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DEMYSTIFYING MANAGED FUTURES

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We show that the returns of Managed Futures funds and CTAs can be explained by time series momentum strategies and we discuss the economic intuition behind these strategies. Time series momentum strategies produce large correlations and high R-squares with Managed Futures indices and individual manager returns, including the largest and most successful managers. While the largest Managed Futures managers have realized significant alphas to traditional long-only benchmarks, controlling for time series momentum strategies drives the alphas of most managers to zero. We consider a number of implementation issues relevant to time series momentum strategies, including risk management, risk allocation across asset classes and trend horizons, portfolio rebalancing frequency, transaction costs, and fees.

1 Introduction

Managed Futures hedge funds and commodity trading advisors (CTAs) have existed at least since Richard Donchian started his fund in 1949 and they have proliferated since the 1970s when futures exchanges expanded the set of tradable contracts.[1] BarclayHedge estimates that the CTA industry has grown to managing approximately $320B as of the end of the first quarter of 2012. Although these funds have existed for decades and have attracted large amounts of capital, they have not been well understood. One potential reason for this is because the ability to charge high fees requires maintaining a certain amount of mystery as to the core underlying strategy. Fung and Hsieh (2001) find that portfolios of look-back straddles have explanatory power for Managed Futures returns, but these look-back straddles are not implementable as they use data from future time periods.

We show that simple implementable trend-following strategies—specifically time series momentum strategies—can explain the returns of Managed Futures funds. We provide a detailed analysis of the economics of these strategies and apply them to explain the properties of Managed Futures funds. Using the returns to time series

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momentum strategies, we analyze how Managed Futures funds benefit from trends, how they rely on different trend horizons and asset classes, and examine the role of transaction costs and fees within these strategies.

Time series momentum is a simple trend-following strategy that goes long a market when it has experienced a positive excess return over a certain look-back horizon, and goes short otherwise. We consider 1-month, 3-month, and 12-month look-back horizons (corresponding to short-, medium-, and long-term trend strategies), and implement the strategies across a liquid set of commodity futures, equity futures, currency forwards, and government bond futures.[2]

Trend-following strategies only produce positive returns if market prices exhibit trends, but why should price trends exist? We discuss the economics of trends based on initial under-reaction to news and delayed over-reaction as well as the extensive literature on behavioral biases, herding, central bank behavior, and capital market frictions. If prices initially under-react to news, then trends arise as prices slowly move to more fully reflect changes in fundamental value. These trends have the potential to continue even further due to a delayed over-reaction from herding investors. Naturally, all trends must eventually come to an end as deviation from fair value cannot continue indefinitely.

We find strong evidence of trends across different look-back horizons and asset classes. A time series momentum strategy that is diversified across all assets and trend horizons realizes a gross Sharpe ratio of 1.8 with little correlation to traditional asset classes. In fact, the strategy has produced its best performance in extreme up and extreme down stock markets. One reason for the strong performance in extreme markets is that most extreme bear or bull markets historically have not happened overnight, but have occurred over several months or years. Hence, in prolonged bear markets, time series momentum takes short positions as markets begin to decline and thus profits as markets continue to fall.

Time series momentum strategies help explain returns to the Managed Futures universe. Like time series momentum, some Managed Futures funds have realized low correlation to traditional asset classes, performed best in extreme up and extreme down stocks markets, and delivered alpha relative to traditional asset classes.

When we regress Managed Futures indices and manager returns on time series momentum returns, we find large R-squares and very significant loadings on time series momentum at each trend horizon and in each asset class. In addition to explaining the time variation of Managed Futures returns, time series momentum also explains the average excess return. Indeed, controlling for time series momentum drives the alphas of most managers and indices below zero. The negative alphas relative to the hypothetical time series momentum strategies show the importance of fees and transaction costs.

Comparing the relative loadings, we see that most managers focus on medium- and long-term trends, giving less weight to short-term trends, and appear to focus on fixed-income markets, giving less weight to other asset classes.

The rest of this paper is organized as follows. Section 2 discusses the economics and literature of trends. Section 3 describes our methodology for constructing time series momentum strategies and presents the strong performance of these strategies. Section 4 shows that time series momentum strategies help explain the returns of Managed Futures managers and indices. Section 5 discusses implementation issues such as transaction costs, rebalance frequency, margin requirements, and fees. Section 6 concludes.

2 The life cycle of a trend: Economics and literature

The economic rationale underlying trend-following strategies is illustrated in Fig. 1, a stylized "life cycle" of a trend. An initial under-reaction to a shift in fundamental value allows a trend-following strategy to invest before new information is fully reflected in prices. The trend then extends beyond fundamentals due to herding effects, and finally results in a reversal. We discuss the drivers of each phase of this stylized trend, as well as the related literature.

2.1 Start of the trend: Under-reaction to information

In the stylized example shown in Fig. 1, a catalyst—a positive earnings release, a supply shock, or a demand shift—causes the value of an equity, commodity, currency, or bond to change. The change in fundamental value is immediate, shown by the solid green line. While the market price (shown by the dotted black line) moves up as a result of the catalyst, it initially under-reacts and therefore continues to go up for a while. A trend-following strategy buys the asset as a result of the initial upward price move, and therefore capitalizes on the subsequent price increases. At this point in the life cycle, trend-following investors contribute to the speeding-up of the price discovery process.

Research has documented a number of behavioral tendencies and market frictions that lead to this *initial under-reaction*:

(i) **Anchor-and-insufficient-adjustment.** Edwards (1968) and Tversky and Kahneman (1974) find that people anchor their views to historical data and adjust their views insufficiently to new information. This behavior can cause prices to under-react to news (Barberis *et al.*, 1998).

(ii) **The disposition effect.** Shefrin and Statman (1985) and Frazzini (2006) observe that people tend to sell winners too early and ride losers too long. They sell winners early because they like to realize their gains. This creates downward price pressure, which slows the upward price adjustment to new positive information. On the other hand, people hang on to losers because realizing losses is painful. They try to "make back" what

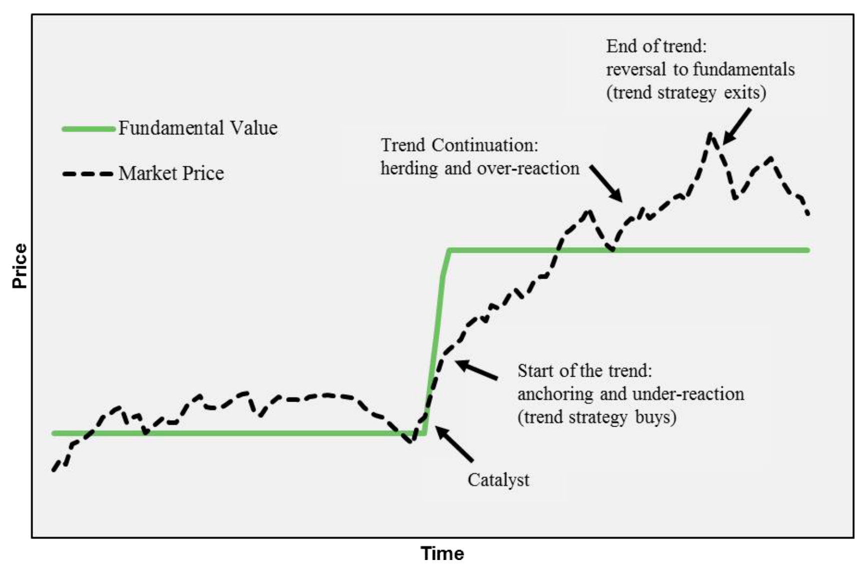


Figure 1 Stylized plot of the life cycle of a trend.

has been lost. Fewer willing sellers can keep prices from adjusting downward as fast as they should.

(iii) **Nonprofit-seeking activities.** Central banks operate in the currency and fixed-income markets to reduce exchange-rate and interest-rate volatility, potentially slowing the price-adjustment to news (Silber, 1994). Also, investors who mechanically rebalance to strategic asset allocation weights trade against trends. For example, a 60/40 investor who seeks to own 60% stocks and 40% bonds will sell stocks (and buy bonds) whenever stocks have outperformed.

(iv) **Frictions and slow moving capital.** Frictions, delayed response by some market participants, and slow moving arbitrage capital can also slow price discovery and lead to a drop and rebound of prices (Mitchell *et al.*, 2007; Duffie, 2010).

The combined effect is for the price to move gradually in response to news, creating a price drift as the market price slowly incorporates the full effect of the news. A trend-following strategy will position itself in relation to the initial news, and profit if the trend continues.

2.2 Trend continuation: Delayed over-reaction

Once a trend has started, a number of other phenomena exist which may extend the trend *beyond* the fundamental value:

(i) **Herding and feedback trading.** When prices have moved in one direction for a while, some traders may jump on the bandwagon because of herding (Bikhchandani *et al.*, 1992) or feedback trading (De Long *et al.*, 1990; Hong and Stein, 1999). Herding has been documented among equity analysts in their recommendations and earnings forecasts (Welch, 2000), in investment newsletters (Graham, 1999), and in institutional investment decisions.

(ii) **Confirmation bias and representativeness.** Wason (1960) and Tversky and Kahneman (1974) show that people tend to look for information that confirms what they already believe, and look at recent price moves as representative of the future. This can lead investors to move capital into investments that have recently made money, and conversely out of investments that have declined, both of which cause trends to continue (Barberis *et al.*, 1998; Daniel *et al.*, 1998).

(iii) **Fund flows and risk management.** Fund flows often chase recent performance (perhaps because of (i) and (ii)). As investors pull money from underperforming managers, these managers respond by reducing their positions (which have been underperforming), while outperforming managers receive inflows, adding buying pressure to their outperforming positions. Further, some risk-management schemes imply selling in down-markets and buying in up-markets, in line with the trend. Examples of this behavior include stop-loss orders, portfolio insurance, and corporate hedging activity (e.g., an airline company that buys oil futures after the oil price has risen to protect the profit margins from falling too much, or a multinational company that hedges foreign-exchange exposure after a currency moved against it) and such risk management practices can create feedback loops (Garleanu and Pedersen, 2007).

2.3 End of the trend

Obviously, trends cannot go on forever. At some point, prices extend too far beyond the fundamental value and, as people recognize this, prices revert toward the fundamental value and the trend dies out. As evidence of such over-extended trends, Moskowitz *et al.* (2012) find evidence of *return reversal* after more than a year.[3] The return reversal only reverses part of the initial price trend, suggesting that the price trend was partly driven by initial under-reaction (since this part of the trend should not reverse) and partly driven by delayed over-reaction (since this part reverses).

3 Time series momentum across trend-horizons and markets

Having discussed why trends might exist, we now demonstrate the performance of a simple trend-following strategy: time series momentum.

3.1 Identifying trends and sizing positions

We construct time series momentum strategies for 58 highly liquid futures and currency forwards from January 1985 to June 2012—specifically 24 commodity futures, 9 equity index futures, 13 bond futures, and 12 currency forwards. To determine the direction of the trend in each asset, the strategy simply considers whether the asset's excess return is positive or negative: A positive past return is considered an "up trend," and leads to a long position; a negative return is considered a "down trend," and leads to a short position.

We consider 1-month, 3-month, and 12-month time series momentum strategies, corresponding to short-, medium-, and long-term trend-following strategies. The 1-month strategy goes long if the preceding 1-month excess return was positive, and short if it was negative. The 3-month and 12-month strategies are constructed analogously. Hence, each strategy always holds a long or a short position in each of 58 markets.

The size of each position is chosen to target an annualized volatility of 40% for that asset, following the methodology of Moskowitz *et al.* (2012).[4] Specifically, the number of dollars bought/sold of instrument s at time t is $40\%/\sigma_t^s$ so that the time series momentum (TSMOM) strategy realizes the following return during the next week:

$$\begin{aligned}\text{TSMOM}_{t+1}^{X\text{-month, Asset-}s} &= \text{sign(excess return of } s \text{ over past} \\ &\quad X \text{ months)} \frac{40\%}{\sigma_t^s} r_{t+1}^s. \qquad (1)\end{aligned}$$

The ex ante annualized volatility σ_t^s for each instrument is estimated as an exponentially weighted average of past squared returns

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

where the scalar 261 scales the variance to be annual and $\bar{r}_t^s$ is the exponentially weighted average return computed similarly. The parameter δ is chosen so that the center of mass of the weights, given by $\sum_i (1-\delta)\delta^i i$, is equal to 60 days.

This constant-volatility position-sizing methodology of Moskowitz *et al.* (2012) is useful for several reasons: First, it enables us to aggregate the different assets into a diversified portfolio which is not overly dependent on the riskier assets—this is important given the large dispersion in volatility among the assets we trade. Second, this methodology keeps the risk of each asset stable over time, so that the strategy's performance is not overly dependent on what happens during times of high risk. Third, the methodology minimizes the risk of data mining, given that it does not use any free parameters or optimization in choosing the position sizes.

The portfolio is rebalanced weekly at the closing price each Friday, based on data known at the end of each Thursday. We therefore are only using information available at the time to make the strategies implementable. The strategy returns are gross of transaction costs, but we note that the instruments we consider are among the most liquid in the world. Section 5 considers the effect of different rebalance rules and discusses the impact of transaction costs. While Moskowitz *et al.* (2012) focus on monthly rebalancing, it is interesting to also consider higher rebalancing frequencies given our focus on explaining the returns of professional money managers who often trade throughout the day.

3.2 *Performance of the TSMOM strategies by individual asset*

Figure 2 shows the performance of each time series momentum strategy in each asset. The strategies deliver positive results in almost every case, a remarkably consistent result. The average Sharpe ratio (excess returns divided by realized volatility) across assets is 0.29 for the 1-month strategy, 0.36 for the 3-month strategy, and 0.38 for the 12-month strategy.

3.3 *Building diversified TSMOM strategies*

Next, we construct diversified 1-month, 3-month, and 12-month time series momentum strategies by averaging returns of all the individual strategies that share the same look-back horizon (denoted, TSMOM^{1M}, TSMOM^{3M}, and TSMOM^{12M}). We also construct time series momentum strategies for each of the four asset classes: commodities, currencies, equities, and fixed income (denoted, TSMOM^{COM}, TSMOM^{FX}, TSMOM^{EQ}, TSMOM^{FI}). Example, the commodity strategy is the average return of each individual commodity strategy for all three trend horizons. Finally, we construct a strategy that diversifies across all assets and all trend horizons that we call the diversified time series momentum strategy (denoted simply, *TSMOM*). In each case, we scale all the positions such that the overall portfolio targets an ex ante volatility of 10% using an exponentially weighted variance–covariance matrix estimated analogously to Eq. (2).

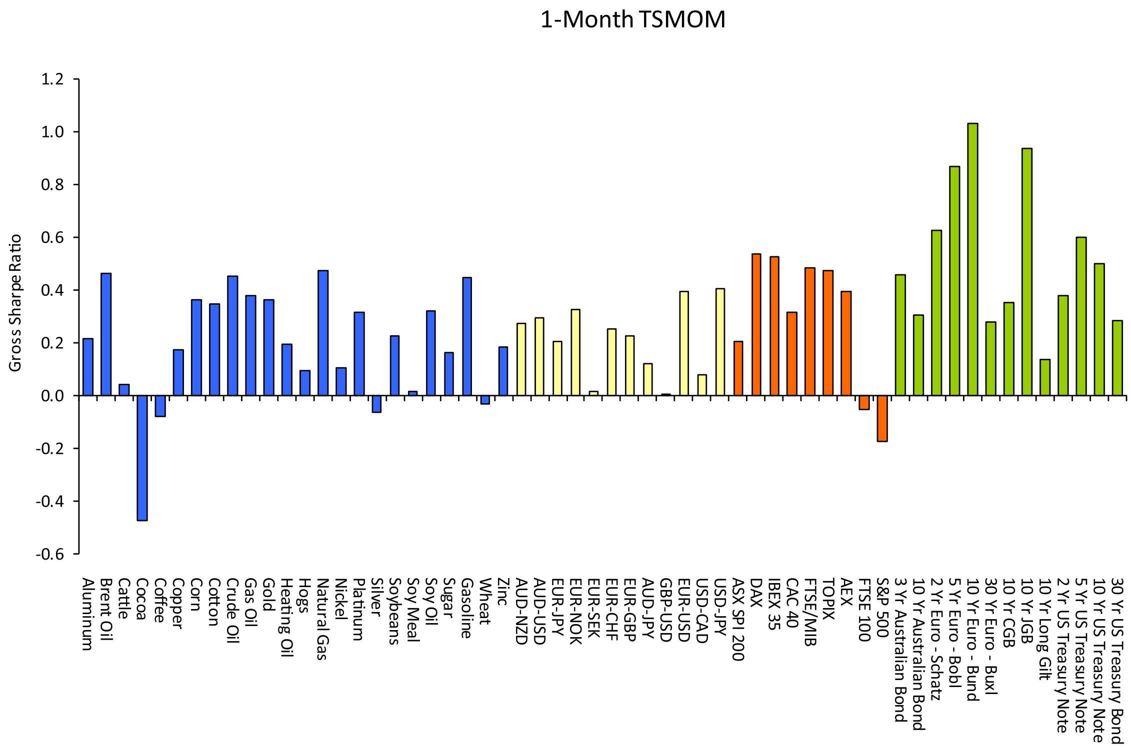
Table 1 shows the performance of these diversified time series momentum strategies. We see that the strategies' realized volatilities closely match the 10% ex ante target, varying from 9.5% to 11.9%. More importantly, all the time series momentum strategies have impressive Sharpe ratios, reflecting a high average excess return above the risk-free rate relative to the risk. Comparing the strategies across trend horizons, we see that the long-term (12-month) strategy has performed the best, the medium-term strategy has done second best, and the short-term strategy, which has the lowest Sharpe ratio out of the 3 strategies, still has a high Sharpe ratio of 1.3. Comparing asset classes, commodities, fixed income, and currencies have performed a little better than equities over the time period analyzed.

In addition to reporting the expected return, volatility, and Sharpe ratio, Table 1 also shows the alpha from the following regression:

$$\text{TSMOM}_t = \alpha + \beta^1 r_t^{\text{Stocks}} + \beta^2 r_t^{\text{Bonds}} + \beta^3 r_t^{\text{Commodities}} + \varepsilon_t. \qquad (3)$$

We regress the TSMOM strategies on the returns of a passive investment in the MSCI world stock index, the Barclays US Aggregate Government Bond index, and the S&P GSCI commodity index. The alpha measures the excess return, controlling for the risk premia associated with simply being long these traditional asset classes. The alphas are almost as large as the excess returns, since the TSMOM strategies are long/short and therefore have small average loadings on these passive factors. Finally, Table 1 reports the t-statistics of the alphas, which show that the alphas are highly statistically significant.

The best performing strategy is the diversified time series momentum strategy with a Sharpe ratio of 1.8. Its consistent cumulative return is seen in Fig. 3 that illustrates the hypothetical growth of $100 invested in 1985 in the diversified TSMOM strategy and the S&P500 stock market index, respectively.



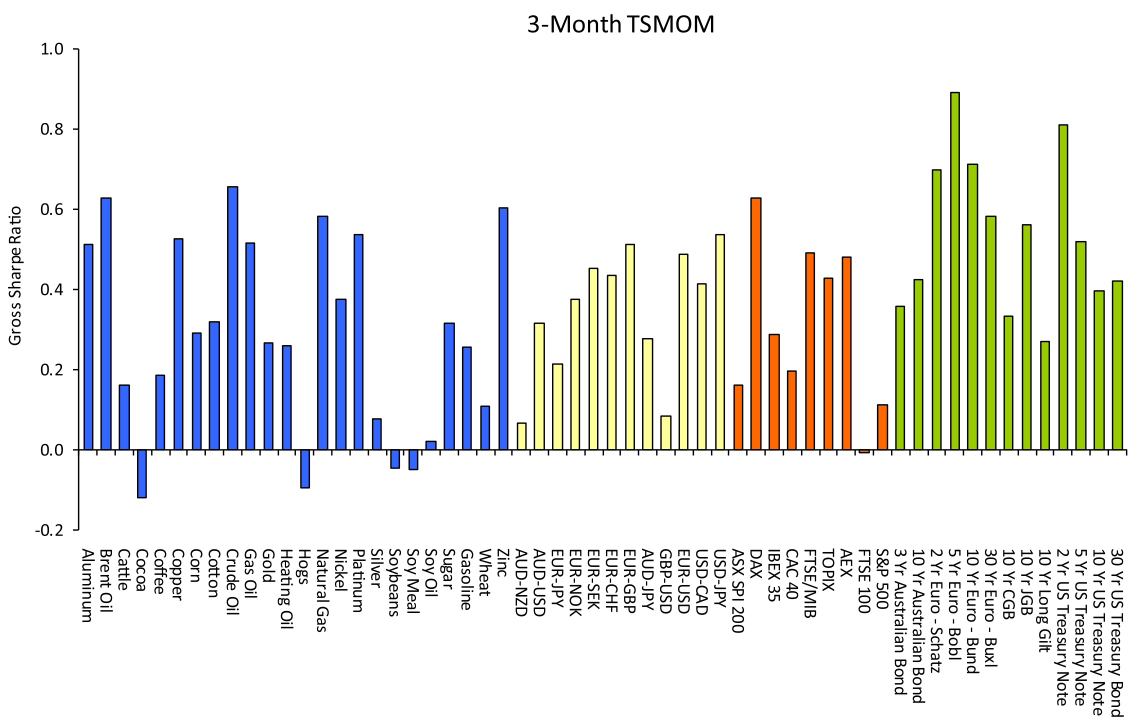


Figure 2 Performance of time series momentum by individual asset and trend horizon. This figure shows the Sharpe ratios of the time series momentum strategies for each commodity futures (in blue), currency forward (yellow), equity futures (orange), and fixed income futures (green). We show this for strategies using look-back horizons of 1-month (top panel), 3-month (middle panel), and 12-month (bottom panel).

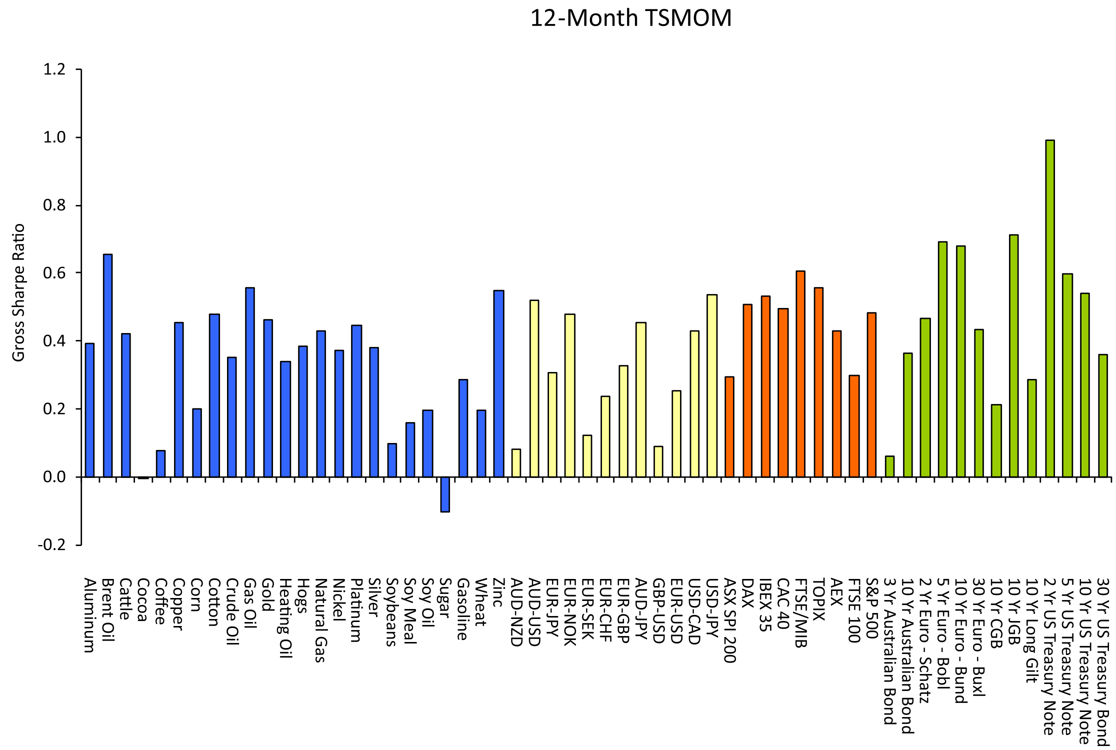


Figure 2 (*Continued*)

Table 1 Performance of time series momentum strategies.

Panel A: Performance of time series momentum across asset classes

	Commodities TSMOM	Equities TSMOM	Fixed income TSMOM	Currencies TSMOM	Diversifed TSMOM
Average excess return	11.5%	8.7%	11.7%	10.4%	19.4%
Volatility	11.0%	11.1%	11.7%	11.9%	10.8%
Sharpe ratio	1.05	0.78	1.00	0.87	1.79
Annualized alpha	12.1%	6.8%	9.0%	10.1%	17.4%
t-Statistic	(5.63)	(3.16)	(4.15)	(4.30)	(8.42)

Panel B: Performance of time series momentum across signals

	1-Month TSMOM	3-Month TSMOM	12-Month TSMOM	Diversifed TSMOM
Average excess return	12.0%	14.5%	17.2%	19.4%
Volatility	9.5%	10.2%	11.3%	10.8%
Sharpe ratio	1.26	1.43	1.52	1.79
Annualized alpha	11.1%	13.3%	14.4%	17.4%
t-Statistic	(6.04)	(6.70)	(6.74)	(8.42)

This table shows the performance of time series momentum strategies diversified within each asset class (Panel A) and across each trend horizon (Panel B). All numbers are annualized. The alpha is the intercept from a regression on the MCSI World stock index, Barclays Bond Index, and the GSCI commodities index. The *t*-statistic of the alpha is shown in parentheses.

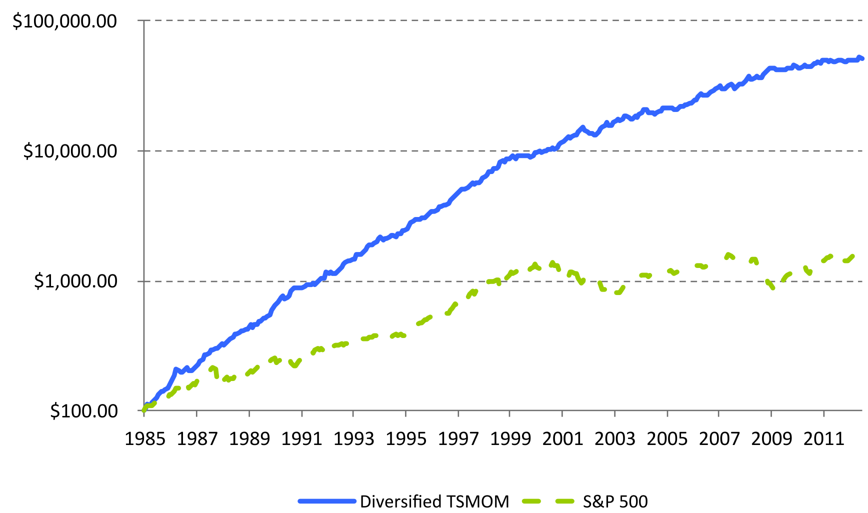


Figure 3 Performance of the diversified time series momentum strategy and the S&P500 index over time. This figure shows the cumulate return gross of transaction costs of the diversified TSMOM strategy and the S&P500 equity index on a log-scale, 1985–2012.

3.4 *Diversification*: *Trends with benefits*

To understand this strong performance of time series momentum, note first that the average pair-wise correlation of these single-asset strategies is less than 0.1 for each trend horizon, meaning that the strategies behave rather independently across markets, so one may profit when another loses. Even when the strategies are grouped by asset class or trend horizon, these relatively diversified strategies also have modest correlations as seen in Table 2. Another reason for the strong benefits of diversification is our equal-risk approach.

Table 2 Correlations of time series momentum strategies.

Panel A: Strategy correlations across asset classes

	Commodities TSMOM	Equities TSMOM	Fixed income TSMOM	Currencies TSMOM
Commodities TSMOM	1.0			
Equities TSMOM	0.2	1.0		
Fixed income TSMOM	−0.1	0.1	1.0	
Currencies TSMOM	0.1	0.2	0.1	1.0

Panel B: Strategy correlations across trend horizons

	1-Month TSMOM	3-Month TSMOM	12-Month TSMOM
1-Month TSMOM	1.0		
3-Month TSMOM	0.6	1.0	
12-Month TSMOM	0.4	0.6	1.0

This table shows the correlation of time series momentum strategies across asset classes (Panel A) and trend horizons (Panel B).

The fact that we scale our positions so that each asset has the same ex ante volatility at each time means that the higher the volatility of an asset, the smaller a position it has in the portfolio, creating a stable and risk-balanced portfolio. This is important because of the wide range of volatilities exhibited across assets. For example, a 5-year US government bond future typically exhibits a volatility of around 5% a year, while a natural gas future typically exhibits a volatility of around 50% a year. If a portfolio holds the same notional exposure to each asset in the portfolio (as some indices and managers do), the risk and returns of the portfolio will be dominated by the most volatile assets, significantly reducing the diversification benefits.

The diversified time series momentum strategy has very low correlations to traditional asset classes. Indeed, the correlation with the S&P500 stock market index is -0.02, the correlation with the bond market as represented by the Barclays US Aggregate index is 0.23, and the correlation with the S&P GSCI commodity index is 0.05. Further, the time series momentum strategy has performed especially well during periods of prolonged bear markets and in sustained bull markets as seen in Fig. 4. Figure 4 plots the quarterly returns of time series momentum against the quarterly returns of the S&P500. We estimate a quadratic function to fit the relation between time series momentum returns and market returns, giving rise to a "smile" curve. The estimated smile curve means that time series momentum has historically done the best during significant bear markets or significant bull markets, performing less well in flat markets. To understand this smile effect, note that most of the worst equity bear markets in history have not happened overnight, but gradually over time. The market first goes from "normal" to "bad", causing a TSMOM strategy to go short (while incurring a loss or profit depending on what happened previously). Often, a deep bear market happens when the market

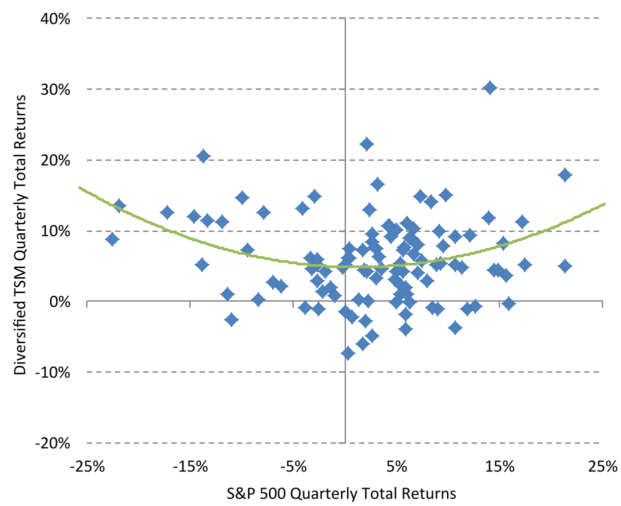


Figure 4 Time series momentum "smile." This graph plots quarterly nonoverlapping hypothetical returns of the diversified time series momentum strategy vs. the S&P500, 1985–2012.

goes from "bad" to "worse", traders panic and prices collapse. This leads to profits on the short positions, explaining why these strategies tend to be profitable during such extreme events. Of course, these strategies will not always profit during extreme events. For instance, the strategy might incur losses if, after a bull market (which would get the strategy positioned long), the market crashed quickly before the strategy could alter its positions to benefit from the crash.

4 Time series momentum explains actual managed futures fund returns

We collect the returns of two major Managed Futures indices, BTOP 50 and DJCS Managed Futures Index,[5] as well as individual fund returns from the Lipper/Tass database in the category labeled "Managed Futures." We highlight the performance of the 5 Managed Futures funds in the Lipper/Tass database that have the largest reported "Fund Assets" as of 06/2012. While looking at the returns of the ex post largest funds naturally bias us toward picking funds that did well, it is nevertheless interesting to compare

Table 3 Performance of Managed Futures indices and managers.

	BTOP50	DJCS MF	Manager A	Manager B	Manager C	Manager D	Manager E
Begin date	30-Jan-87	31-Jan-94	30-Apr-04	31-Oct-97	31-May-00	29-Mar-96	31-Dec-98
Average excess return	5.2%	3.2%	12.4%	13.3%	11.8%	12.3%	8.1%
Volatility	10.3%	11.7%	14.0%	17.7%	14.8%	17.2%	16.4%
Sharpe ratio	0.50	0.27	0.88	0.75	0.80	0.72	0.49
Annualized alpha	3.5%	1.1%	10.7%	9.3%	8.5%	9.4%	5.1%
t-Statistic of alpha	(1.69)	(0.41)	(2.15)	(2.05)	(2.05)	(2.22)	(1.17)

This table shows the performance of Managed Futures indices and the five largest Managed Futures managers in the Lipper/Tass database as of 6/2012. All numbers are annualized. The alpha is the intercept from a regression on the MCSI World stock index, Barclays Bond Index, and the GSCI commodities index. The t-statistic of the alpha is shown in parenthesis.

these most successful funds with time series momentum.

Table 3 reports the performance of the Managed Futures indices. We see that the index and manager returns have Sharpe ratios between 0.27 and 0.88. All of the alphas with respect to passive exposures to stocks/bonds/commodities are positive and most of them are statistically significant. We see that the diversified time series momentum strategy from Table 1 has a higher Sharpe ratio and alpha than the indices and managers, but we note that the time series momentum strategy returns are gross of fees and transaction costs while the managers and indices are after fees and transaction costs. Further, while the time series momentum strategy is simple and subject to minimal data mining, it does benefit from some hindsight in choosing its 1-month, 3-month, and 12-month trend horizons—managers experiencing losses in real time would have had a more difficult time sticking with these strategies through tough times than our hypothetical strategy.

Fees make a significant difference, given that most CTAs and Managed Futures hedge funds have historically charged at least 2% management fees and a 20% performance fee. While we cannot know the exact before-fee manager returns, we can simulate the hypothetical fee for the time series momentum strategy. With a 2-and-20 fee structure, the average fee is around 6% per year for the diversified TSMOM strategy.[6] We calculate this average fee using a 2-and-20 fee structure, high water marks, quarterly payments of management fees, and annual payments of performance fees. Further, transaction costs are on the order of 1–4% per year for a sophisticated manager and possibly much higher for less sophisticated managers and higher historically.[7] Hence, after these estimated fees and transaction costs, the Sharpe ratio of the diversified time series momentum strategy would historically have been near 1, still comparing well with the indices and managers, but we note that historical transaction costs are not known and associated with significant uncertainty.

Rather than comparing the performance of the time series momentum strategy with those of the indices and managers, we want to show that time series momentum can explain the strong performance of Managed Futures managers. To explain Managed Futures returns, we regress the returns of Managed Futures indices and managers (r_t^{MF}) on the returns of 1-month, 3-month, and 12-month time series momentum:

$$r_t^{MF} = \alpha + \beta^1 \mathrm{TSMOM}_t^{1M} + \beta^2 \mathrm{TSMOM}_t^{3M} + \beta^3 \mathrm{TSMOM}_t^{12M} + \varepsilon_t. \quad (4)$$

Table 4 Time series momentum explains Managed Futures returns.

Panel A: Managed Futures loadings across asset classes

	1-Month TSMOM		3-Month TSMOM		12-Month TSMOM		Intercept (annualized)		R-Sq	Correlation to diversified TSMOM
DJCS managed futures	0.26	(3.65)	0.56	(7.69)	0.23	(3.86)	−8.8%	(−4.58)	0.58	0.73
BTOP 50	0.27	(4.87)	0.53	(9.00)	0.08	(1.78)	−6.6%	(−4.24)	0.53	0.69
Manager A	0.39	(2.85)	0.59	(4.51)	0.31	(2.69)	2.8%	(0.80)	0.54	0.73
Manager B	0.66	(5.00)	0.35	(2.56)	0.47	(4.03)	−0.8%	(−0.23)	0.46	0.66
Manager C	0.55	(4.93)	0.52	(4.47)	0.25	(2.55)	0.6%	(0.19)	0.55	0.72
Manager D	0.50	(4.54)	0.80	(6.85)	0.22	(2.25)	−3.6%	(−1.19)	0.57	0.70
Manager E	0.35	(3.32)	0.70	(6.42)	0.48	(5.29)	−6.0%	(−2.09)	0.64	0.78
% Positive betas, all MF funds in Lipper/Tass DB	76%		78%		76%					

Panel B: Managed Futures loadings across trend horizons

	Commodities TSMOM		Equities TSMOM		Fixed income TSMOM		Currencies TSMOM		Intercept (annualized)		R-Sq	Correlation to diversified TSMOM
DJCS managed futures	0.28	(5.70)	0.28	(4.98)	0.47	(8.52)	0.31	(6.13)	−7.2%	(−3.56)	0.53	0.73
BTOP 50	0.30	(7.35)	0.14	(3.27)	0.34	(8.85)	0.30	(7.89)	−6.2%	(−3.71)	0.47	0.69
Manager A	0.43	(4.41)	0.38	(3.43)	0.38	(3.37)	0.26	(2.43)	5.5%	(1.46)	0.48	0.73
Manager B	0.51	(5.05)	0.31	(2.69)	0.61	(5.49)	0.23	(2.30)	1.2%	(0.32)	0.36	0.66
Manager C	0.22	(2.88)	0.33	(3.82)	0.68	(8.13)	0.49	(6.50)	1.7%	(0.60)	0.59	0.72
Manager D	0.41	(4.82)	0.51	(5.47)	0.57	(6.32)	0.37	(4.44)	−1.6%	(−0.48)	0.49	0.70
Manager E	0.49	(5.94)	0.42	(4.54)	0.65	(6.98)	0.38	(4.58)	−3.1%	(−0.99)	0.55	0.78
% Positive betas, all MF funds in Lipper/Tass DB	83%		72%		82%		73%					

This table shows the multivariate regression of Managed Futures indices and managers on time series momentum returns by asset class (Panel A) and by trend horizon (Panel B). t-Statistics are reported in parenthesis. Managers 1–5 are the largest managed futures managers in the Lipper/Tass database as of 12/2012. The bottom row reports the percentage of all funds in the Lipper/Tass database with positive coefficients. The right-most column reports the correlation between the Managed Futures returns and the diversified TSMOM strategy.

Similarly, we regress the returns of Managed Futures indices and managers on the returns of TSMOM strategies in commodities (TSMOM_t^{COM}), equities (TSMOM_t^{EQ}), fixed income (TSMOM_t^{FI}), and currencies (TSMOM_t^{FX}):

$$r_t^{MF} = \alpha + \beta^1 \text{TSMOM}_t^{COM} + \beta^2 \text{TSMOM}_t^{EQ} + \beta^3 \text{TSMOM}_t^{FI} + \beta^4 \text{TSMOM}_t^{FX} + \varepsilon_t. \tag{5}$$

Table 4 reports the results of these regressions. We see the time series momentum strategies explain the Managed Futures Index and manager returns to a large extent in the sense that the R-squares of these regressions are large, ranging between 0.36 and 0.64. Table 4 also reports the correlation of the Managed Futures indices and managers with the diversified TSMOM strategy. These correlations are also large, ranging from 0.66 to 0.78, which provides another indication that time series momentum can explain the Managed Futures universe.

The intercepts reported in Table 4 indicate the excess returns (or alphas) after controlling for time series momentum. While the alphas relative to the traditional asset classes in Table 3 were significantly positive, almost all the alphas relative to time series momentum in Table 4 are negative. Even though the returns of the largest managers are biased be to be high (due to the ex post selection of the managers), time series momentum nevertheless drives these alphas to be negative. This is another expression that time series momentum can explain the Managed Futures space and an illustration of the importance of fees and transaction costs.

Another interesting finding that arises from Table 4 is the relative importance of short-, medium-, and long-term trends for Managed Futures funds, as well as the relative importance of the different asset classes. We see that all the indices and managers have positive loadings on all the trend horizons and all the asset classes, and almost all the loadings are statistically significant. Focusing on the DJCS Managed Futures index, Fig. 5 illustrates the relative loadings on the different trend horizons and the different asset classes. As seen in Table 4 and Fig. 5, the majority of

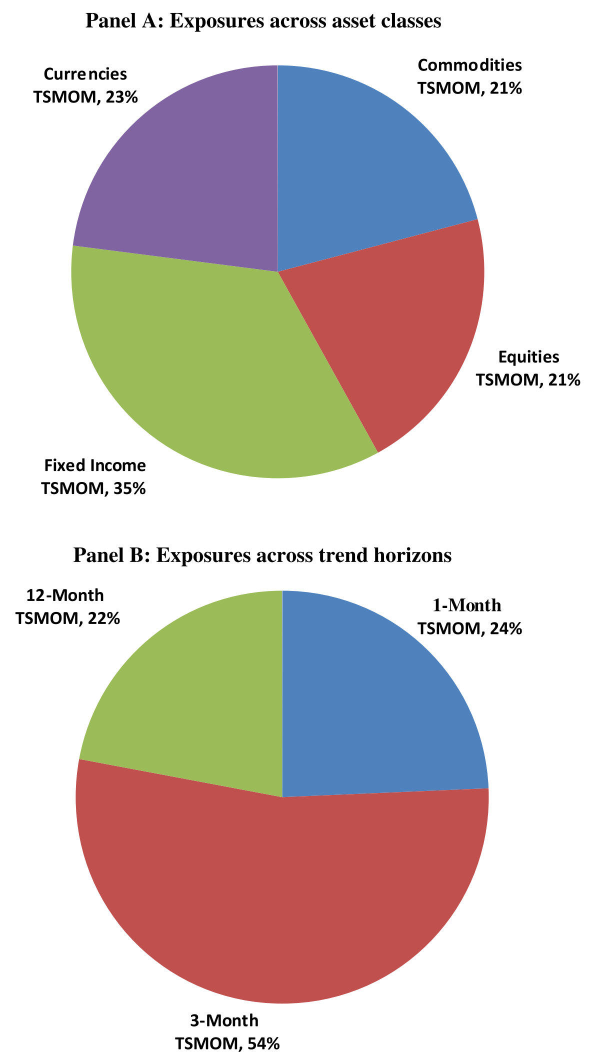


Figure 5 Managed futures exposures across asset classes and trend horizons. This figure shows the regression coefficients from a regression of the DJCS Managed Futures Index on the time series momentum strategies by asset class (Panel A) and by trend horizon. The regression coefficients are scaled by their sum to show their relative importance.

managers appear to put most weight on medium-term trends and, in terms of asset classes, most weight on fixed income, perhaps because of the liquidity of these markets and the strong performance of fixed income trend following in the past decades.

In summary, while many Managed Futures funds pursue many other types of strategies besides time series momentum, such as carry strategies and global macro strategies, our results show that time series momentum explains the average alpha in the industry and a significant fraction of the time variation of returns.

5 Implementation: How to manage managed futures

We have seen that time series momentum can explain Managed Futures returns. In fact, this relatively simple strategy has realized a higher Sharpe ratio than most managers, at least on paper. This suggests that fees and other implementation issues are important for the real-world success of these strategies. Indeed, as mentioned in Sec. 4, we estimate that a 2-and-20 fee structure implies a 6% average annual fee on the diversified time series momentum strategy run at a 10% annualized volatility. Other important implementation issues include transaction costs, rebalance methodology, margin requirements, and risk management.

To analyze the effect of how often the portfolio is rebalanced, Fig. 6 shows the gross Sharpe ratio for each trend horizon and the diversified time series momentum strategy as a function of rebalancing frequency. Daily and weekly rebalancing perform similarly, while the performance trails off with monthly and quarterly rebalancing frequencies. Naturally, the performance falls more quickly for the short- and medium-term strategies as these signals change more quickly, leading to a larger alpha decay.

As mentioned, the annual transaction costs of a Managed Futures strategy are typically about 1–4% for a sophisticated trader, possibly much higher for less sophisticated traders, and higher historically given higher transactions costs in the past. Transaction costs depend on a number of things. Transaction costs increase with rebalance frequency if the portfolio is mechanically

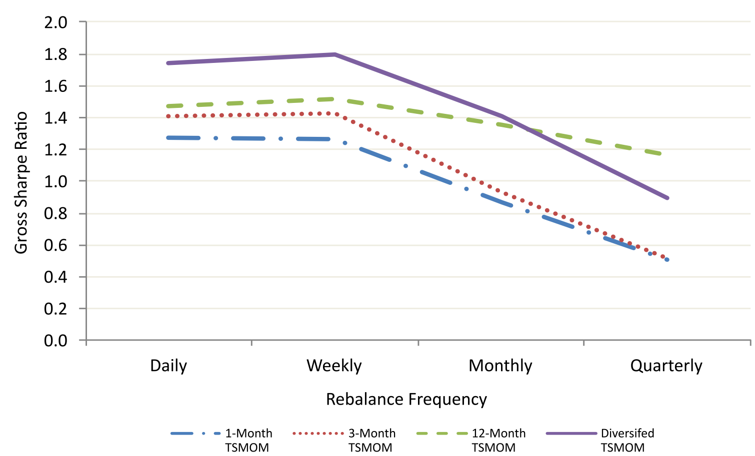


Figure 6 Gross Sharpe ratios at different rebalance frequencies. This figure shows the Sharpe ratios gross of transaction costs of the 1-month, 3-month, 12-month, and diversified time series momentum strategies as a function of the rebalancing frequency.

rebalanced without transaction cost optimization, although more frequent access to the market can also be used to source more liquidity. Garleanu and Pedersen (2013) derive an optimal portfolio-rebalancing rule for many assets with several returns predictors (such as trend signals) and transaction costs. They find that transaction cost optimization leads to a larger optimal weight on signals with slower alpha decay, that is, longer-term trends. Hence, larger managers may allocate a larger weight to medium- and long-term trend signals and relatively lower weight to short-term signals. Transaction costs rise with the weight given to more illiquid assets, and rise with the size of the fund for a given trading infrastructure, although large funds should have the ability to develop better trading infrastructure and negotiate lower commissions. Transaction costs are lower for managers who have more direct market access (saving on commissions and indirect broker costs) with advanced trading algorithms that can partly provide liquidity and have minimal information leakage.

To implement managed futures strategies, managers must post margin to counterparties, namely the Futures Commission Merchant and the currency intermediation agent (or currency prime broker). The time series momentum strategy would typically have margin requirements of 8–12% for a large institutional investor, and more than double that for a smaller investor. Hence, time series momentum is certainly implementable from a funding liquidity standpoint as it has a significant amount of free cash.

Risk management is the final implementation issue that we discuss. Our construction of trading strategies is systematic and already has built-in risk controls due to our constant volatility methodology. This methodology is important for several reasons. First, it controls the risk of each security by scaling down the position when risk spikes up. Second, it achieves a risk-balanced diversification across markets at all times. Third, our systematic implementation means that our strategies are not subject to behavioral biases. Moreover, our methodology can be overlaid with an additional layer of risk management and drawdown control and some Managed Futures managers further seek to identify over-extended trends to limit the losses from sharp trend-reversals, and try to identify short-term countertrends to improve performance in range-bound markets.

6 Conclusion

We find that 1-month, 3-month, and 12-month time series momentum strategies have performed well over time and across asset classes. Combining these into a diversified time series momentum strategy produces a gross Sharpe ratio of 1.8, performing well both in extended bear and bull markets. Time series momentum can explain Managed Futures indices and manager returns, even for the ex post largest and most successful funds, demystifying the strategy. Indeed, time series momentum has a high correlation to Managed Futures returns, large R-squares, and explains the average returns (that is, leaves only a small unexplained intercept or alpha in a regression). Thus investors can get exposure to Managed Futures using time series momentum strategies, and should pay attention to implementation issues such as fees, trading infrastructure, and risk management procedures used by different managers.

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Notes

1 Elton *et al.* (1987).

2 Our methodology follows Moskowitz *et al.* (2012), but to more closely match practices among Managed Futures managers, we focus on weekly rebalanced returns using multiple trend horizons rather than the monthly-rebalanced strategy using only 12-month trends in Moskowitz *et al.* (2012). Section 5 considers the effect of rebalancing frequencies. Baltas and Kosowski (2013) consider the relation to CTA indices and perform an extensive capacity analysis. Time series momentum is related to cross-sectional momentum discovered in individual stocks by Asness (1994) and Jegadeesh, and Titman (1993), and studied for a wide set of asset classes by Asness *et al.* (2013) and references therein.

3 Such long-run reversal is also found in the cross section of equities (De Bondt and Thaler, 1985) and the cross section of global asset classes (Asness *et al.*, 2013).

4 Our position sizes are chosen to target a constant volatility for each instrument, but, more generally, one could consider strategies that vary the size of the position based on the strength of the estimated trend. Example, for intermediate price moves, one could take a small position or no position and increase the position depending on the magnitude of the price move. However, the goal of our paper is not to determine the optimal trend-following strategy, but to show that even a simple approach performs well and can explain the returns in the CTA industry.

5 These index returns are available at the following websites: http://www.barclayhedge.com/research/indices/btop/index.html http://www.hedgeindex.com/hedgeindex/secure/en/indexperformance.aspx?cy=USD&indexname=HEDG_MGFUT.

6 The average fee is high due to the high Sharpe ratio realized by the simulated TSMOM strategy. In practice, Managed Futures indices have realized lower Sharpe ratios.

7 This estimate of transaction costs is based on proprietary estimates of current transaction costs in global futures and forward markets combined with the turnover of these strategies for a manager with about USD1 Billion under management. These estimates do not account for the fact that transaction costs were higher in earlier years when markets were less liquid and trading was not conducted via electronic markets.

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