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Trends' Signal Strength and the Performance of CTAs

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We propose a new asset-based factor that relies on aggregating momentum signals over different horizons. Aggregating signals this way captures assets' trend signal strength, thereby addressing a limitation in existing time series momentum strategies. Our factor mimics a trend-following manager that increases exposure to markets where trends develop and decreases exposure to markets where trends fade. Taking into account a number of practical implementation issues, we found that our proposed factor performs better at replicating the stylized facts of Commodity Trading Advisors' returns than previous methods and allows a more meaningful assessment of fund alpha.

According to BarclayHedge, a hedge fund database with extensive coverage of Commodity Trading Advisors (CTAs), total assets under management in the CTA, or managed futures, industry stood at USD333 billion at the end of the third quarter of 2015. This amount makes the CTA industry the second-biggest hedge fund category after the fixed-income arbitrage category.

Until recently, no asset-based benchmarks were available for the CTA industry. Instead, practitioners benchmarked CTAs' performance to manager-based indexes. To some extent, the reliance on manager-based benchmarks is related to the challenge with constructing appropriate CTA benchmarks, because CTA strategies have no clear long or short bias. Although CTAs generally disclose their list of markets traded, their actual positions, which can be long or short, are unlikely to be revealed.

Benchmarking against peers has several limitations. First, manager-based benchmarks are essentially a combination of managers' alpha and beta. Second, as Fung and Hsieh (2004) pointed out, hedge fund indexes can be expected to inherit some of the biases inherent in hedge fund databases. Therefore, the alphas estimated for individual managers may be hard to interpret because they may not accurately reflect managerial skill. Finally, manager-based indexes tell us little about style drift, sector exposures, or other aspects of the funds' performance that are typically assessed by investors.

We suggest that benchmarking managers against simple, transparent, and completely asset-based trend-following strategies is more valuable than benchmarking against peers. Our study contributes to the emerging strand of the literature that builds on the work of Moskowitz,

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Ooi, and Pedersen (2012) and Baltas and Kosowski (2013). First, we evaluated the performance of a trend-following strategy that captures signal strength by aggregating a wide range of short-term and longer-term signals. The original specification of Moskowitz et al. relied on a binary signal, but aggregating time series momentum signals of different look-back horizons results in a signal $S_t \in [-1,1]$ that measures the strength of a trend. This result allows the strategy to allocate to a position in proportion to a trend's strength. Such an approach is likely to be closer to actual practices of trend-following managers and should yield a robust time series momentum factor that anticipates reversals. From a modeling perspective, aggregating over a wide range of potential specifications avoids an arbitrary choice among candidate models. This characteristic considerably reduces data-mining and calibration concerns. These model considerations are separate from the diversification benefits that justify combining signals over different horizons; Baltas and Kosowski showed that time series strategies across different look-back horizons have low correlations.

Second, we incorporated a number of market frictions and real-life limitations, such as contract-specific transaction costs, the impact of exchange rate risk on contracts' profit and loss, and delays between signal generation and trade execution. Earlier work by Hurst, Ooi, and Pedersen (2013) pointed out the importance of some of these frictions. Incorporating these aspects ensured that our benchmark would be an investable asset-based benchmark. Not taking into account real-life frictions tends to raise the bar for managers too much, hampering a meaningful interpretation of manager alpha.

Turning to the performance evaluation using our new factors, we next investigated the drivers of the observed alpha vis-à-vis our model, and we analyzed the relationship between risk-adjusted performance and fund characteristics.

A Stylized Example

Before we continue, we provide the intuition for why combining various trend-following signals adds value and improves the overall performance of a strategy. Suppose we have two securities whose price paths are those in **Table 1**. Both securities have the same initial value and terminal value, and the securities' returns exhibit identical levels of volatility over the period considered. In other words, the two securities differ only in their interim price paths. Application of a simple (long-term) time series momentum strategy over the period t through $t - 3$ yields a long signal in both instances. When we include the intermediate signals, however, we observe that the trends in the securities are considerably different. Aggregating all the time series momentum (TSMOM) signals suggests that a reversal may be taking place in Security A, whereas at t, Security B exhibits a strong and persistent trend. This simple example suggests that aggregating signals over different look-back periods may add value because it captures trends' signal strength.

In addition to capturing signal strength, aggregating a wide range of individual signals has several other desirable properties. Obviously, a smooth signal has the advantage that it allows the manager to gradually adjust positions to changing conditions. This particular property is in contrast to a binary signal,

Table 1. Example of Aggregated Trend-Following Signals

Period	Security A Return	Security B Return	$r_{t,A}$	$r_{t,B}$
$t - 3$	90	90		
$t - 2$	130	83	44.44%	–8.28%
$t - 1$	140	120	7.69%	45.37%
t	125	125	–10.71%	4.17%
	Signal	Signal	σ_A	σ_B
Sign(t–1,t)	–1	1	28.08%	28.08%
Sign(t–2,t)	–1	1		
Sign(t–3,t)	1	1		

which generally dictates that any position should be reversed overnight.

To illustrate this feature, **Figure 1** presents a time series momentum signal that captures *signal strength* for futures data on the S&P 500 Index over the period 2007–2017. Panel A of Figure 1 provides simply the value of the index over the period. Panel B illustrates how a signal that incorporates the strength of the trend adjusts quickly to reversals. For example, the signal is quicker in picking up the recovery in the second quarter of 2009. At the same time, in periods in which markets went sideways (e.g., 2015–2016), signal strength provides a smoother signal than the binary signal, which continuously moves from long to short.

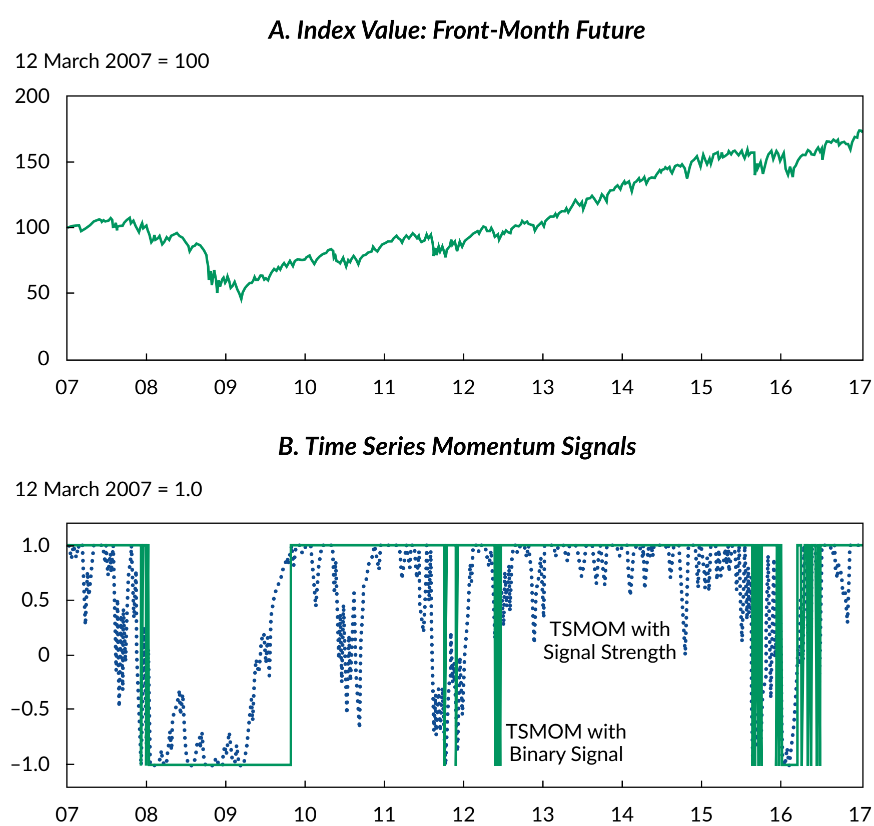
Literature Review

Mutual funds are benchmarked to a combination of market indexes and risk factors, such as the factors suggested by Fama and French (1993) and Carhart (1997). Similarly, most hedge fund categories are evaluated in relation to the seven-factor (or eight-factor) model of Fung and Hsieh (2004).[1] Although these factor models perform well in explaining the returns of mutual funds and most hedge fund categories, their performance in explaining variation in CTAs' returns is limited. Instead, the CTA industry still largely relies on manager-based indexes.

Despite the apparent hurdles in modeling CTAs' strategies, several studies have attempted to replicate CTA returns. Fung and Hsieh (2001) were among the first to focus on replicating trend-following hedge funds' returns. The authors suggested the use of primitive trend-following strategies based on look-back straddles, which capture the returns of a market timer. Although implementing these factors in practice is possible, Harvey, Rattray, Sinclair, and Van Hemert (2016) noted that such a strategy is neither straightforward nor cheap.

Recently, renewed attention has been paid to modeling the returns accruing to CTAs. Moskowitz et al. (2012) were the first to document in a systematic manner the presence of a "trend" effect for a broad range of futures and forward contracts. They termed this effect "time series momentum," and it relies solely on the continuation of the price direction of the asset under consideration. This momentum is different from cross-sectional momentum, which relies on past winners outperforming past losers. Moskowitz et al. showed that a portfolio of TSMOM

Figure 1. Signal Strength and S&P 500, 2007–2017



strategies diversified across asset classes consistently delivers large and significant excess returns.

Baltas and Kosowski (2013) built on the work of Moskowitz et al. (2012) to suggest a set of futures-based trend-following strategies. The authors extended the existing literature on time series momentum by considering weekly and daily strategies. Baltas and Kosowski also provided clear evidence that CTAs attempt to exploit momentum in the time series domain. In particular, the authors showed that their TSMOM factors significantly improve the explanatory power of multifactor models applied to CTAs' returns and outperform the factors suggested by Fung and Hsieh (2001).

Our approach borrows from and extends the works of Moskowitz et al. (2012) and Baltas and Kosowski (2013). In particular, we investigated the economic gains of using more than one signal or a limited number of signals. The use of a wide array of signals can be motivated by several areas of research. First, aggregating a large number of signals results in a combined signal that captures signal strength, as we discussed in the previous section. This feature addresses a potential limitation in existing strategies that rely on a binary signal. It seems reasonable to assume that CTAs also consider the strength of a particular trend. Second, an investor does not know *ex ante* the performance of a particular specification (e.g., a 15-day specification). From this perspective, a prudent approach is to combine a considerable number of signals. Relying on a limited number of signals based on historical performance also introduces some hindsight bias. Such hindsight bias may raise the bar for managers too much, as pointed out by Hurst et al. (2013). By combining various candidate signals, we avoid having to select a specific set of parameter specifications. This approach reduces model risk and, at the same time, enhances diversification.

Combining trend signals from different look-back periods matches a new avenue in academic research. Han, Zhou, and Zhu (2016) analyzed the gains of combining short-, intermediate-, and long-term moving-average signals in individual equities. They found that portfolios relying on a combination of price trends outperform portfolios formed on the basis of a single price trend.

Data

The futures data that we used consist of the daily close price, open interest, and volume for 98 futures contracts in four asset classes. Individual futures contract data were obtained from Commodity Systems Inc. and cover the period from January 1990 to September 2015. We report the list of futures contracts covered in **Table 2**. Our list of futures contracts is one of the most comprehensive used in the literature because we included a number of metals-related futures and a number of currency pairs that are commonly traded by CTAs.

Because futures contracts are short-lived contracts that expire at a predetermined date, we first constructed a continuous time series of futures prices for each contract. (In the online supplemental material, available at www.tandfonline.com/doi/suppl/10.1080/0015198X.2018.1547052, we describe the particular approach used.) The daily returns calculated from the continuous futures prices are equivalent to fully collateralized (unleveraged) returns in excess of the risk-free rate.[2] As such, daily excess returns are constructed as

$$r_{i,t} = \frac{F_{i,t} - F_{i,t-1}}{F_{i,t}}, \tag{1}$$

where $F_{i,t}$ corresponds to the futures price of asset i at time t.

For the CTA-related data, we collected monthly net-of-fee returns to live and dead funds labeled "CTA" in the BarclayHedge database. We restricted the data on CTAs to the period from January 1994 to September 2015.[3]

We filtered the sample of funds by looking at the self-declared strategy description and removing funds whose descriptions were not consistent with the definition of a CTA. In the process, we identified the fund's flagship program and discarded the other share classes. To account for backfill bias, we dropped the first 12 observations (see Kosowski, Naik, and Teo 2007).[4] We also dropped funds with assets under management (AUM) below USD10 million to restrict the set of funds to the investable universe. Finally, we focused on funds that reported their returns in either US dollars or euros. The euro-denominated returns and AUM were converted to US dollars.

We focused on systematic trend-following managers because their performance is most clearly related to time series momentum. These managers trade systematically and are diversified among many liquid futures contracts. Applying the adjustments described, we obtained a sample of 433 systematic trend-following CTAs. From this universe, we

Table 2. Futures Contracts

Foreign Exchange	Equities	Fixed Income	Commodities
USD/MXN	CAC-40	Canada 10-year	Gas oil
USD/SEK	Nikkei 225	Australia 10-year	Natural gas
USD/GBP	Russell 2000	Australia 3-year	Brent crude
USD/CAD	S&P MidCap 400	Japan 10-year	Heating oil
USD/JPY	Hang Seng	Long gilt	Light crude
USD/AUD	DAX	US 2-year	Unleaded gas
Dollar Index (DXY)	S&P 500	US 3-year	RBOB
EUR/USD	TOPIX	US 5-year	Copper
USD/ZAR	FTSE 100	US 10-year	Platinum
USD/BRL	Swiss Market	Muni note	Silver
USD/SEK	IBEX 35	BUXL	Gold
USD/NOK	MIB 30	BUND	Palladium
USD/NZD	NASDAQ 100	BOBL	Live cattle
AUD/NZD	MSCI Taiwan	SCHATZ	Live hogs
AUD/JPY	DJIA	Korean 3-year	Pork bellies
EUR/JPY	KOSPI 200	PIBOR	Feeder cattle
EUR/NOK	DJ Stoxx 50	Euribor 3-month	Corn
EUR/SEK	DJ Euro Stoxx	Eurodollar 3-month	Oat
EUR/GBP	S&P Canada 60	US 90-day bank bill	Soybeans
EUR/CHF	CBOE VIX		Soybean meal
	OMX		Soybean oil
	US MSCI EAFE		Wheat
	AEX		KC HRW Wheat
	NYSE Comp		Cocoa
	All Ordinary SPI		Cotton No. 2
	SPI 200		Coffee
			Frozen orange juice
			Sugar No. 11
			Lumber
			Nickel

constructed an AUM-weighted index and an equal-risk-weighted index, both rebalanced monthly.

Methodology

In this section, we first describe the construction of the "adaptive time series momentum" (ATSMOM) strategy. Then, we account for real-life trading frictions.

Adaptive Time Series Momentum. We constructed a portfolio that we refer to as ATSMOM and that follows a strategy that is diversified across both time and asset classes. The construction of our benchmark built on the works of Moskowitz et al. (2012) and Baltas and Kosowski (2013). Analytically, a traditional diversified TSMOM strategy with a look-back period of

t days can be constructed from daily returns as follows:

$$r_{T+1}^{TSMOM} = \frac{1}{L}\sum_{l=1}^{L} \text{sgn}\left(r_{T-261,T-1}^{l}\right)\left(\frac{0.4/\sqrt{261}}{\sigma_{T-60,T-1}^{l}}\right) r_{T+1}^{l}, \quad (2)$$

where sgn denotes the signum function—that is, $\text{sgn}\left(r_{T-t,T-1}^{l}\right)$ is the sign of the two-day lagged return over the look-back period $\left[T-t,\ldots,T-1\right]$; L is the number of assets in the strategy; and $\sigma_{T-60,T-1}^{l}$ is the two-day lagged exponentially weighted moving average (EWMA) estimator of volatility with a 60-day rolling window. Algebraically, the EWMA estimator in Equation 2 is calculated as

$$\sigma_{T-60,T-1}^{2} = \left(1-\lambda\right)\sum_{t=0}^{59}\lambda^{t}\left(r_{T-t-1}-\bar{r}\right)^{2}, \quad (3)$$

where λ is the decay factor, which we chose so that the center of mass is at approximately 60 days. We followed Moskowitz et al. (2012) in using this simple model for estimating volatility. The correction factor of 0.4 to the estimated volatility in Equation 2 was suggested by Moskowitz et al. as a way to achieve an *ex ante* volatility of 40% per security. This percentage was motivated by the observation that a 40% scaling factor can be expected to yield risk factors with an *ex post* volatility of approximately 12% per year, which roughly matches the volatility of the equity risk factors of Fama and French (1993) (see Moskowitz et al. 2012). A typical CTA also targets a volatility of around 12%.

The ATSMOM strategy is defined as a time series momentum strategy in which we average the signal for any given security in the portfolio over a wide set of look-back horizons:

$$r_{T+1}^{ATSMOM} = \frac{1}{L}\sum_{l=1}^{L} \text{sgn}\left[\frac{\sum_{t=10}^{260}\text{sgn}\left(r_{T-t,T-1}^{l}\right)}{251}\right]\left[\frac{0.4/\sqrt{261}}{\sigma_{T-60,T-1}^{l}}\right] r_{T+1}^{l}. \quad (4)$$

We did not consider look-back periods of strictly less than 10 trading days. Trading within such short intervals probably involves other methods than those based on daily closing prices (e.g., order flow and intraday data).[5]

From Equation 4, clearly, the signal for every futures contract will vary between –1 and +1 (i.e., $S_t \in \left[-1,1\right]$), depending on the strength of the trend. This characteristic is desirable because a simple TSMOM strategy based on one look-back period can be criticized for being a binary signal. As a result, a standard time series momentum signal does not capture signal strength.[6] Our approach will allocate more to the futures contracts that exhibit clearer trends. When trends start to fade, however, the short-term signals will force the strategy to lower exposure more quickly than in the case of a strategy that considers only one long-term signal. At the portfolio level, the strategy reduces exposure to markets where trends are becoming less pronounced and adds to futures contracts where trends are becoming more pronounced. The strategy does so in a more "adaptive" way than a standard TSMOM strategy based on a single look-back horizon.

Incorporating Trading Frictions. In addition to improving the signal of existing TSMOM strategies, we considered trading frictions. We believe that incorporating such frictions may improve the explanatory power of our strategy as a benchmark for CTAs. First, the available benchmarks imply signal generation and trade execution on the same day—that is, for example, signal generation at the close price and entering the market during the same closing session. When the rebalancing frequency is low, as in Moskowitz et al. (2012), who used monthly rebalancing, the impact of the exact closing price used may be limited. In our approach, however, the impact may be sizable because the strategy rebalances and thus may shift positions daily.

In line with the work of Hurst et al. (2013), we systematically skipped one trading day between signal generation and trade execution. For example, we entered a position only at Tuesday's closing price if that decision relied on a signal generated on the basis of Monday's closing price. Similarly, the first day we closed that position was during Wednesday's closing session. And the return of such a position was the percentage difference between Wednesday's and Tuesday's closing prices.

We also considered the impact of exchange rates when the futures were traded in a currency other than the US dollar. We assumed that the collateral or margin was always held in the base currency (the US dollar). Thus, only the daily profit or loss generated from positions in the contracts traded in a foreign currency was exchanged to the US dollar at the daily closing exchange rate. The margin itself, which was held in domestic currency, was not exposed to exchange rate risk (see Appendix A in Koijen, Moskowitz, Pedersen, and Vrugt 2018).

To allow for meaningful performance measurement, we accounted for transaction costs. A prerequisite to incorporating these costs is, of course, appropriate estimates of the trading costs actually incurred by CTAs. To this end, we estimated the explicit trading costs from actual charges incurred by the managers in one of RPM Risk & Portfolio Management's flagship funds over the one-year period from August 2013 to August 2014.[7] Explicit trading costs include gross commissions, clearing fees, exchange fees, National Futures Association charges, and brokerage and execution charges.

We also accounted for implicit transaction costs arising from the bid–ask spread that traders usually pay market makers for providing liquidity. Using the bid–ask spread to estimate implicit transaction costs dates back to Demsetz (1968), who argued that when participants trade through market makers, they will pay the difference between the true price and the bid or ask price on every trade. Following the standard approach in the literature, we approximated the bid–ask spread, in a round trip, by the reported tick size for every contract.[8]

For completeness, we note that transaction costs are likely to be a nonlinear function of trading volume. To estimate the relationship between volume and transaction costs, an extensive dataset is needed that includes the price at which a trade arrives in the market and the trading volume.[9] Taking into account transaction costs and other frictions (such as position limits) requires assumptions on the strategy's size (see the work of Greyserman and Kaminski 2014, who analyzed the implications of fund size for trend-following strategies' implementability). In this study, we assumed that transaction costs increase linearly with trading volume.

Unfortunately, we had data for transaction costs only for recent years. Following Hurst, Ooi, and Pedersen (2012), we assumed that in the first half of the sample period (1991–2002), transaction costs were twice as high as in the second half of the sample period (2003–2015).

We found that trading costs vary considerably for the different asset classes; short-rate futures are the least expensive to trade, although these contracts are also the least volatile.[10] Trading in VIX and grains futures is most expensive. This finding was driven mainly by the large tick sizes, indicating lower liquidity in these markets. On average, across all markets traded, we found that the bid–ask spread is responsible for almost three-quarters of the overall transaction cost.

Results

This section discusses the standalone performance of the ATSMOM strategy, ATSMOM as a benchmark for CTAs, and the decomposition of time series momentum strategies into ATSMOM and the speed factor.

ATSMOM's Standalone Performance.

Table 3 reports performance statistics for our strategy and for the factors suggested by Moskowitz et al. (2012; hereafter MOP) and Baltas and Kosowski (2013; hereafter BK).[11] ATSMOM is reported both gross and net of transaction costs in Panel A. The other benchmarks, in Panel B, are gross of transaction costs. All the factors are scaled to 10% *ex post* volatility.

Based on Panels A and B of Table 3, ATSMOM yields somewhat higher minimum and maximum (gross) returns than MOP and the BK daily and BK weekly strategies. This finding suggests that the strategy is successful at limiting downside risk and allocating more to better-performing assets. The lower downside risk is probably the consequence of signal diversification as well as the higher rebalancing frequency. More frequent rebalancing alone, however, does not guarantee lower downside risk, as is evident from the maximum drawdown of the BK daily strategy. Taking into account transaction costs, the benefits resulting from the proactive nature of ATSMOM clearly come at a cost; the Sharpe ratio net of transaction costs drops to 0.96.

The higher upside of ATSMOM also translates into a higher skewness. Positive skewness is consistent with one of the stylized facts of CTAs. These funds tend to produce positively skewed returns (see, among others, Fung and Hsieh 2001; Lamm 2005; Ding and Shawky 2007). Table 3 shows that this feature is also present in the BK daily and BK weekly strategies. Before transaction costs, ATSMOM reported slightly lower average annual returns than MOP. The difference in risk-adjusted performance, however, is not statistically significant; using the approach of Ledoit and Wolf (2008) to test the statistical significance of the difference in Sharpe ratios, we obtained a p-value of 0.288.

Although the focus of this work is not on standalone performance, the results so far indicate that our

Table 3. Descriptive Statistics for Asset- and Manager-Based CTA Benchmarks

Measure	*A. ATSMOM* Gross	Net of Trading Costs	*B. Existing asset class–based benchmarks* MOP Gross	BK Monthly Gross	BK Weekly Gross	BK Daily Gross	BK Average Gross
Min (%)	–5.78	–5.91	–8.04	–7.11	–8.43	–7.81	–5.70
Max (%)	15.26	15.22	10.50	8.88	15.29	12.38	14.95
Annual mean (%)	11.05	9.62	12.42	12.67	10.98	9.00	14.28
Annual median (%)	9.05	7.73	12.61	13.80	10.16	6.62	8.55
Annual st. dev. (%)	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Skewness	0.70	0.71	0.04	–0.20	0.63	0.77	0.90
Kurtosis	5.55	5.61	3.26	3.12	5.85	4.81	5.56
Sharpe ratio	1.11	0.96	1.24	1.27	1.10	0.90	1.43
Sortino ratio	2.26	1.93	2.24	2.07	2.09	1.95	3.07
Max. drawdown (%)	–11.24	–14.13	–13.23	–14.96	–10.17	–13.12	–12.69
Period	1/92–9/15	1/92–9/15	1/92–9/15	1/92–1/12	1/92–1/12	1/92–1/12	1/92–1/12

C. Existing industry benchmarks

	BarclayHedge CTA	BTOP50	SG CTA	SG Trend Following	SG Trend Indicator	BarclayHedge Systematic Trend Following (AUM)	BarclayHedge Systematic Trend Following (ERW)
Min (%)	–6.55	–8.30	–9.03	–9.53	–6.28	–7.13	–6.13
Max (%)	8.86	10.86	9.66	9.62	11.09	10.41	9.94
Annual mean (%)	6.74	3.99	4.36	3.99	3.13	7.07	9.25
Annual median (%)	3.10	1.26	2.84	5.34	2.71	6.46	7.13
Annual st. dev. (%)	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Skewness	0.37	0.34	0.13	0.13	0.55	0.33	0.29
Kurtosis	3.32	3.71	3.34	3.65	3.87	3.28	3.01
Sharpe ratio	0.67	0.40	0.44	0.40	0.31	0.71	0.93
Sortino ratio	1.31	0.74	0.80	0.72	0.62	1.42	1.88
Max. drawdown (%)	–13.67	–21.62	–14.70	–14.77	–28.94	–11.61	–14.06
Period	1/92–9/15	1/92–9/15	1/00–9/15	1/00–9/15	1/00–9/15	1/94–9/15	1/94–9/15

Notes: The BarclayHedge indexes are based on the sample of systematic trend-following CTA funds selected in the "Data" section. All time series in the table have been adjusted to 10% annualized volatility for comparison purposes.

proposed benchmark is able to compete with existing benchmarks. In addition, transaction costs do not erode risk-adjusted performance.

Next, we turn to the use of ATSMOM as a benchmark for the CTA industry. Does an approach that considers signal strength match CTAs' returns better than alternative methods?

A Benchmark for CTAs. Panel C of Table 3 reports the performance of existing industry indexes. These indexes are often used by practitioners to benchmark individual managers. The two most commonly used benchmarks are the BarclayHedge CTA Index and the SG CTA Index. BarclayHedge also publishes a large-cap index called BTOP50, and SG provides a trend-following subindex.[12] In addition to these manager-based indexes, SG constructs an asset-based benchmark called the SG Trend Indicator Index, which reflects the returns of a strategy that relies on a simple 20/120 moving-average crossover model. The index is reported net of transaction costs and a hypothetical 2% management fee and 20% performance fee.

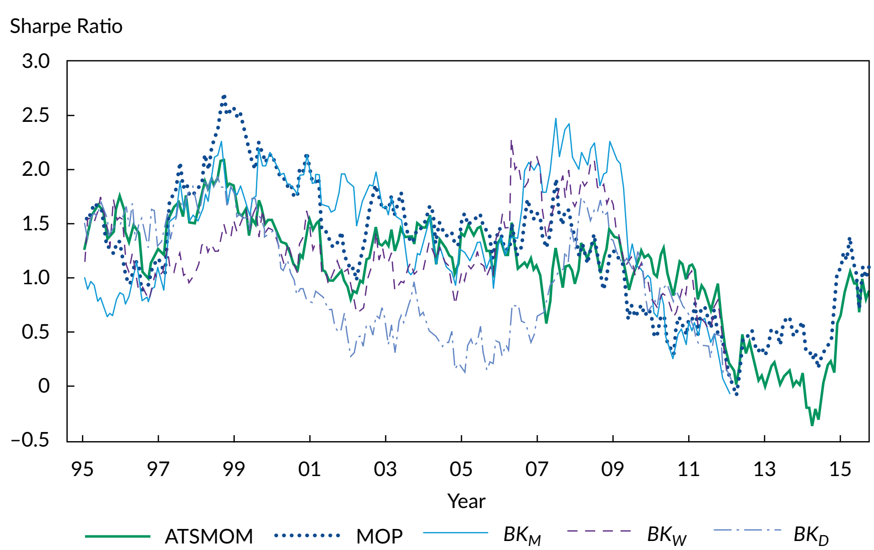
In addition to these indexes, we constructed an index weighted by AUM and an equal-risk-weighted (ERW) index from the systematic trend followers from the "Data" section. These indexes are not investable because one cannot rebalance a CTA portfolio on a monthly basis. Lengthy due diligence and legal processes to open and close managers make such an approach impractical. Nevertheless, the indexes are representative of then-current CTAs.

The indexes in Panel C of Table 3 exhibit positive skewness. Most of the indexes (with the exception of the BTOP50) exhibit drawdowns of approximately 15% at 10% annual volatility and Sharpe ratios between 0.31 and 0.93. The Trend Indicator Index reports the highest drawdown, perhaps the result of the fact that this strategy uses only one medium-term moving-average crossover.

Figure 2 plots the three-year rolling-window Sharpe ratio of the various benchmarks reported in Panels A and B of Table 3. The performance of ATSMOM is almost always between the slower-to-react MOP and faster BK strategies and is less likely to significantly outperform or underperform the other benchmarks. Longer-term strategies usually outperform shorter-term strategies. This characteristic was clearly the case in 2013–2015, when MOP outperformed ATSMOM. In periods when shorter-term strategies outperform, however, longer-term strategies tend to suffer. Greyserman and Kaminski (2014) noted that it may be difficult, if not impossible, to determine *ex ante* the horizon that will perform best over a given period. In such an environment, trading based on a wide set of signals may be best.

Moving beyond summary statistics, in **Table 4**, we formally report the result of our investigation into the relationship between the proposed ATSMOM strategy and existing (equity-based) risk factors, the primitive trend-following strategies (PTFS) of Fung and Hsieh (2001), and a number of other recently proposed risk factors.

Figure 2. Three-Year Rolling Sharpe Ratios of Rival Objective Benchmarks, January 1995–September 2015



Note: BK_M refers to the BK monthly benchmark; BK_W, to the BK weekly benchmark; and BK_D, to the BK daily benchmark.

Table 4. ATSMOM Strategy Regressed against Existing Risk Factors, 31 January 1994–30 September 2015 (robust standard errors in parentheses)

A. Results for returns gross of transaction costs

	(1)	(2)	(3)
MKT	−0.0565	−0.0691	
	(0.066)	(0.063)	
SMB	−0.0045	0.0589	
	(0.055)	(0.048)	
HML	0.0350		
	(0.070)		
MOM	0.1964**		
	(0.043)		
LIQ	−0.0865		
	(0.056)		
PTFSBD		0.0010	
		(0.014)	
PTFSFX		0.0288*	
		(0.013)	
PTFSCOM		0.0441**	
		(0.015)	
PTFSIR		0.0008	
		(0.012)	
PTFSSTK		0.0408*	
		(0.018)	
EM		0.0495	
		(0.043)	
BOND		−0.0157	
		(0.012)	
CREDIT		12.142	
		−1.460	
GVAL			0.3489*
			(0.137)
GMOM			0.8587**
			(0.123)
Annual alpha	0.1188**	0.1512**	0.0744**
	(−0.024)	(−0.024)	(−0.024)
R^2	0.129	0.237	0.239

(continued)

Table 4. ATSMOM Strategy Regressed against Existing Risk Factors, 31 January 1994–30 September 2015 (robust standard errors in parentheses) (continued)

B. Results for returns net of transaction costs

	(1)	(2)	(3)
Annual alpha	0.1016**	0.1335**	0.0579**
	(–0.024)	(–0.024)	(–0.024)
R^2	0.125	0.236	0.236

Notes: The Fama–French original factors are MKT = the market risk factor; SMB = the size factor (small minus large); HML = the value factor (high book to market minus low book to market). MOM is the Carhart momentum factor. The factors for the Fama and French (1993) and Carhart (1997) models are from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. LIQ is the Pástor and Stambaugh (2003) liquidity factor, which was obtained from Luboš Pástor's website: https://faculty.chicagobooth.edu/lubos.pastor/research/. The Fung and Hsieh (2001) PTFS factors are for bonds, foreign exchange, commodities, the interest rate, and stocks plus the equity market factor (EM), bond market factor (BOND, the monthly change in the 10-year US Treasury constant maturity yield), and credit spread factor (CREDIT, the monthly change in the Moody's Baa yield less 10-year Treasury constant maturity yield). They were taken from David A. Hsieh's Hedge Fund Data Library: https://faculty.fuqua.duke.edu/~dah7/HFData.htm. GVAL (for Global Value) and GMOM (for Global Momentum) are from AQR's website: https://www.aqr.com/Insights/Datasets/Value-and-Momentum-Everywhere-Factors-Monthly.

*Significant at the 5% level.

**Significant at the 1% level.

Column 1 reports the regression of ATSMOM returns on a number of equity-based risk factors. We found that only cross-sectional momentum is related to our benchmark. Next, consider the results for the eight-factor model of Fung and Hsieh (2004) in Column 2, where we included all five PTFS factors plus the equity market factor, bond market factor, and credit spread factor. The extended Fung-Hsieh model generally worked well for most hedge fund categories. The same was not true for CTAs in this study; only the PTFS factors were significant in explaining ATSMOM.[13]

We also regressed the strategy's returns against the Global Value and Global (cross-sectional) Momentum factors proposed by Asness, Moskowitz, and Pedersen (2013), which are appropriate for this part of the study because these factors cover multiple asset classes. In Column 3 of Table 4, the coefficients of the global factors are significantly positive. These factors perform better than many of the other factors explaining the variation in ATSMOM returns. Our strategy continued to generate a significant and substantial alpha (5.64% per year), however, vis-à-vis these factors.

Panel A of **Table 5** reports the explanatory power of a number of asset-based style regressions in which we regressed the manager-based CTA indexes against the competing asset-based benchmarks. The period is 2000 through January 2012, for which data for all the benchmarks were publicly available. The PTFS explain up to 30% of the variation in the CTA indexes. The 10-factor model, which considers the other hedge fund asset-based style factors proposed by Fung and Hsieh (2004) in addition to the PTFS, performed only marginally better. Turning to the SG Trend Indicator Index, an industry benchmark that has gained traction among practitioners in the CTA industry, we found that it performed surprisingly well over the sample period. MOP also performed consistently across the CTA benchmarks and produced R^2s of around 45%, slightly lower than the R^2 of the SG Trend Indicator Index. The three-factor BK model yielded comparable results, with adjusted R^2s ranging from 40% to 50%. ATSMOM, however, performed best across the board.

To determine whether the observed improvement of our proposed factor in capturing CTAs'

Table 5. Explanatory Power of Market-Based Indexes, 31 January 2000–30 January 2012 (robust standard errors in parentheses)

	BarclayHedge CTA	BTOP50	SG CTA	SG Trend Indicator	BarclayHedge Systematic Trend Following (AUM)	BarclayHedge Systematic Trend Following (ERW)
A. Adjusted R^2*s for CTA manager–based indexes against asset-based factors*						
PTFS	0.294	0.190	0.199	0.153	0.218	0.303
F&H 10-factor	0.329	0.251	0.246	0.198	0.266	0.344
Trend indicator	0.492	0.482	0.540	0.522	0.507	0.549
MOP	0.431	0.430	0.421	0.459	0.484	0.458
BK	0.413	0.399	0.396	0.419	0.489	0.490
ATSMOM	0.592	0.595	0.604	0.612	0.649	0.658
B. Value added by ATSMOM beyond BK results						
BK_M	0.2692**	0.4169**	0.4028**	0.4680**	0.5580**	0.2717**
	(0.045)	(0.053)	(0.052)	(0.055)	(0.057)	(0.039)
BK_W	0.2025**	0.2840**	0.3033**	0.3015**	0.3340**	0.2090**
	(0.061)	(0.076)	(0.077)	(0.082)	(0.091)	(0.051)
BK_D	0.0895	0.1009	0.0837	0.0723	0.1979**	0.1055**
	(0.049)	(0.063)	(0.068)	(0.070)	(0.073)	(0.038)
Residual	0.2966**	0.4584**	0.4756**	0.4771**	0.4969**	0.2866**
	(0.052)	(0.079)	(0.075)	(0.083)	(0.092)	(0.044)
Constant	−0.0006	−0.0040*	−0.0037*	−0.0045*	−0.0023	−0.0003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Adjusted R^2	0.593	0.596	0.607	0.613	0.652	0.676

*Significant at the 5% level.

**Significant at the 1% level.

returns is meaningful, we compared ATSMOM to the model proposed by BK.[14] To this end, we first estimated the incremental value added from using ATSMOM by calculating the residuals from a regression of ATSMOM against the futures-based trend-following benchmark (FTB) strategies of BK. For comparison purposes, we scaled all the regressors, including the residuals, to exhibit 10% volatility. We then reran the specification of BK, including the obtained residuals. If the coefficient on the residuals was statistically significant, the result confirmed that our proposed factors add value over and above the FTBs. The results are reported in Panel B of Table 5.

Not only did we find that the coefficient is significant at conventional levels and leads to a meaningful increase in the explanatory power of the models (i.e., a 15–20 percentage point increase over the initially reported adjusted R^2; see Panel A of Table 5), but we also observed that the relationship is economically significant. In particular, we found that the coefficient on the residuals, when scaled to the same volatility, is comparable in magnitude to BK monthly and weekly factors. This finding indicates that the BK factors alone may fall short of explaining CTAs' returns

Decomposing Adaptive Time Series Momentum. Our proposed strategy is equivalent to an equal-weighted combination of a set of TSMOM portfolios with look-back horizons from 10 days to 260 days. Our ATSMOM discussed so far traded the net position. We can look at these 251 portfolios as separate variables, jointly describing trend-following strategies. In an attempt to improve understanding of CTAs' returns, we decomposed the ATSMOM's returns into its constituent (significant) components. The question we wished to answer was whether a single factor, which we call ATSMOM and which is a simple average of a wide set of TSMOM portfolios, is enough to fully describe time series momentum strategies in general. The evidence in Greyserman and Kaminski (2014) suggests that factors beyond ATSMOM may be driving CTA returns.

One way to address this empirical question is to apply a principal component analysis to the constituting TSMOM portfolios. To analyze the statistical significance of the various principal components in time series momentum returns, we drew 10,000 bootstrapped samples (see Peres-Neto, Jackson, and Somers 2003) to calculate *p*-values for the estimated eigenvalues. The eigenvalues were compared with both "broken-stick" and Marchenko–Pastur distributions.[15]

At the 90% confidence level, both distributions indicated that the first three principal components, corresponding to the three largest eigenvalues, are significant. At the 95% level of significance, the Marchenko–Pastur critical values pointed to three significant components. The broken-stick model, however, suggested that only the first two principal components are significant. Regressing the manager-based indexes against the first three principal components, we found that only the first two are significant.

In our results, the first principal component (PC1) is similar to an equal-weighted portfolio of TSMOM portfolios, which is consistent with the definition of ATSMOM.[16] Indeed, PC1 had a correlation of 0.99 with ATSMOM's net returns. ATSMOM, by design, assigns an equal weight to each TSMOM strategy with a look-back window of between 10 and 260 days. This correlation implies a significant amount of overlap in the look-back windows. For example, the 10-day window is also part of the 11-day window, the 12-day window, and so forth, up to the 260-day window (although it becomes increasingly less important in determining the trend).

The second principal component did not load uniformly on the various constituent portfolios. Instead, we found that PC2 is equivalent to a strategy that buys short-horizon strategies (strategies that react fast to changes in trends) and sells long-horizon momentum strategies (strategies that react slowly to changes in trends). It can thus be interpreted as a "speed factor." This speed factor is close to the opposite of the speed factor in Greyserman and Kaminski (2014), which buys long-horizon (slow) and sells short-horizon (fast) momentum strategies. Nevertheless, without loss of generality, we take the negative of PC2 to get a speed factor similar to that of Greyserman and Kaminski.[17]

A possible practitioner criticism of this approach relates to correlation. When one equal-weights the signs of a set of returns that are overlapping, the signals are not independent. So, the ATSMOM factor is loaded more heavily on the longer time horizons than the shorter ones. In this case, if managers in the space account for this weighting when measuring and combining various signals, ATSMOM could be a long-term-tilted signal by construction.[18]

We know that long-term momentum strategies tend to outperform their shorter-term counterparts. At the same time, long-term strategies also exhibit lower skewness (see Table 3). Return to the speed factor may, therefore, be a compensation for bearing tail risk that results from long-term strategies (for a more detailed discussion, see Greyserman and Kaminski 2014).

Next, we investigated the Sharpe ratio of a portfolio that combines ATSMOM with the speed factor, net of transaction costs, as a function of the weight of the speed factor. When the speed factor was scaled to the volatility of ATSMOM and its weight was capped at 20%, we found that the speed factor contributed positively to overall performance because of lower trading costs and diversification. Diversification comes into play because, by construction, the speed factor has a correlation of zero with ATSMOM.

Note that, although ATSMOM is a tradable factor, PC2 is not yet tradable because it is based on loadings that are estimated in-sample. In addition, the factor is not net of transaction costs. To turn it into a tradable factor, we calculated the weights of the horizon portfolios in the speed factor at any point in time. To avoid a look-ahead bias, the weights were made proportional to the loadings estimated from an expanding window up to the penultimate day. The initial estimation period was one year.

Although we do not argue that a CTA would trade our proposed speed factor on a standalone basis, the factor can be used as an overlay to complement a more general trend-following strategy, in which case, only the net position would be traded. From this perspective, only the additional trading costs related to the speed factor are relevant. In what follows, we discuss the speed factor's performance from this perspective.

By construction unrelated to ATSMOM, we found (in unreported results) that the speed factor is related to the BK factors, PFTS, cross-sectional momentum, and liquidity. The (positive) loading on liquidity may be surprising in light of our earlier finding that ATSMOM is unrelated to liquidity risk. The speed factor, however, invests in longer-term (slower-to-react) momentum strategies and sells shorter-term (faster-to-react) momentum strategies than ATSMOM and is thus more exposed to liquidity risk (from reacting only slowly) and more likely to trade during, rather than ahead of, periods of distress and lower liquidity.

The Speed Factor, Asset Class–Based Factors, and CTA Performance. With the introduction of the speed factor, we repeated the previous regressions of the various CTA indexes against the newly introduced factors. We also extended the analysis by considering asset class–specific ATSMOM for commodity, equity, fixed-income, and foreign exchange (FX) futures. The asset class–based factors were scaled to 10% volatility. **Table 6** reports the results.

As we have discussed, ATSMOM is able to explain a substantial part of the variation in CTAs' returns (Table 5). This finding suggests that ATSMOM captures CTAs' trading behavior fairly accurately. Extending the model with the speed factor, however, increases the fit of most of the regressions, with the exception of the SG indexes (Table 6, Panel A).

In Panel B of Table 6, we report the results for the asset class–based ATSMOM. Applying asset class–based ATSMOM has two advantages over a diversified ATSMOM strategy. First, the asset class–based benchmarks improve the explanatory fit because the relative importance of the various sectors is left unconstrained. Second, asset class benchmarks allow for a style analysis. Because we scaled the asset class–based factors to 10% volatility per year, the loadings can be compared directly. Panel B of Table 6 indicates that CTAs allocate most to fixed-income futures and least to FX and commodity futures. The weight of the asset class, however, tends to depend on fund size; large-capitalization indexes—the BTOP 50 and the AUM-weighted BarclayHedge systematic trend-following indexes—invest more in the more liquid markets (i.e., fixed income) and less in commodities. Small-cap managers, proxied by the BarclayHedge CTA and equal-risk-weighted BarclayHedge systematic trend-following indexes, invest more evenly across asset classes.

Next, consider individual CTAs. We applied the asset class–based ATSMOM and the speed factor to all the individual funds included in the BarclayHedge sample with at least a one-year track record after inclusion (see the "Data" section).[19] **Table 7** reports the mean and median of the parameter estimates for 335 funds that produced jointly significant betas at the 10% level of significance, according to the Wald parametric statistical test.

On average, our model explains 40% of the variation in individual CTAs' returns. The average (median) alpha is positive at 0.29% (0.82%) per year, with 16% of the fund alphas significantly positive and 6% significantly negative. For the funds for which we obtained a significant alpha, we observe considerable variation; funds with positive alphas generated mean (median) alphas of 4.77% (3.91%) a year, whereas funds with negative alphas underperformed the ATSMOM strategies by an average (median) of 9.55% (6.56%) a year.

Interestingly, fixed income is significant for 70% of the funds. Thus, we found that CTAs tend to be exposed to fixed income most frequently, which corroborates the earlier finding that CTA indexes load most heavily on this factor. Commodities, being significant in 64% of the cases, make up the second most important exposure. Equity is significant in 53%, and FX is significant for 48% of the funds. The speed factor is also an important driver of CTA returns; it is significant in half the regressions. The negative average coefficient of the speed factor is an indication that managers tend to add shorter-horizon momentum strategies as an overlay to their main strategies. This result is the consequence of ATSMOM being a long-term-tilted strategy because of the high degree of correlation between the constituent signals that make up the ATSMOM signal. As managers incorporate this aspect into their signal weights, they place more emphasis on shorter horizons.[20]

Table 6. Asset-Pricing Regressions on Manager-Based Indexes (robust standard errors in parentheses)

	BarclayHedge	BTOP50	SG CTA	SG Trend Indicator	BarclayHedge Systematic Trend Following (AUM)	BarclayHedge Systematic Trend Following (ERW)
A. Manager-based indexes vs. ATSMOM and speed factor						
ATSMOM	0.4638**	0.6541**	0.6878**	0.6842**	0.8258**	0.4398**
	(0.041)	(0.051)	(0.065)	(0.072)	(0.074)	(0.032)
Constant	0.0001	−0.0024*	−0.0018	−0.0021	0.0002	0.0011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.483	0.503	0.611	0.605	0.565	0.617
B. Manager-based indexes vs. asset class–based ATSMOM and speed factor						
ATSMOM_{COM}	0.5617**	0.5490**	0.6454**	0.6479**	0.6837**	0.5016**
	(0.109)	(0.113)	(0.142)	(0.144)	(0.151)	(0.072)
ATSMOM_{EQ}	0.2544**	0.3936**	0.4770**	0.5898**	0.6848**	0.2952**
	(0.068)	(0.081)	(0.091)	(0.089)	(0.095)	(0.047)
ATSMOM_{FI}	0.6630**	1.1086**	1.2303**	1.2743**	1.4943**	0.6705**
	(0.090)	(0.126)	(0.152)	(0.154)	(0.140)	(0.064)
ATSMOM_{FX}	0.4739*	0.7027*	0.6464*	0.4394	0.6500	0.4030*
	(0.215)	(0.292)	(0.298)	(0.274)	(0.360)	(0.179)
Speed factor	−0.1370**	−0.1154**	−0.0008	−0.0074	−0.1617**	−0.1062**
	(0.036)	(0.038)	(0.046)	(0.045)	(0.056)	(0.025)
Constant	0.0005	−0.0021*	−0.0021	−0.0023*	0.0005	0.0012*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.564	0.591	0.676	0.667	0.653	0.697

Notes: The asset class–based factors were adjusted to 10% annualized volatility. The returns of the various manager-based indexes are net of transaction costs.

*Significant at the 5% level.

**Significant at the 1% level.

Having obtained individual alphas for the CTAs, we investigated the role of fund characteristics in generating alpha. We regressed the alpha for each fund for every year on yearly fund characteristics that included lagged alpha, fund size, fund age, a standard fund flow variable, R^2 and the relative factor exposures of the performance regressions, management and incentive fees, the margin-to-equity (ME) ratio, and round turns per million US dollars per year.

The estimated alphas are subject to measurement error. If one does not account for this aspect, the measurement error will generate heteroskedasticity in the panel regression residuals, making standard significance tests invalid. To correct for this issue, we weighted each observation by the reciprocal of the standard errors of the performance regressions, as in Dahlquist, Engström, and Söderlind (2000).

Table 8 reports the results after we controlled for period-specific fixed effects. Column 1 omits the ME ratio and round turns per million US dollars per year statistics because these data are available only for a subset of the CTAs. Specifications that included the

Table 7. Asset-Pricing Regressions on Individual Trend-Following Managed Futures, 31 January 1994–30 September 2015

Measure	Annual Alpha (%)	ATSMOM COM	ATSMOM EQ	ATSMOM FI	ATSMOM FX	Speed Factor	Adj. R^2	Wald Test
Mean	0.29	0.20	0.12	0.21	0.21	−0.14	0.40	0.00
Mean*(–)	−9.55	−0.37	−0.36	−0.30	−0.18	−0.34		
Mean*(+)	4.77	0.32	0.27	0.31	0.38	0.19		
Median	0.82	0.19	0.13	0.22	0.15	−0.10	0.41	
Median*(–)	−6.56	−0.35	−0.24	−0.25	−0.12	−0.26		
Median*(+)	3.91	0.29	0.23	0.28	0.29	0.15		
t-Statistic	0.22	0.64	0.53	0.70	0.48	0.50		
t-Statistic (–)	0.06	0.03	0.04	0.02	0.03	0.42		
t-Statistic (+)	0.16	0.60	0.49	0.68	0.46	0.08		

Notes: The rows marked *(–) refer to significant negative estimates, and rows marked *(+) refer to significant positive estimates. The row "*t*-Statistic" shows the share of funds that produced significant parameter estimates at the 10% significance level. The row "*t*-Statistic (–)" shows the percentage of funds that produced, at a 10% level, significant negative parameters, and the row "*t*-Statistic (+)" shows the percentage of funds that produced, at a 10% level, significant positive parameters. The asset class–based ATSMOM and the speed factor were adjusted to 10% annualized volatility and are net of transaction costs. The individual fund returns are net of transaction costs and gross of fees. Fees were added under the assumption of a 2/20 fee structure with quarterly crystallization, which is the frequency of the payment schedule for the incentive fee (see Elaut, Frömmel, and Sjödin 2015).

ME ratio are reported in Column 2, and specifications that included round turns per million US dollars are reported in Column 3.

The results in Table 8 suggest persistence in CTAs' performance. CTAs that outperformed our benchmarks over the previous year tended to repeat that superior performance the following year. Fund size—that is, Log (FuM)—negatively affected risk-adjusted performance. Somewhat surprisingly, age is positively related to alpha. However, the expected risk-adjusted performance of a five-year-old CTA that had USD1 billion under management is, all else being equal, 1.7% per year less than that of a CTA that managed only USD10 million and was only two years old. This result indicates that interpreting one of the variables alone can be misleading.

Contemporaneous fund flows do not affect risk-adjusted performance, which suggests that capacity constraints are generally not an issue. Adding the R^2s of the performance regressions, we tested and rejected the hypothesis in Sun, Wang, and Zheng (2012) that hedge funds whose returns are less explainable by risk factors exhibit more managerial skill. In contrast, funds that engage in pure trend-following approaches tend to generate higher risk-adjusted performance. Thus, alpha does not appear to derive from not being mainstream but from other sources—including, perhaps, superior risk management and better trade execution, which lead to lower implicit and explicit transaction costs.

The relative factor weights are simply calculated from absolute loadings in the individual performance regressions. All else being equal, we found that higher exposure to equity momentum is likely to result in higher risk-adjusted performance. In contrast, funds with higher allocations to fixed-income trend-following strategies tended to generate lower alpha. Interestingly, CTAs that had high exposures to the speed factor significantly outperformed those with less exposure. Because our results suggest that some benefit comes from allocating to the speed factor in terms of diversification and lower transaction costs, speed factor exposure may proxy for the level of sophistication of the manager.

The ME ratio appears to be a sign of better performance, probably because of economies of scale. This result suggests that increased risk taking does not, per se, imply inferior risk management and poor performance.

Table 8. Panel Regressions on Alphas, 31 January 1994–30 September 2015 (robust standard errors in parentheses)

	(1)	(2)	(3)
$Alpha_{t-1}$	0.167**	0.200**	0.205**
	(0.018)	(0.020)	(0.022)
Log(FuM)	–0.069*	–0.121**	–0.145**
	(0.039)	(0.042)	(0.050)
Fund age	0.100**	0.094**	0.093**
	(0.019)	(0.020)	(0.023)
Fund flow variable	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
R^2 performance regression	3.526**	3.500**	4.256**
	(0.482)	(0.484)	(0.532)
Commodity exposure	–1.110	–0.309	–0.168
	(0.685)	(0.713)	(0.809)
Equity exposure	3.208**	3.114**	2.679**
	(0.747)	(0.793)	(0.895)
Fixed-income exposure	–1.472*	–1.455*	–1.307
	(0.678)	(0.705)	(0.783)
FX exposure	–1.110	–1.072	–0.148
	(0.725)	(0.760)	(0.852)
Speed exposure	3.571**	3.694**	3.467**
	(0.626)	(0.674)	(0.745)
Management fee	–0.251	–0.337	–0.292
	(0.178)	(0.194)	(0.226)
Incentive fee	–0.092**	–0.118**	–0.162**
	(0.031)	(0.035)	(0.039)
ME ratio		0.106**	0.128**
		(0.023)	(0.026)
Round turns/USD million			0.000
			(0.000)
Observations	2,254	2,007	1,615
R^2	0.30000	0.33000	0.37000

Notes: Cross-sectional analysis of the estimated alphas for 335 individual CTAs. The reported coefficients rely on a weighted-least-squares panel regression that accounted for CTA period-specific fixed effects. The standard errors are clustered on both the specific manager and period. The fund flow variable is contemporaneous fund flows—new funds that investors allocate with the fund manager.

*Significant at the 5% level.

**Significant at the 1% level.

Finally, more trading (in terms of rounds per millions of US dollars per year) does not affect risk-adjusted performance. Only a small part of the cross-sectional variation in estimated alphas is attributable to such fund characteristics as past performance, fund age, fund size, fees, and style. We conclude that the alphas obtained vis-à-vis our new risk factors can, to some extent, be interpreted as capturing managerial skill.

Conclusion

We have proposed a novel trend-following strategy benchmark that incorporates signal strength and relies on an adaptive time series momentum strategy (as opposed to the simpler TSMOM strategy that builds on a binary long/short signal). ATSMOM matches a number of stylized facts of manager-based indexes better than existing benchmarks and outperforms those benchmarks in explaining the returns of CTAs. ATSMOM changes exposures to futures markets dynamically by aggregating time series momentum signals over a wide range of horizons. In this way, the model increases the allocation to the markets where trends are developing and decreases exposure to markets where trends are fading.

Decomposing time series momentum strategies' returns by using a principal component analysis, we found that another significant factor appears to be present, together with ATSMOM, in time series momentum returns. We termed this factor "the speed factor" because it buys long-term and sells shorter-term time series momentum strategies. In addition, we incorporated a number of real-life frictions that may affect strategy returns.

We found in our tests that ATSMOM alone or augmented with the speed factor explains CTA funds' reported returns better than other approaches. Therefore, our approach can aid practitioners in benchmarking and manager selection. We documented that a subset of funds continues to exhibit positive alpha when compared with our new risk factors. Moreover, the abnormal returns of these funds can be only partly explained by observable fund characteristics; thus, the returns appear indicative of skill.

An important aspect is that we document strong momentum in CTA risk-adjusted performance: We found that strong performance in one year tends to repeat in the subsequent year. We also found evidence that fund size is negatively related to risk-adjusted performance whereas fund age is positively related to risk-adjusted performance. Fund style (i.e., asset class exposure and the applied trading strategy) also contributes to CTA alphas. Moreover, allocation to the speed factor appears to be related to manager skill. Contemporaneous fund flows, in contrast, did not affect risk-adjusted performance, which suggests capacity constraints are not much of an issue for CTAs. Higher management and performance fees did not signal prospects for better performance.

Finally, we note that, although our analysis captures many of the real-life frictions associated with systematic trading, it does not consider the nonlinear relationship between trading volume and market impact. Larger funds may be forced to trade more liquid markets as well as more slowly moving signals (see Greyserman and Kaminski 2014). If so, our factors may still be setting the bar too high for funds with large AUM.

Editor's Note

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Notes

1. Or, recently, in relation to the factor model specification of Buraschi, Kosowski, and Trojani (2014), who proposed a factor that tries to capture correlation risk.

2. For a thorough discussion, see Baltas and Kosowski (2013) and the references in it.

3. Although reporting to hedge fund databases is voluntary, Joenväärä, Kosowski, and Tolonen (2012), in an analysis of the various publicly available hedge fund databases, concluded that BarclayHedge is the most comprehensive, especially for CTAs. Data from January 1994 were used to mitigate a potential survivorship bias; most databases started collecting information on defunct programs only from 1994 on (see Joenväärä et al.).

4. By keeping track of the number of months that were backfilled when a fund was first included in the BarclayHedge database, RPM Risk & Portfolio Management tracked backfill bias in the database for the 2005–10 period. For that sample period, the median (average) backfill bias was 12 (14) months, which is consistent with the correction proposed by Kosowski et al. (2007).

5. Results for a trading strategy that also included horizons between 1 and 9 days were qualitatively unchanged from results reported here and are available upon request.

6. Recently related to our work, Lempérière, Deremble, Seager, Potters, and Bouchaud (2014) and Dudler, Gmür, and Malamud (2015) suggested TSMOM specifications that account for the signal strength.

7. RPM Risk & Portfolio Management is a fund of funds specializing in CTA strategies and liquid global macro managers. It is based in Stockholm.

8. Effective spread estimators (Roll 1984; Smith and Whaley 1994) and approaches to estimate the bid–ask spread directly from the order book (Locke and Venkatesh 1997) have also been proposed. Szakmary, Shen, and Sharma (2010) and Locke and Venkatesh pointed out, however, that these estimates are close to the tick size. Because estimating the bid–ask spread from the order book was beyond the scope of the current study, we stuck to the simplification that the tick size is a good proxy for the bid–ask spread.

9. See Frazzini, Israel, and Moskowitz (2012) for details on estimating nonlinear transaction cost functions and their implications for exploiting asset-pricing anomalies.

10. When a futures contract is rolled over to a further-dated contract, the strategy closes the nearby contract and opens a position in the new contract. The date of the contract rollover coincides with the rollover used for the construction of the continuous futures (see the online supplemental material, available at www.tandfonline.com/doi/suppl/10.1080/0015198X.2018.1547052, for the continuous contract construction as well as the estimated transaction costs). On such days, turnover is usually much higher than on other days. Daily turnover of the strategy is fairly limited except in the case of short-rate futures. These contracts exhibit low levels of volatility (0.01% average daily volatility) in comparison with other contracts (1.2% average daily volatility) and thus require a large notional position to obtain similar levels of risk. Each short-rate futures contract included generated an average daily turnover of 22%–23%, whereas the average turnover for the other contracts is just 0.3%.

11. The time series momentum factor (of MOP) is available from AQR's website: www.aqr.com/Insights/Datasets/Time-Series-Momentum-Factors-Monthly. The BK monthly, weekly, and daily futures-based trend-following benchmarks are available from Robert Kosowski's website: www.imperial.ac.uk/people/r.kosowski/research.html.

12. The BarclayHedge and SG manager-based indexes are equal weighted. As a consequence, these indexes overweight CTAs that target high levels of volatility. The manager-based indexes are rebalanced once a year. The BarclayHedge CTA Index is a broad index of CTAs, some of which are not trend followers or systematic. The SG CTA Index includes only the 20 largest CTAs that are open to investment and report performance and AUM on a daily basis.

13. Following the work of MOP; Asness, Moskowitz, and Pedersen (2013); and Koijen et al. (2018), we regressed ATSMOM's returns on a number of macroeconomic, liquidity, volatility, and sentiment variables. The results, reported in the online supplemental material (available at www.tandfonline.com/doi/suppl/10.1080/0015198X.2018.1547052), indicate that variation in these variables does not explain ATSMOM's excess returns.

14. We refrained from using an incremental *F*-test because of potential multicollinearity issues. The pairwise Pearson correlation between our factor and the average of BK's factors is 0.8.

15. A Marchenko–Pastur distribution is the asymptotic behavior of singular values of large rectangular random matrixes. See also, for example, Süss (2012).

16. Results are available in the online supplemental material (available at www.tandfonline.com/doi/suppl/10.1080/0015198X.2018.1547052).

17. Principal components are indifferent to scaling because they are extracted in such a way as to show zero pairwise correlation.

18. We thank an anonymous referee for this valuable insight.

19. Note that dropping funds that stopped reporting before turning two years old unavoidably introduced some survivorship bias.

20. We thank an anonymous referee for this valuable insight.

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