We find that the impact on performance is small in economic and statistical terms; therefore, the daily strategies are potentially more implementable than the traditional monthly strategies of Hurst, Ooi, and Pedersen (2017).

PORTFOLIO CONTRIBUTION OF SHORT-TERM MOMENTUM

This section investigates the portfolio contribution of the short-term momentum strategy introduced in the previous section. We start with the standard benchmark portfolio of Hurst, Ooi, and Pedersen (2017), henceforth Standard, which allocates equally to the three strategies of TSMOMDV 252-21, 63-21, and 21-21. Then we introduce two alternative portfolios that include short-term momentum. In both cases, allocations to the longer-term 252-21 and 63-21 strategies remain unchanged, but the allocation to the shorter-term 21-21 strategy declines. This approach is reasonable because Exhibit 6 suggests that the 21-21 strategy could be redundant. The first balanced approach, henceforth Balanced I, replaces the 21-21 strategy with the 21-5 short-term momentum strategy. The second balanced portfolio, henceforth Balanced II, equally splits the original allocation to the 21-21 strategy between the 21-5 and 21-21 strategies. We examine whether short-term momentum positively contributes to portfolio performance by evaluating the performance of the three strategies gross and net of fees.[10]

Performance of Balanced Portfolios That Include Short-Term Momentum

Exhibit 7 reports the annualized excess returns, annualized standard deviations, Sharpe ratios, and correlations with the S&P 500 Total Return Index for three portfolios (Standard, Balanced I, and Balanced II) as well as the annualized alphas, *t*-statistics of alpha, annualized

EXHIBIT 7
Performance of Time-Series Portfolios with and without Short-Term Momentum

	Standard	Balanced I	Balanced II
Annualized Excess Return	10.21%	11.35%	10.76%
Annualized Standard Deviation	9.30%	8.85%	8.93%
Sharpe Ratio		1.28***	1.21***
Annualized α	1.10	2.27%***	1.12%***
t-Statistic of α		4.19	4.09
Annualized Tracking Error		3.33%	1.67%
Information Ratio		0.34**	0.33**
Correlation to S&P 500	–0.07	–0.11	–0.09

*Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.*

tracking errors, and information ratios of the balanced portfolios with respect to the standard benchmark portfolio. The differences in the Sharpe ratio between the balanced portfolios and the standard portfolio are evaluated for statistical significance using a block bootstrap approach described by Molyboga (2018).

Although the standard portfolio of Hurst, Ooi, and Pedersen (2017) delivers a solid Sharpe ratio of 1.10, the balanced portfolios yield Sharpe ratios of 1.28 and 1.21, which are superior in economic terms and statistically significant at the 1% level. Both balanced portfolios yield positive alphas and information ratios that are also statistically significant. The tracking error of the second balanced portfolio is lower than that of the first balanced portfolio because the weight of the short-term strategy is lower. The correlations of all three portfolios to the S&P 500 Total Return Index are slightly negative and very similar to one another. This result indicates that short-term momentum can improve the performance of time-series momentum portfolios as both standalone investments and diversifiers to stock portfolios.

We repeat the analysis after excluding commodities from the short-term momentum strategy, primarily because they are less liquid than the financial asset classes of equities, fixed income, and FX. Haynes and Roberts (2015) reported that nonelectronic and manual trading are significantly more common in commodities such as agricultural, energy, and metals futures contracts than in financials. By contrast, the automated trading often

[10] Because monthly strategies perform at least as well as daily strategies, we repeat the analysis using monthly strategies and find that our findings are robust to data frequency.

EXHIBIT 8

Performance of Time-Series Portfolios with and without Short-Term Momentum That Excludes Commodities

	Standard	Balanced I	Balanced II
Annualized Excess Return	10.21%	11.47%	10.82%
Annualized Standard Deviation	9.30%	8.75%	8.84%
Sharpe Ratio		1.31***	1.22***
Annualized α	1.10	2.66%***	1.31%***
t-Statistic of α		4.47	4.39
Annualized Tracking Error		3.69%	1.85%
Information Ratio		0.34**	0.33**
Correlation to S&P 500	–0.07	–0.11	–0.09

*Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.*

associated with shorter-term strategies is more pervasive in financials than in commodities.

Exhibit 8 reports the annualized excess returns, annualized standard deviations, Sharpe ratios, and correlations with the S&P 500 Total Return Index for the three portfolios (Standard, Balanced I, and Balanced II) as well as the annualized alphas, *t*-statistics of alpha, annualized tracking errors, and information ratios of the balanced portfolios with respect to the standard benchmark portfolio. The balanced portfolios are based on the short-term momentum strategy that excludes commodities. The performance results are qualitatively very similar to those based on the short-term momentum strategy that includes commodities. The balanced strategies deliver Sharpe ratios of 1.31 and 1.22—very similar to those of the balanced strategies based on the short-term momentum strategy with commodities. The balanced strategies still outperform the standard portfolio in economic terms; the outperformance is statistically significant at the 1% level while showing very similar correlations to the S&P 500 Total Return Index. The differences in Sharpe ratio between the balanced portfolios and the standard portfolio are evaluated for statistical significance using a block bootstrap approach described by Molyboga (2018). This result indicates that excluding commodities from the short-term momentum strategy has no negative impact on the balanced portfolios, consistent with the empirical evidence of Haynes and Roberts (2015).

EXHIBIT 9

Net Performance of Time-Series Portfolios with and without Short-Term Momentum That Excludes Commodities

	Standard	Balanced I	Balanced II
Panel A: Conservative Cost Estimates			
Annualized Excess Return	6.88%	6.26%	10.82%
Annualized Standard Deviation	9.36%	8.77%	8.84%
Sharpe Ratio	0.73	0.71	0.74
Annualized α		0.37%	0.18%
t-Statistic of α		0.60	0.53
Turnover	510%	893%	598%
Transaction Cost	3.33%	5.21%	4.27%
Panel B: Optimistic Cost Estimates			
Annualized Excess Return	8.54%	8.87%	8.68%
Annualized Standard Deviation	9.32%	8.75%	8.84%
Sharpe Ratio	0.92	1.01*	0.98**
Annualized α		1.50%**	0.73%
t-Statistic of α		2.52	2.44
Turnover	510%	893%	598%
Transaction Cost	1.66%	2.60%	2.13%

*Notes: * and ** indicate significance at 10% and 5% levels, respectively.*

Robustness to Trading Costs

Although including short-term momentum in well-diversified portfolios of time-series momentum strategies improves gross-of-fee performance, it is important to consider the impact of transaction costs. In our analysis, we consider two sets of assumptions: the conservative estimate of Hurst, Ooi, and Pedersen (2017), summarized in Exhibit D1 in the online appendix, and an optimistic estimate that reflects 50% of the original cost estimate of Hurst, Ooi, and Pedersen (2017). It is reasonable to assume less conservative costs because managers using short holding periods tend to heavily invest in optimal execution by relying on co-located servers and sophisticated proprietary execution algorithms. Frazzini, Israel, and Moskowitz (2018) confirmed this assumption and reported that previous studies substantially overstate transaction costs.

Exhibit 9 reports the annualized excess returns, annualized standard deviations, and Sharpe ratios as well as the annualized alphas and *t*-statistics of alpha of the balanced portfolios with respect to the standard benchmark portfolio after accounting for transaction costs, annual turnover, and annual transaction costs. The annual transaction costs are calculated as the difference between the annualized excess gross returns and the annualized excess net returns. The standard benchmark portfolio of Hurst, Ooi, and Pedersen (2017) allocates equally to the three strategies of TSMOMDV 252-21, 63-21, and 21-21. The first balanced portfolio allocates equally to the 252-21, 63-21, and 21-5 strategies of TSMOMDV.[11] The second balanced portfolio allocates one-third each to the 252-21 and 63-21 strategies and one-sixth each to the TSMOMDV 21-21 and 21-5 strategies. Panel A reports results based on the conservative transaction cost assumptions of Hurst, Ooi, and Pedersen (2017). Panel B reports results based on 50% of the conservative cost assumptions of Hurst, Ooi, and Pedersen (2017). The differences in Sharpe ratios between the balanced and standard portfolios are evaluated for statistical significance using the block bootstrap approach described by Molyboga (2018).

Although all portfolios that include short-term momentum perform on par with or better than the standard portfolio of Hurst, Ooi, and Pedersen (2017), assumptions regarding transaction costs are important, particularly because short-term momentum is associated with high turnover. The annual turnover of the standard portfolio of Hurst, Ooi, and Pedersen (2017) is 510%, which is already meaningful. Including short-term momentum within the balanced strategies increases the turnover to 598% and 893% for the second balanced portfolio and the first balanced portfolio, respectively.

Using the conservative estimate of transaction costs, short-term momentum fails to improve the net-of-fee performance of the original portfolio of Hurst, Ooi, and Pedersen (2017). By contrast, imposing a less conservative cost assumption that represents 50% of the original estimate of Hurst, Ooi, and Pedersen (2017) results in a Sharpe improvement due to the portfolio contribution for short-term momentum; this is significant at the 10% significance level for the first balanced approach and at the 5% level for the second balanced approach. The improvement in the Sharpe ratio from 0.92 to 0.98–1.01 and corresponding alphas of 1.5% and 0.73% per annum, both significant at the 5% significance level, are also meaningful in economic terms.

Thus, we conclude that, although short-term momentum has the potential to improve the net-of-fee performance of time-series momentum portfolios, the degree of improvement depends on the quality of execution. Although many aspects of execution, such as speed or quality of execution algorithms, are similar for monthly and daily signals, daily signals have the benefit of extending trading horizon across as many as 21 days instead of having to execute all trades at month end.

Why Does Short-Term Momentum Improve Performance?

Having showed that short-term momentum improves the performance of time-series momentum portfolios, we turn to examining why short-term momentum improves the performance of well-diversified portfolios of time-series momentum. Because Hurst, Ooi, and Pedersen (2013) reported that daily and weekly rebalancing frequencies are superior to monthly frequencies for 1-month, 3-month, and 12-month strategies before considering transaction costs, we investigate the impact of rebalancing frequency before and after transaction costs.

Exhibit 10 compares the Sharpe ratios of time-series momentum strategies with monthly and weekly rebalancing. Monthly rebalancing is based on 21 days, and weekly rebalancing is based on five days. Panel A reports results that are based on gross performance. Panel B reports net results that are based on the conservative transaction cost assumptions of Hurst, Ooi, and Pedersen (2017). Panel C reports net results that are based on 50% of the conservative cost assumptions of Hurst, Ooi, and Pedersen (2017). The differences in the Sharpe ratios of the strategies with monthly and weekly rebalancing are evaluated for statistical significance using a block bootstrap approach described by Molyboga (2018).

We find that weekly rebalancing is superior to monthly rebalancing for each strategy before transaction costs. Although the 0.06 improvement in the Sharpe ratios for the 252-day lookback period is modest and statistically insignificant, it ranges between 0.23 and 0.29 for the 63-day and 21-day lookback periods, which is meaningful in economic terms and significant at the 5% level. After transaction costs are considered,

[11] The 21-5 short-term momentum strategy excludes commodities.

EXHIBIT 10

Impact of Rebalancing Frequency on Performance of Time-Series Momentum Strategies

	252	63	21
Panel A: Gross			
Monthly	1.27	0.87	0.54
Weekly	1.33	1.10	0.83
Difference	0.06	0.23**	0.29**
Panel B: Net with Conservative Cost Estimates			
Monthly	1.14	0.61	0.05
Weekly	1.08	0.60	–0.05
Difference	–0.06	–0.01	–0.10
Panel C: Net with Optimistic Cost Estimates			
Monthly	1.21	0.74	0.30
Weekly	1.21	0.85	0.39
Difference	0.00	0.11	0.09

*Note: ** indicates significance at the 5% level.*

EXHIBIT 11

Performance of Time-Series Momentum Strategies during Ten Worst Months for the 252-21 Time-Series Momentum Strategy

Date	252–21	63–21	21–21	21–5
October 1987	–20.13	–25.33	–14.14	2.77
February 1994	–7.27	–5.24	–2.73	0.73
March 1994	–5.88	0.32	6.41	5.52
April 2001	–5.74	–5.09	–3.79	–5.35
March 2003	–5.93	–1.73	1.75	4.94
April 2004	–5.81	–5.6	–6.49	–3.96
May 2009	–7.46	4.49	2.49	5.81
May 2010	–5.96	–2.51	0.67	7.02
September 2011	–7.05	7.7	10.21	5.11
June 2012	–7.25	–7.51	–4.99	–5.21
Average	–7.85	–4.05	–1.06	1.74
Percentage Positive		30%	50%	70%

the improvement from rebalancing vanishes. Thus, we conclude that rebalancing frequency is not the key driver behind the portfolio contribution of short-term momentum.

We further investigate the diversifying properties of short-term momentum as well as 63-21 and 21-21 time-series momentum strategies by considering their performance during the worst 10 months for the 252-21 time-series momentum strategy. Exhibit 11 reports the gross performance for each of the 10 worst months and their summary statistics, including average return and percentage of positive returns. Returns are shown in percentage points. Short-term momentum is the only strategy with a positive average return and the only strategy that delivers positive performance more than 50% of the time.

The online appendix section E extends our analysis by examining the performance of time-series momentum strategies during the 10 worst months for the 252-21 time-series momentum strategy by asset class; we find that the short-term momentum performs best during challenging periods, regardless of the asset class. This result indicates that the positive contribution of short-term momentum is driven by its superior diversifying characteristics rather than by the rebalancing frequency effect. It is also consistent with the findings of Israelov and Katz (2011), who reported that long-term investors who tend to change their portfolios slowly can benefit from incorporating short-term information (signals) to time their trades, even after accounting for transaction costs.

CONCLUDING REMARKS

In this article, we have examined 1-month, 3-month, and 12-month time-series momentum strategies based on monthly and daily signals. We find that time-series momentum delivers attractive returns across the four major asset classes of commodities, equities, fixed income, and FX, and volatility adjusting positions following Moskowitz, Ooi, and Pedersen (2012) consistently improves performance regardless of asset class or lookback period. We find no evidence that monthly signals are inferior to daily signals for all lookback periods considered and some evidence that daily signals are inferior to monthly signals for a one-month lookback period. This finding is consistent with the pervasive practice in the literature of relying on monthly time-series momentum signals.

We introduce a short-term momentum strategy with a holding period of five days that cannot be replicated with the monthly returns commonly used to implement time-series momentum strategies (e.g., Moskowitz, Ooi, and Pedersen 2012 and Hurst, Ooi, and Pedersen 2017). We find that, before fees, short-term momentum improves the performance of time-series momentum portfolios but that positive contribution is substantially reduced if execution quality is lacking. Therefore, high-quality execution is required to fully benefit from the strong diversification potential of short-term momentum. We also find that the positive contribution of short-term momentum is driven by its superior diversifying characteristics rather than by the rebalancing frequency effect reported by Hurst, Ooi, and Pedersen (2013).

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ADDITIONAL READING

A Modified Hierarchical Risk Parity Framework for Portfolio Management
Marat Molyboga
The Journal of Financial Data Science
https://jfds.pm-research.com/content/2/3/128

ABSTRACT: *This article introduces a modified hierarchical risk parity (MHRP) approach that extends the HRP approach by incorporating three intuitive elements commonly used by practitioners. The new approach (1) replaces the sample covariance matrix with an exponentially weighted covariance matrix with Ledoit–Wolf shrinkage; (2) improves diversification across portfolio constituents both within and across clusters by relying on an equal volatility, rather than an inverse variance, allocation approach; and (3) improves diversification across time by applying volatility targeting to portfolios. The author examines the impact of the enhancements on portfolios of commodity*

trading advisors within a large-scale Monte Carlo simulation framework that accounts for the realistic constraints of institutional investors. The author finds a striking improvement in the out-of-sample Sharpe ratio of 50%, on average, along with a reduction in downside risk.

Carry and Time-Series Momentum: *A Match Made in Heaven*

Marat Molyboga, Junkai Qian, and Chaohua He
The Journal of Alternative Investments
https://jai.pm-research.com/content/early/2020/08/01/jai.2020.1.106

ABSTRACT: *This article introduces a novel approach to combining time-series momentum and carry trade by conditioning trading signals of time-series momentum on the sign of the basis, a key input for the carry trade. We find that this new technique applied to four major asset classes improved the Sharpe ratio of time-series momentum by approximately 0.17 net of fees. The improvement in performance is greater during recessions and, therefore, conditioning time-series momentum signals on the sign of the basis improves performance when it matters the most. Thus, the new approach has practical importance for investors and asset managers who attempt to improve their long-term performance without increasing downside risk during periods of market turbulence.*

A Century of Evidence on Trend-Following Investing

Brian Hurst, Yao Hua Ooi, and Lasse Heje Pedersen
The Journal of Portfolio Management
https://jpm.pm-research.com/content/44/1/15

ABSTRACT: *In this article, the authors study the performance of trend-following investing across global markets since 1880, extending the existing evidence by more than 100 years using a novel data set. They find that in each decade since 1880, time-series momentum has delivered positive average returns with low correlations to traditional asset classes. Further, time-series momentum has performed well in 8 out of 10 of the largest crisis periods over the century, defined as the largest drawdowns for a 60/40 stock/bond portfolio. Lastly, the authors find that time-series momentum has performed well across different macro environments, including recessions and booms, war and peace, high- and low-interest-rate regimes, and high- and low-inflation periods.*