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TRENDS EVERYWHERE

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We provide new out-of-sample evidence on trend-following investing by studying its performance for 82 securities not previously examined and 16 long–short equity factors. Specifically, we study the performance of time series momentum for emerging market equity index futures, fixed income swaps, emerging market currencies, exotic commodity futures, credit default swap indices, volatility futures, and long–short equity factors. We find that time series momentum has worked across these asset classes and across several trend horizons. We examine the co-movement of trends across asset classes and factors, the performance during different market environments, and discuss the implications for investors.

1 Introduction

Trend-following investing has attracted a lot of attention over the past decade due to its strong performance during the global financial crisis and the fact that the recent literature has demystified the strategy. Indeed, the recent literature shows that trend following can be captured using a simple time series momentum strategy, which estimates an "up trend" based on observed positive excess returns over the past year, and a "down trend" when the past return is negative (Moskowitz *et al.*, 2012). Further, this time series momentum strategy can explain most of the performance of real-world CTAs and managed futures funds (Hurst *et al.*, 2013).[1]

Nevertheless, time series momentum has been challenged by some researchers. Indeed, Kim *et al.* (2016) and Huang *et al.* (2018) argue that the returns to time series momentum may be partly due to static bets and the benefits of volatility scaling. We perform tests designed to address these challenges and consider out-of-sample evidence on trend-following investing based on the idea that the best way to test the robustness and efficacy of a trading strategy is to consider whether it works across many different assets, especially

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assets that were not part of the original study where the strategy was uncovered.

To pursue such an out-of-sample test, we collect data for a host of new test assets. Our full data contains 156 assets, of which 58 are the "traditional assets" studied in the literature cited above, 82 are "alternative assets," meaning futures, forwards, and swaps not previously studied, and 16 are "factors" constructed as long–short equity portfolios. In other words, we collect so much new data that the number of new assets outnumbers the "traditional assets" studied in the literature. While we broaden the universe, we only consider investable liquid assets or strategies. While many private alternative assets would appear in paper backtests to be good candidates for trend following, their apparent autocorrelation is exaggerated by lack of regular mark-to-market pricing or even active secondary markets. Since paper gains in such illiquid assets would not translate into actual trading profits, we do not include private assets.

We find strong evidence for time series momentum across the assets and factors that we study. Over our sample period, the gross Sharpe ratio of 12-month time series momentum for traditional assets is 1.17, and the strategy delivers an even higher Sharpe ratio of 1.34 for the alternative assets. The Sharpe ratio for long–short equity factors is 0.95, and, when we diversify across all three asset groups, the combined trend-following strategy yields a gross Sharpe ratio of 1.60.

We also test for the existence of trends using regression analysis, and find strong statistical evidence for time series predictability across these assets and factors. Lastly, we examine the correlation structure across traditional assets, alternative assets, and factors, and the potential diversification benefits of these strategies relative to standard long-only investments.

In summary, we provide new out-of-sample evidence on the efficacy, robustness, and drivers of trend-following investing across numerous asset classes. We therefore complement the studies that extend the evidence on trend-following investing using long time periods for a more limited set of assets (Greyserman and Kaminski, 2014; Hurst *et al.*, 2017) by instead studying a broader set of assets for a more limited time period.

2 Data and test instruments: Traditional assets, alternative assets, and factors

We classify the test assets into three categories: "traditional assets" consists of the forwards and futures studied in the literature following Moskowitz *et al.* (2012), "alternative assets" consists of other forwards and futures not studied in this literature, and "factors" consists of long–short equity factors. Table 1 provides details on the specific instruments that we use and Appendix A reports the data sources.

Traditional assets. Our data for traditional assets are the prices of 58 liquid futures and forwards, consisting of 9 developed equity index futures, 13 developed bond futures, 12 cross-currency forward pairs (from 9 underlying currencies), and 24 commodity futures as described in Moskowitz *et al.* (2012). We update this data through December 2017. For each instrument, we construct a return series as follows. Each day, we compute the daily excess return of the current contract of interest (a liquid contract based on the roll schedule, typically the nearest or next nearest-to-delivery contract), and then compound the daily returns to a cumulative return index from which we can compute returns at any horizon.

Alternative assets. As shown in Table 1, our data for alternative assets consist of prices for 7 emerging market equity index futures, 17 fixed income swaps, 24 emerging market cross-currency pairs,

Table 1 Summary statistics on alternative assets and factors.

Asset	Date	Std	Asset	Date	Std	Asset	Date	Std
Commodities			**Vol Futures**			**Fixed income swaps**		
S. African Wheat	Aug-00	21.0%	VSTOXX 1	Jun-09	56.9%	Australia 2 Yr FI Swap	Oct-94	2.2%
S. African White Maize	Nov-96	34.4%	VSTOXX 2	Jun-09	42.5%	Germany 2 Yr FI Swap	Jan-94	2.7%
S. African Yellow Maize	Feb-97	28.0%	VSTOXX 3	Jun-09	34.1%	Canada 2 Yr FI Swap	Jun-93	2.2%
Canola	Jan-85	20.1%	VIX 1	Mar-07	81.9%	Japan 2 Yr FI Swap	Sep-89	1.3%
EU Emissions	Apr-05	57.6%	VIX 2	Mar-07	52.6%	Norway 2 Yr FI Swap	Jul-92	2.0%
Feeder Cattle	Jan-84	14.3%	VIX 3	Mar-07	43.4%	New Zealand 2 Yr FI Swap	Oct-94	2.0%
German Power	Dec-02	18.8%	VIX 4	Mar-07	38.0%	Sweden 2 Yr FI Swap	Jan-92	2.1%
Iron Ore	Apr-13	37.0%	VIX 5	Mar-07	34.4%	Switzerland 2 Yr FI Swap	Jan-88	1.8%
Lead	Jan-95	28.3%				United Kingdom 2 Yr FI Swap	Oct-87	2.4%
Lumber	Jan-79	30.5%				United States 2 Yr FI Swap	Jan-94	3.5%
Milk	Jan-98	26.8%	**Emerging FX**			Czech Republic 2 Yr FI Swap	Feb-97	2.9%
Orange Juice	Jan-79	30.9%	BRL vs. USD	Apr-99	17.1%	Hong Kong 2 Yr FI Swap	Oct-93	3.4%
Palm Oil	Jan-97	29.9%	COP vs. USD	Feb-98	12.4%	Hungary 2 Yr FI Swap	Jul-01	3.7%
Milling Wheat	Feb-99	22.2%	CLP vs. USD	Apr-99	11.2%	Mexico 2 Yr FI Swap	Nov-01	3.1%
Rapeseed	Jan-99	17.9%	HUN vs. EUR	Jan-97	7.6%	Poland 2 Yr FI Swap	Mar-98	3.9%
Rough Rice	Jan-93	27.0%	IDR vs. USD	Sep-97	24.8%	South Africa 2 Yr FI Swap	Apr-99	3.2%
Robusta Coffee	Oct-08	25.8%	INR vs. GBP	Jan-97	9.4%	Singapore 2 Yr FI Swap	Jan-00	1.4%
Rubber	Jan-94	31.1%	INR vs. USD	Jan-97	7.3%			
TOCOM Crude	Sep-01	32.4%	ILS vs. USD	Jan-97	8.0%	**Factors**		
UK Natural Gas	Feb-97	45.4%	KRW vs. JPY	Aug-97	17.1%	SMB	Jan-65	10.6%
White Sugar	Jan-89	23.5%	KRW vs. USD	Aug-97	15.3%	HML	Jan-65	9.8%
Credit			MXN vs. USD	Jan-97	10.4%	CMA	Jan-65	7.1%
Emerging Credit	Mar-04	5.1%	PHP vs. USD	Jan-97	8.7%	RMW	Jan-65	7.7%
European HY Credit	Jun-04	4.7%	PLN vs. EUR	Jan-97	9.1%	UMD	Jan-65	14.6%
European IG Credit	Jun-04	5.5%	PLN vs. USD	Jan-97	13.4%	Industry MOM	Jan-68	14.4%
N. American HY Credit	Mar-04	3.9%	ZAR vs. AUD	Jan-97	13.0%	Industry Neutral MOM	Jan-68	13.0%
N. American IG Credit	Oct-03	4.4%	ZAR vs. EUR	Jan-97	14.8%	BAB	Jan-68	11.3%
Emerging equities			ZAR vs. GBP	Jan-97	16.1%	Cash Flow to Price	Jan-68	8.2%
South Africa All Share Index	Feb-73	23.1%	ZAR vs. USD	Jan-97	15.9%	Dividend to Price	Jan-68	14.3%
MSCI Taiwan Index	Oct-87	33.0%	SGD vs. JPY	Apr-86	10.0%	Earnings to Price	Jan-68	12.4%
SGX CNX Nifty Index	Jan-93	25.9%	SGD vs. USD	Apr-86	5.4%	Profit	Jan-68	6.6%
China A-Shares	Aug-03	31.0%	TWD vs. JPY	Jan-97	10.3%	Growth	Jan-68	6.4%
Ibovespa Index	May-94	31.0%	TWD vs. USD	Jan-97	5.8%	Safety	Jan-68	10.9%
KOSPI 200 Index	Sep-87	30.3%	TRY vs. EUR	Jan-97	15.7%	Payout	Jan-68	7.5%
HSCEI China Index	Feb-96	34.8%	TRY vs. USD	Jan-97	15.5%	Seasonality	Jan-68	5.9%

This table reports the instruments used, the start date of the data, and the annualized volatility of the alternative assets and factors in our sample. The traditional assets are seen in Moskowitz *et al.* (2012).

21 commodity futures, 5 credit default swap indices, and 8 volatility futures. We compute cumulative return indices as above.

Equity factors. For equity factors, our data consist of 16 of the most well-cited and robust single-name stock selection factors as seen in Table 1. These factors are based on different characteristics that capture valuation, size, investment, profitability, and market beta. We construct long–short equity factors as follows. We start with our universe of over 4000 US common stocks, sourced from the union of the CRSP tape and the Xpressfeed database. At the end of each month, we first classify each stock as large-cap or small-cap based on whether its market capitalization is above or below the NYSE median. Within each of these cap-based groups, we form long–short portfolios, which are long a value-weighted average of the top 30% stocks based on the relevant characteristic (e.g., the top 30% cheapest stocks) and short stocks with the bottom 30% of the characteristics (e.g., the bottom 30% most expensive stocks), rebalanced monthly.

To construct the final long–short factor portfolio, we take an equal-weighted average of large-cap and small-cap long–short portfolio returns. We apply this factor construction methodology to all equity factors, except some slight modifications for the industry momentum factors and the betting-against-beta (BAB) factor, which is constructed using the methodology of Frazzini and Pedersen (2014).

All equity factor data begin in 1968, but alternative assets have varying data start dates ranging from 1973 to 2008. For the evaluation of time series momentum strategies, we rely on a sample starting in 1985 to ensure that a comprehensive set of instruments has data, unless otherwise noted.

Asset pricing benchmarks. We evaluate returns of our strategies relative to the S&P 500 Index, the MSCI World Index, the Barclays Aggregate Bond Index, and the S&P GSCI Index.

3 Methodology: Time series momentum portfolio construction

We construct time series momentum strategies as follows.[2] The position taken in each instrument is determined by assessing its excess return over a recent time period. For example, the 12-month time series momentum signal for "EU Emissions" considers the past 12-month return on the futures contract for EU Emissions. A positive past excess return is considered an "up" trend, leading to a long position. A negative past excess return signals a "down" trend, leading to a short position.

Since volatility varies dramatically across assets and factors as shown in Table 1, we size positions by their volatilities in order to make meaningful comparisons across assets. For each position, long or short, we scale the position so that it has an ex-ante annualized volatility of 40%. Specifically, we choose the position size as $\frac{40\%}{\sigma_t^s}$ for any instrument s that has an annualized volatility of σ_t^s at time t. This means, for example, that we invest \$1 if the instrument has a volatility of exactly 40%, we invest less than \$1 if the volatility is higher than 40%, and we invest more than \$1 if the volatility is lower than 40%. The choice of 40% is inconsequential for most of the statistics that we report (e.g., Sharpe ratios and t-statistics of alphas), but it is a natural choice because it makes it easy to compare our portfolios with those in the literature[3] and because a diversified portfolio of such strategies has a realistic volatility of 10–15% (due to the power of diversification). The resulting excess return of the monthly-rebalanced trend-following strategy in this instrument is:

$$r_{t,t+1}^{TSMOM,s} = sign(r_{t-12,t}^s)\frac{40\%}{\sigma_t^s} r_{t,t+1}^s$$

where $sign(r_{t-12,t}^s)$ is $+1$ or -1 depending on whether the estimated trend is up or down, and $r_{t,t+1}^s$ is the instrument's excess return next month. We compute this excess return of 12-month time series momentum for each instrument and each available month from January 1985 to December 2017, and similarly for other trend horizons. We report strategy returns gross of transaction costs.[4]

We estimate each instrument's ex-ante volatility using exponentially-weighted squared daily returns:

$$(\sigma_t^s)^2 = 261\sum_{i=0}^{\infty}(1-\delta)\delta^i(r_{t-i-1,t-i}^s - \bar{r}_t^s)^2$$

where the scalar 261 annualizes the volatility, $\bar{r}_t^s$ is the exponentially-weighted average return, and the parameter $\delta = 0.98$ is chosen so that the center of mass of the weights is 60 days. The volatility model is the same for all assets and factors at all times.

We construct diversified time series momentum strategies simply by averaging the individual trend strategies across instruments in each asset group (e.g., across traditional assets, alternative assets, or equity factors). The diversified time series momentum return in an asset group with S_t instruments at time t is:

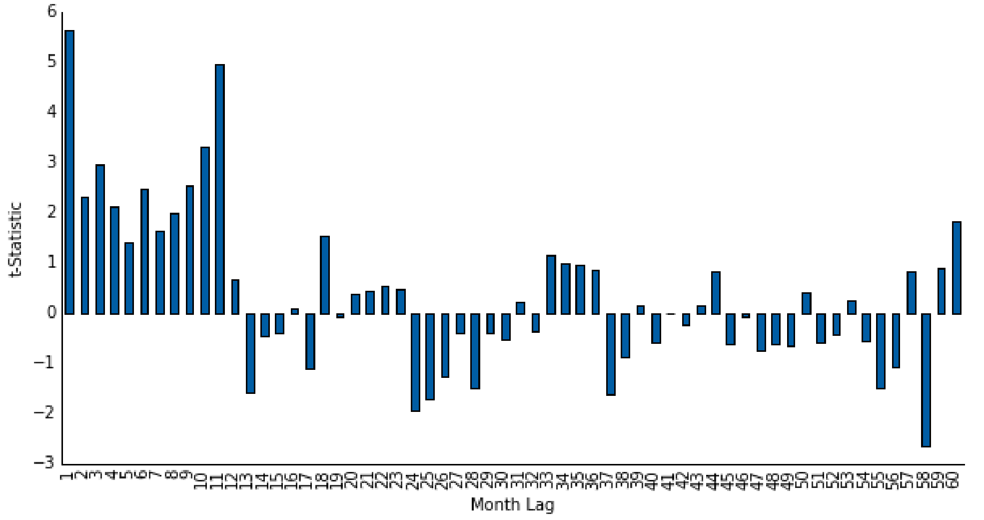
$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t} \sum_{s=1}^{S_t} r_{t,t+1}^{TSMOM,s}.$$

4 Trends everywhere: Out-of-sample performance

We first consider the performance of 12-month time series momentum strategies across each individual instrument in our sample. As described above, this strategy goes long if the past 12-month excess return is positive, short if the return is negative, and scales the position to target a constant risk level. Later, we consider the results for other trend horizons (Table 3, discussed below, presents results for short-, medium-, and long-term trends).

For the traditional and alternative assets, each trend strategy is very simple since it only trades a single index on each rebalance date. For the factors, the strategy is more involved as we must first construct a factor based on thousands of stocks—e.g., a value factor that goes long cheap stocks and shorts expensive stocks—and then decide whether to go long or short the factor based on its recent performance. Going long a factor means to hold all the underlying stocks, long and short, based on the factor construction, while going short a factor means doing the reverse. For example, if the value factor is trending down, the trend-following strategy shorts this factor by shorting the cheap stocks and buying the expensive ones, betting that the factor will continue to lose for the next month such that expensive stocks will beat cheap ones (even though the reverse generally happens more often).

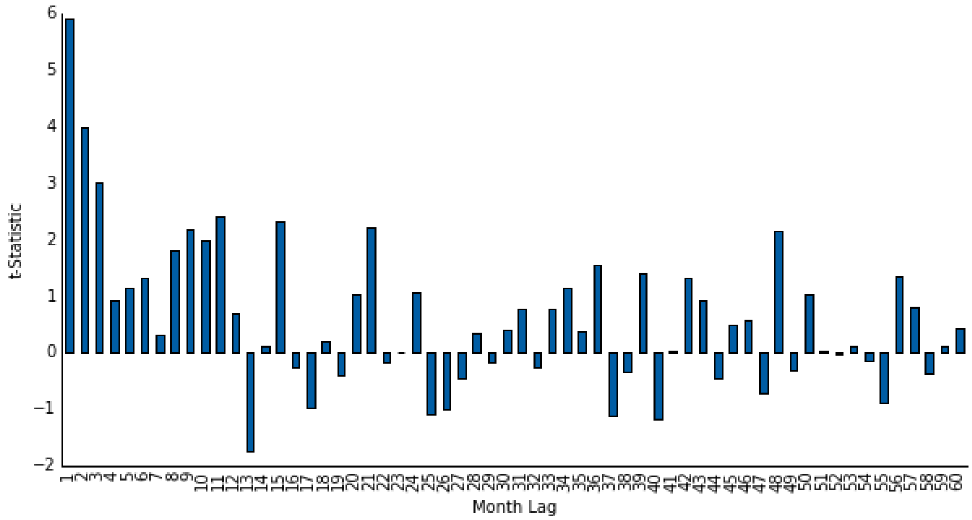
Figure 2 reports the Sharpe ratios of 12-month time series momentum for each of the traditional assets (Panel A), alternative assets (Panel B), and equity factors (Panel C). Recall that the Sharpe ratio (SR) is the average excess return divided



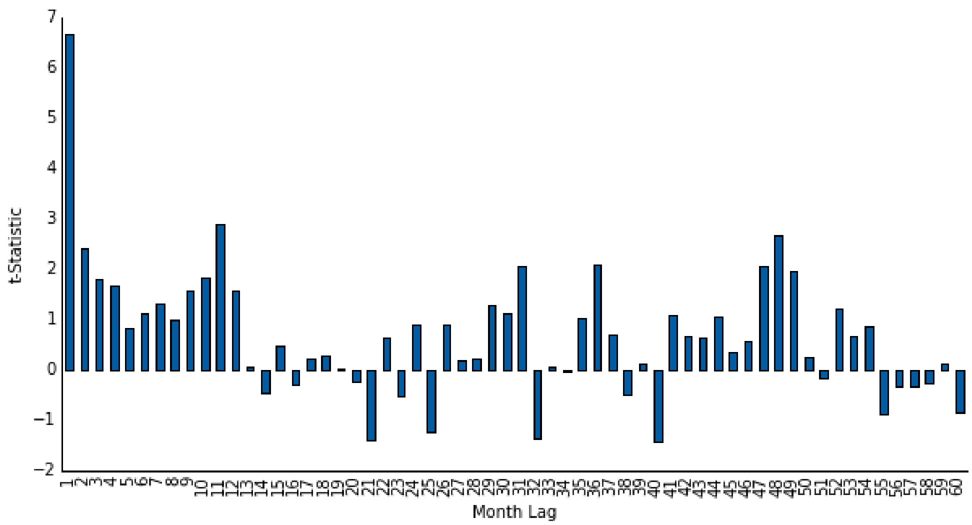
Panel A: Traditional Assets, t-statistic by month.

Figure 1 Time series predictability across assets and factors.

We regress the monthly excess return of each instrument on the sign of its own lagged excess returns. We report the t-statistics from the following pooled regression: $r_t^s/\sigma_{t-1}^s = \alpha + \beta_h sign(r_{t-h}^s) + \epsilon_t^s$. Standard errors are clustered by time (i.e., month). Panel A reports results for Traditional Assets, Panel B reports results for Alternative Assets, and Panel C reports results for Factors. The sample period is from January 1965 to December 2017.



Panel B: Alternative Assets, t-statistic by month.

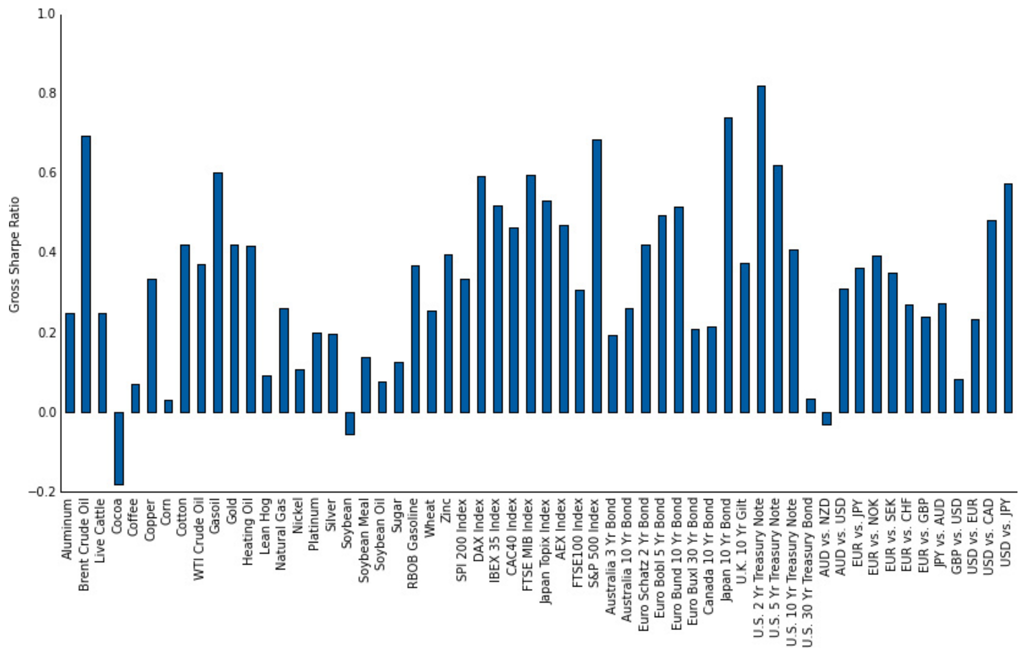


Panel C: Factors, t-statistic by month.

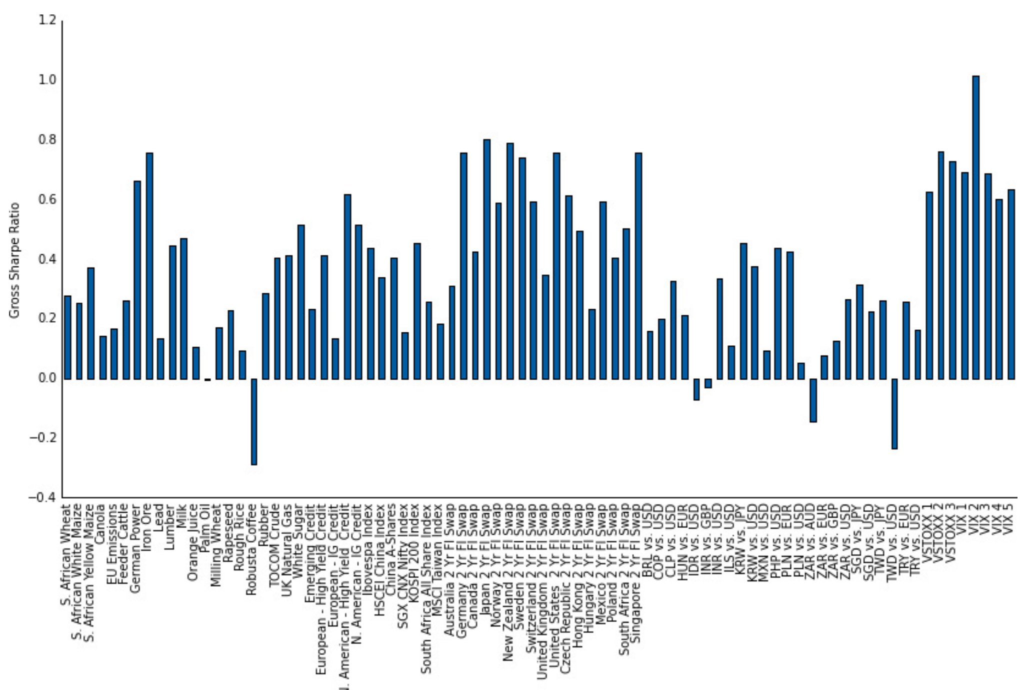
Figure 1 (*Continued*)

by the standard deviation of excess returns, so a positive SR means that the strategy is making money, and, the higher the SR, the more money it makes relative to its risk. We see remarkably consistent performance across assets and factors. Panel A is in line with the literature, it simply extends the analysis of Moskowitz *et al.* (2012) that ended in 2009 to include the most recent data up until the end of 2017. Panels B and C serve as out-of-sample evidence relative to the traditional markets, showing the efficacy of trend following in new places.

Table 2 provides further evidence on the strong performance of time series momentum across markets. Indeed, this table both shows how the performance of individual instruments aggregates at the portfolio level and it also considers higher-order statistics, such as skewness and kurtosis. Once again, we see robust performance



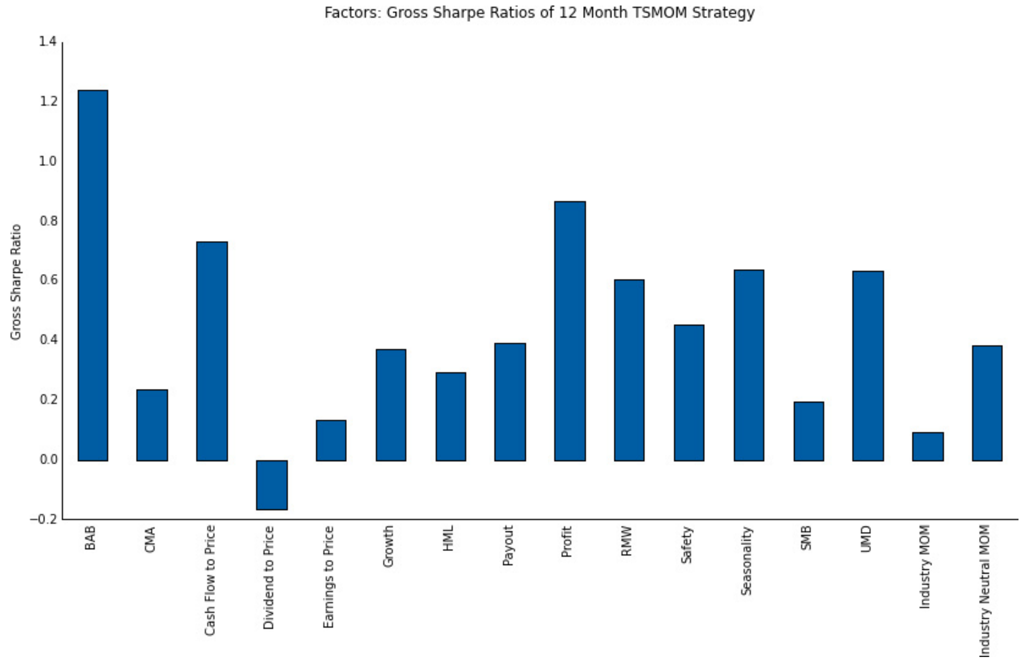
Panel A: Traditional Assets TSMOM gross Sharpe ratios.



Panel B: Alternative Assets TSMOM gross Sharpe ratios.

Figure 2 12-Month time series momentum Sharpe ratios by individual assets and factors.

This figure shows the gross Sharpe ratio of time series momentum by asset and factor, from 1985 to 2017. For each asset or factor, the trend strategy goes long (short) if the excess return over the past 12 months is positive (negative), and scales the size of the bet to be inversely proportional to the ex-ante volatility. Panel A reports results for Traditional Assets, Panel B reports results for Alternative Assets, and Panel C reports results for Factors.



Panel C: Factor TSMOM gross Sharpe ratios.

Figure 2 (*Continued*)

Table 2 Risk-adjusted performance and higher-order moments of 12-month time series momentum.

	Traditional Assets	Alternative Assets	Factors	All Assets and Factors
Sharpe Ratio				
Median Across Individual Assets	0.34	0.34	0.39	0.35
Diversified Portfolio	1.17	1.34	0.95	1.60
Sortino Ratio				
Median Across Individual Assets	0.54	0.52	0.61	0.56
Diversified Portfolio	2.25	2.63	1.75	3.35
Skewness				
Median Across Individual Assets	0.02	−0.12	0.09	−0.02
Diversified Portfolio	0.18	0.18	0.32	−0.01
Excess Kurtosis				
Median Across Individual Assets	1.22	2.10	1.09	1.43
Diversified Portfolio	0.56	1.37	1.38	0.35

This table both shows how the performance, skewness, and kurtosis of individual instruments aggregate at the portfolio level. To evaluate performance, we report Sharpe ratios and Sortino ratios of diversified portfolios, and median Sharpe ratios and median Sortino ratios across assets and factors. Sharpe ratios and Sortino ratios are reported gross of transaction costs.

across assets and factors. Notably, the median Sharpe ratio per asset is positive for every group we consider. Further, we see similarly strong results for the Sortino ratio, which is the average excess return in relation to the downside risk.[5] We also observe that portfolio Sharpe ratios are considerably larger than median asset Sharpe ratios, indicative of strong diversification benefits across all groups. Similarly, kurtosis statistics also reveal large diversification benefits. In particular, we note that the maximum portfolio kurtosis across all groups is 1.38, which is only half the kurtosis of the U.S. equity market portfolio during the same time period. Furthermore, we observe that portfolio skewness is more positive than median asset skewness for every group considered.

We note that there exist two ways to detect trends in markets: by considering trend-following strategies and through regression analysis. Having already studied trend strategies, we next consider a regression analysis that further highlights trend dynamics across time horizons, ranging from short-term trends to long-run trends. For each group of instruments (traditional assets, alternative assets, and equity factors), we run the following pooled panel regressions of volatility-scaled excess returns on the sign of excess return lagged h months:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + \epsilon_t^s.$$

Figure 1 reports the t-statistics from the regression above, using lags ranging from 1 month to 60 months.[6] Panel A reports the results for traditional assets. The positive t-statistics for the first 12 months indicate return continuation—that is, trends—and t-statistics larger than 2 in magnitude are statistically significant, consistent with earlier findings. For lags above 12 months, we see some negative coefficients, indicating trend reversals, although these tend to be statistically insignificant. Panel B extends the analysis to alternative assets, which also display strong return continuation for the first 12 months, and more mixed returns beyond 12 months. Panel C extends the analysis to equity factor portfolios, showing that time series predictability is feature of more than just traditional and alternative assets, but also of equity factors, with positive t-statistics across the most recent 12 months. These results demonstrate the remarkable pervasiveness of return continuation for the most recent 12 months, but not for returns beyond 12 months, across a range of assets and equity factors.

5 Trend alpha: Controlling for static market exposures and other factors

We next consider the alpha of time series momentum, that is, the performance when we control for passive market exposures and other known factors. At the same time, we test the hypothesis of Kim *et al.* (2016) and Huang *et al.* (2018) that time series momentum profits are primarily driven by volatility scaling and static bets on differences in mean returns.[7] To control for the effects of volatility scaling and static bets, we compute time series momentum alphas from the following regression:

$$r_t^{TSMOM} = \alpha + b\, r_t^{Passive-Vol\,Scaled} + \epsilon_t.$$

In each regression, we include a passive volatility-scaled portfolio, $r_t^{Passive-Vol\,Scaled}$, which contains all assets and factors used in the corresponding time series momentum strategy. We form this passive portfolio by holding a long position in each asset or factor, sized to have equal ex-ante volatility (i.e., exactly in the same construction as the time series momentum factor above, except that *sign* is replaced by $+1$).

Panel A of Table 3 shows the t-statistics of the estimated alphas for each of the traditional assets, alternative assets, and equity factors for several time series momentum strategies, varying the

Table 3 Alphas of time series momentum.

Panel A: Time series momentum alpha t-statistics across trend horizons

TSMOM Lookback (Months)	Traditional Assets	Alternative Assets	Factors	All Assets and Factors
1	4.12	8.17	3.75	7.61
3	4.65	8.37	3.42	7.60
6	4.34	6.17	2.31	5.33
9	5.15	6.95	2.00	6.01
12	5.72	6.78	2.05	6.27

Panel B: Panel B: 12-Month time series momentum loadings across asset classes

Asset Class	Annualized Alpha		Equal Volatility Passive Portfolio Beta		R-Squared
All Assets and Factors	12.3%	(6.27)	0.34	(6.58)	10%
Traditional Assets	12.4%	(5.72)	0.21	(3.82)	4%
Factors	8.4%	(2.05)	0.50	(9.85)	20%
Alternative Assets	15.9%	(6.78)	0.14	(3.50)	3%
Exotic Commodities	13.6%	(4.44)	0.10	(2.30)	1%
Credit Indices	4.4%	(0.49)	0.52	(8.84)	33%
Emerging Equities	10.3%	(2.01)	0.29	(6.70)	10%
FI Swaps	19.6%	(4.13)	0.29	(6.62)	11%
Emerging FX	9.6%	(2.29)	0.20	(4.21)	5%
Vol Futures	23.6%	(1.92)	0.24	(2.91)	7%

Panel A reports the t-statistics of the estimated alphas of TSMOM strategies over equal volatility-scaled passive portfolios, for various TSMOM lookback periods. Panel B shows the regression of 12-month TSMOM strategies on equal volatility-scaled passive portfolios, for individual alternative asset classes and other asset groupings. t-Statistics are reported in parentheses.

lookback period from 1 month (short-term trend) to 12 months (long-term trend). We see that time series momentum has a significant alpha even after controlling for these factors. This finding of a significant alpha is robust across trend horizons and asset classes.

Additionally, we consider the alphas of various individual alternative asset classes, ranging from exotic commodity futures to emerging market currencies. Panel B of Table 3 shows the regression of 12-month time series momentum strategies on passive volatility-scaled portfolios for individual alternative asset classes and other asset groupings. Every alternative asset class has positive alpha over its passive volatility-scaled counterpart, with four out of six alternative asset classes exhibiting statistically significant levels of alpha. In aggregate, traditional assets, factors, and alternative assets also exhibit statistically significant alphas over passive volatility-scaled portfolios.

Thus, volatility scaling and static exposures do not fully explain the strong performance of time series momentum strategies as suggested by Kim *et al.* (2016) and Huang *et al.* (2018). These papers do not themselves directly test whether a time series momentum portfolio has alpha over its long-only counterpart.[8] Instead, we directly test whether time series momentum is valuable controlling for other effects by including volatility-scaled long-only strategies on the right-hand side and by considering asset-fixed effects.[9]

6 Correlations within and across asset classes

We next examine the co-movement of different trend-following strategies across asset classes. Panel A of Table 4 reports the average pairwise correlations of the returns of the 12-month time series momentum strategy for each instrument, within and across the 3 asset groups. We see that all these average pairwise correlations are small and positive, indicating a mild tendency for these strategies to perform well at similar times. However, the small magnitudes imply significant diversification benefits from combining time series momentum strategies within and across traditional assets, alternative assets, and equity factors. These strong diversification benefits are also clear from Table 2, where we see that the portfolio Sharpe ratios are far above the median individual Sharpe ratios.

Panel B of Table 4 reports the realized correlations of diversified 12-month time series momentum strategies for each of these groups. Here, we first compute the return of a diversified portfolio of time series momentum strategies within each group, and then estimate the correlations of monthly portfolio returns across groups. Notably, all portfolio correlations are moderate. In particular, a portfolio of traditional assets only has a correlation of 0.30 to a portfolio of factors, and 0.49 to a portfolio of alternative assets, another sign of the diversification benefits from combining time series momentum strategies across these groups.

Table 4 Correlations of 12-month time series momentum within and across asset classes.

Panel A: Average asset-level TSMOM correlations, within and across groups

	Traditional Assets	Alternative Assets	Factors
Traditional Assets	0.07		
Alternative Assets	0.06	0.06	
Factors	0.04	0.04	0.17

Panel B: Diversified TSMOM strategy correlations

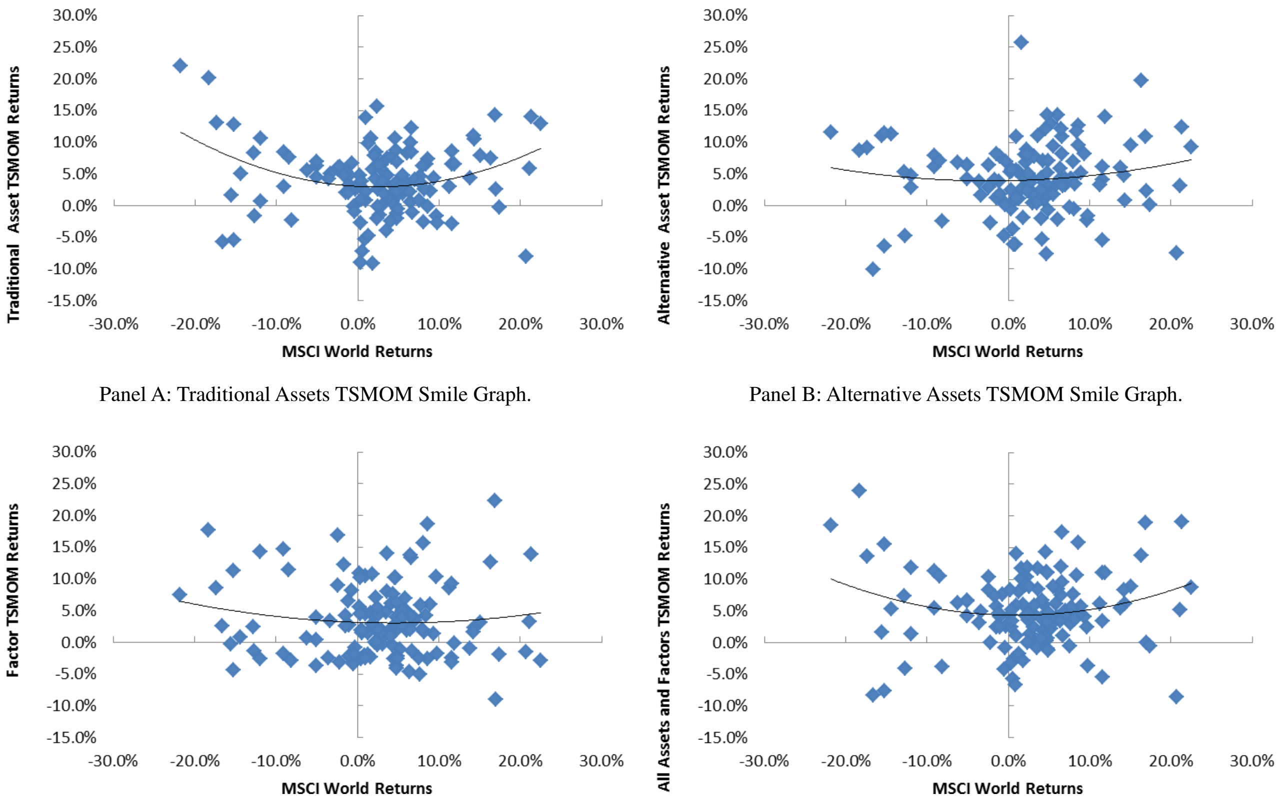
	Traditional Assets	Alternative Assets	Factors
Traditional Assets	1.00		
Alternative Assets	0.49	1.00	
Factors	0.30	0.11	1.00

Panel A reports the average pairwise correlations of each instrument's trend strategy return within and across asset groups (traditional assets, alternative assets, and factors). Panel B reports realized correlations of diversified time series momentum strategies across groups. Correlations are calculated using monthly returns from January 1985 to December 2017.

Table 5 Correlations of 12-month time series momentum to passive benchmarks.

	S&P 500	MSCI World	Barclays U.S. Agg	GSCI Index
Traditional Assets	−0.03	−0.03	0.24	−0.02
Alternative Assets	0.00	0.01	0.11	−0.04
Factors	−0.12	−0.06	0.13	0.05
All Assets and Factors	−0.04	−0.01	0.25	0.02

This table reports realized correlations of diversified time series momentum strategies to passive benchmarks. We calculate correlations using monthly returns, from January 1985 to December 2017.



Panel A: Traditional Assets TSMOM Smile Graph.

Panel B: Alternative Assets TSMOM Smile Graph.

Panel C: Factors TSMOM Smile Graph.

Panel D: All assets and factors TSMOM Smile Graph.

Figure 3 Time series momentum smile.

This figure shows the non-overlapping quarterly returns of diversified 12-month time series momentum strategies plotted against contemporaneous MSCI World returns. Panel A reports results for Traditional Assets, Panel B for Alternative Assets, Panel C for Factors, and Panel D for All Assets. The sample period is January 1985 to December 2017 and TSMOM returns are scaled to 10% annualized volatility ex post for comparability across panels.

7 Performance in relation to standard long-only investments

We next consider the relation to standard long-only investments. Table 5 shows that diversified 12-month time series momentum strategies have low correlations to standard long-only exposures to equities (S&P 500 and MSCI World), bonds (Barclays U.S. Aggregate Bond Index), and commodities (GSCI). These low correlations imply significant diversification benefits for an investor who has large parts of his assets in the standard long-only investments.

While the low correlations of the standard factors echo earlier results in the literature, the low correlations for alternative assets and equity factors can be seen as out-of-sample evidence of the diversification benefits of trend-following investing. Hence, in the context of an overall portfolio, time series momentum on a range of assets displays an overall diversifying profile relative to traditional assets.

Figure 3 presents another way to consider how trend-following investing diversifies standard long-only investments. In particular, this figure plots the quarterly returns of 12-month time series momentum in each asset group against the quarterly returns of the MSCI World Index. Let us first consider Panel A with traditional assets. We see what Hurst *et al.* (2013) call the "time series momentum smile", with the strategy performing especially well during periods of sustained bear markets (to the left in the plot) and sustained bull markets (to the right in the plot), while performing less well in flat markets (in the middle). We estimate a quadratic function to fit the relation between time series momentum returns and market returns, giving rise to the "smile" curve. We see a similar smile in Panel B for alternative assets. One reason that it may not be as pronounced is mechanical—in that the set of alternative assets may have smaller conditional correlation to equities during significant bull and bear market environments. Panel C shows that time series momentum for equity factors shows a less pronounced smile, but at least the smile still does not invert into a "frown". Still, in combination, an overall time series momentum portfolio that includes alternative assets and factor portfolios alongside traditional assets would be expected to display the "smile" property, as shown in Panel D.

8 Conclusion

Our analysis demonstrates that trends are a pervasive feature of markets and even factors, providing the broadest cross-section of evidence of time series momentum to date. We document significant time series momentum across nearly seven dozen instruments not previously studied in the literature. A diversified 12-month time series momentum strategy that holds these instruments alongside trend-following strategies for traditional assets and equity factors yields an impressive gross Sharpe ratio of 1.60, with strong performance across equity bull and bear markets. Notably, alternative asset and equity factor trend-following strategies provide meaningful diversification benefits to various passive benchmarks as well as traditional trend-following programs.

We also examine the effects of volatility scaling and static bets on trend-following performance. Controlling for these phenomena, we find that trend-following strategies exhibit significant alpha over long-only investments and other known risk factors. In fact, these alphas are robust across both trend horizons and asset classes.

We therefore conclude that the strong historical performance of trend-following strategies is robust across a large number of instruments, and this strong performance is neither explained by volatility scaling nor static exposures, but, rather, out-of-sample evidence of the trending nature of capital markets around the world.

Appendix

Appendix A: Data sources

Traditional assets

These are the same as described in Moskowitz *et al.* (2012) updated through 2017.

Alternative assets

Equity indices

The universe of equity index futures consists of the following seven emerging equity markets: South Africa All Share Index, MSCI Taiwan Index, SGX CNX Nifty Index (India), China A-Shares, Ibovespa Index (Brazil), KOSPI 200 Index (South Korea), and HSCEI China Index. Returns are obtained from Datastream and Bloomberg. We use MSCI country-level index returns prior to the availability of futures returns.

Fixed income swaps

We cover 17 developed and emerging market 2-Year fixed income swaps, across the following

Exhibit A1: List of equity factors.

Equity Factor	Description	Authors	Source	Year
BAB	Market beta	Frazzini and Pedersen	Journal of Financial Economics	2014
Cash Flow to Price	Cash flow to price	Lakonishok, Shliefer, and Vishny	Journal of Finance	1994
CMA	Investment	Fama and French	Journal of Financial Economics	2015
Dividend to Price	Dividend yield	Litzenberger and Ramaswamy	Journal of Finance	1982
Earnings to Price	Earnings yield	Basu	Journal of Financial Economics	1983
Growth	Growth in profits	Asness, Frazzini, and Pedersen	Review of Accounting Studies	2019
HML	Book value	Fama and French	Journal of Finance	1992
Industry MOM	Industry momentum	Moskowitz and Grinblatt	Journal of Finance	1999
Industry Neutral MOM	Industry neutral momentum	Moskowitz and Grinblatt	Journal of Finance	1999
Payout	Fraction of profits paid out to shareholders	Asness, Frazzini, and Pedersen	Review of Accounting Studies	2019
Profit	Profit per unit of book value	Asness, Frazzini, and Pedersen	Review of Accounting Studies	2019
RMW	Operating profitability	Fama and French	Journal of Financial Economics	2015
Safety	Return-based and fundamental-based measures of safety	Asness, Frazzini, and Pedersen	Review of Accounting Studies	2019
Seasonality	Return seasonalities	Heston and Sadka	Journal of Financial Economics	2008
SMB	Market equity	Banz	Journal of Financial Economics	1981
UMD	Momentum	Jegadeesh and Titman	Journal of Finance	1993

countries: Australia, Germany, Canada, Japan, Norway, New Zealand, Sweden, Switzerland, United Kingdom, United States, Czech Republic, Hong Kong, Hungary, Mexico, Poland, South Africa, and Singapore. Swaps are priced using curves from Bloomberg. We scale daily returns to a constant duration of 2 years for 2-Year fixed income swaps.

Currencies

The universe of currency forwards covers the following 14 countries: Australia, Germany spliced with the Euro, Hungary, Indonesia, India, Israel, Mexico, Philippines, Poland, Singapore, South Africa, South Korea, Taiwan, and Turkey. From these, we construct 24 cross-currency pairs. We use spot and forward interest rates from Citigroup to calculate currency returns. Prior to the availability of data from Citigroup, we use spot exchange rates from Datastream and Interbank Offered Rate (IBOR) short rates from Bloomberg to calculate returns.

Commodities

We cover 21 different commodity futures, including: South African Wheat, South African White Maize, South African Yellow Maize, Canola, EU Emissions, German Power, Feeder Cattle, Iron Ore, Lead, Lumber, Milk, Orange Juice, Palm Oil, Milling Wheat, Rapeseed, Rough Rice, Robusta Coffee, Rubber, TOCOM Crude, UK Natural Gas, and White Sugar. Returns are sourced from Bloomberg.

Credit default swap indices

We cover five credit default swap indices, including: North American High Yield Credit, North American Investment Grade Credit, European Investment Grade Credit, European High Yield Credit, and Emerging Markets Credit. Returns are obtained from Markit, and scaled to maintain a constant duration times spread exposure of 1000 bps.

Volatility futures

We cover eight VIX and VSTOXX futures across various maturities. Maturities range from 1 to 5 months for VIX futures, and 1 to 3 month for VSTOXX futures. Returns are obtained from Bloomberg.

Equity factors

We cover 16 long–short US equity factor portfolios. Our sample of equity data includes all available US common stocks from the union of the Center for Research in Security Prices (CRSP) tape and the Xpressfeed Global database. Exhibit A1 reports the list of factors used in our sample.

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Notes

[1] Research on time series momentum includes Moskowitz *et al.* (2012), Baltas and Kosowski (2013, 2015), Hurst *et al.* (2013, 2017), Georgopoulou and Wang (2017), and Gupta and Kelly (2019); other research on price trends includes Cutler *et al.* (1991), Silber (1994), Erb and Harvey (2006), and Menkhoff *et al.* (2012); Levine and Pedersen (2016) provide a unified framework for all trend-following strategies. Fung and Hsieh (1997, 2001) show that trend-following can help explain managed futures hedge fund returns. Time series momentum is related to cross-sectional momentum, which is seen in equities (Jegadeesh and Titman, 1993; Asness, 1994),

global asset classes (Asness *et al.*, 2013), U.S. equity factors (Arnott *et al.*, 2018), and a wide range of global equity factors (Gupta and Kelly, 2019; Ilmanen *et al.*, 2018).

[2] We use the methodology of Moskowitz *et al.* (2012) to construct time series momentum strategies, including their method for estimating volatilities.

[3] Moskowitz *et al.* (2012) scale each position to an annualized ex ante volatility of 40%, implying that, once they average the return across all securities, the resulting portfolio has an annualized volatility of 11%, which is roughly the level of volatility exhibited real-world CTAs and by other factors in the academic literature.

[4] While a study of transaction costs is beyond the scope of our analysis, we note that the trading costs are likely higher for alternative assets and factors than for traditional assets. To ensure implementability, we primarily focus on 12-month time series momentum, which has the lowest turnover among any of the lookback horizons we consider. Indeed, the strong gross performance and low turnover of 12-month time series momentum demonstrate that the strategy is implementable even across alternative assets and factors.

[5] We calculate the Sortino ratio as

$$S = \left(\frac{1}{T} \sum_{t=1,\ldots,T} r_{t,t+1}^{TSMOM} \right) \Big/ \sigma^{\text{downside}},$$

where σ^{downside} is kind of a standard deviation of the time series of returns focused on the downside: $\sqrt{\frac{1}{T}\sum_{t=1,\ldots,T}\min(r_{t,t+1}^{TSMOM}, 0)^2}$.

[6] *t*-Statistics are computed using standard errors that account for group-wise clustering by time (at the monthly level).

[7] We note that Moskowitz *et al.* (2012) analyze time series momentum without volatility scaling, and find that most of its profits can be attributed to serial correlations in futures returns. Following the framework of Lo and Mackinlay (1990) and Lewellen (2002), they decompose TSMOM profits into autocovariance and squared mean excess returns components. Indeed, even without volatility scaling, they find that autocovariances in returns are primarily responsible for TSMOM profits. Conversely, mean returns comprise a much smaller portion of profits.

[8] Kim *et al.* (2016) and Huang *et al.* (2018) examine whether time series momentum strategies and various passive portfolios exhibit different levels of alpha relative to a common set of factors. We note that this test is insufficient in determining whether volatility scaling or static exposures explain time series momentum performance, because two portfolios may exhibit similar levels of alpha relative to a common set of factors, yet still have alpha relative to each other.

[9] In order to rule out that prior pooled panel regression results are driven by different mean returns across instruments, we also confirm that adding entity fixed effects does not significantly change the reported *t*-statistics in Figure 1. Similarly, demeaning asset returns by their lagged expanding means—which avoids any potential look-ahead bias introduced by including full-sample fixed effects—also yields similar *t*-statistics.

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