Asymmetry, tail risk and time series momentum

Asymmetry, Tail Risk and Time Series Momentum*,**

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Abstract

In this paper, we investigate how to improve the time series momentum strategy by using partial moments. We find that reversals of time series momentum can be partly predicted by tail-distributed upper and lower partial moments derived from daily returns of commodity futures. Based on such information, we propose rule-based approaches to improve the trading signals suggested by the time series momentum strategy. The empirical results based on Chinese commodity futures document statistically significant improvements of the Sharpe ratio in the out-of-sample period. These improvements are robust to different look-back windows.

Keywords: Commodity futures, Time series momentum, Momentum reversal, Partial moments

JEL: G13, G17

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1. Introduction

As a systematised strategy, time series momentum is supported by nearly a quarter century of positive academic evidence and a century of successful empirical results (Asness et al., 2013). Since the seminal work of Moskowitz et al. (2012), literature on time series momentum has focused on its presence across asset classes (Baltas & Kosowski, 2013; Georgopoulou & Wang, 2016), on its performance in developed and emerging markets (Georgopoulou & Wang, 2016), on its relation with volatility states (Pettersson, 2014) and volatility scaling approach (Kim et al., 2016; Fan et al., 2018), and on its implementation by traders (Hurst et al., 2013; Baltas & Kosowski, 2015; Levine & Pedersen, 2016). In the assets management industry, particularly for hedge fund managers, time series momentum (TSM hereafter) has already been implemented as their primary investment strategy.

Managed futures, also known as Commodity Trading Advisors (CTA hereafter), is one of the crucial investment classes in the asset management industry. Using BarclayHedge estimates at the end of 2014, managed futures funds manage a total of USD318 billion of assets, which is about 11% of the USD2.8 trillion hedge fund industry (Georgopoulou & Wang, 2016). These funds typically trade futures contracts in various asset classes (equity indices, commodities, government bonds, and foreign exchange rates) and earn profit from asset price trends by implementing the TSM strategy (Baltas & Kosowski, 2015).

However, CTA managers have also suffered significantly from severe drawdowns under the TSM strategy. The TSM strategy is prone to deep and persistent drawdowns similar to cross-sectional momentum crashes. Figure 1 depicts the cumulative gains made by a TSM strategy with a look-back window of 30 days compared to a buy and hold (BAH hereafter) investment strategy, both based on an equally weighted index constructed from the daily return series of 31 commodity futures contracts that traded on the Chinese futures markets from January 2008 to

December 2019.[1] It shows that one would have earned nearly CNY6.00 if investing CNY1.00 on the equally weighted index by following the TSM strategy since 2008. By comparing the two lines shown on the graph, we find that TSM strategy losses occur during the price dynamics of slumps in the uptrend (e.g., 2008, 2009, 2010, 2016), rebounds in the downtrend (e.g., 2008, 2013, 2015), and during sideways markets (e.g., 2017, 2019).

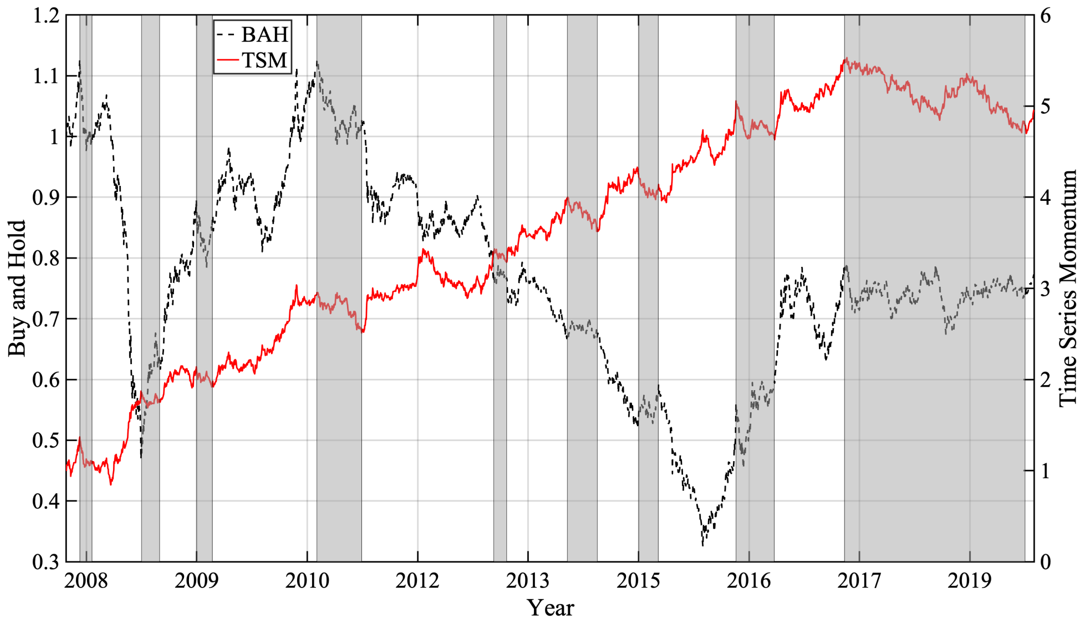

Figure 1: Cumulative gains of the time series momentum investment on the equally weighted index of 31 futures contracts on the Chinese commodity futures markets from January 2008 to December 2019. *BAH* is the equity curve of the simple buy-and-hold investing strategy (black dash line, left axis), and *TSM* is the equity curve of the time series momentum investment with a look-back window of 30 trading days and one day holding period (red solid line, right axis).

Recent studies on time series momentum have begun to explore the under-performance of CTA in the assets management industry. Baltas & Kosowski (2013) considered that recent poor performance of CTA is possibly caused by the TSM strategy capacity constraint. However, their final results demonstrated that there is no significant capacity constraint on the time series momentum. Moreover, Georgopoulou & Wang (2016) investigated the correlation across all equity and

[1]We use the equity curve of BAH investment as a proxy to compare the underlying price trajectory of futures contracts with dynamics of TSM investment. Since time series momentum focus on individual asset, we employ the equally weighted index here as an example to avoid asset picking issue.

commodity indices with respect to the pre-quantitative easing (pre-QE), at-QE, and post-QE periods. They suggested that market interventions by central banks in recent years have challenged the performance of the TSM portfolio. Huang et al. (2020) provided evidence for doubt regarding the predictability of time series returns on a monthly basis that was advocated by Moskowitz et al. (2012) and suggested future work on testing alternative time horizons and developing new predictable patterns in time series returns.

Our study is based on the linkages between time series momentum and partial moments. As we discussed earlier, TSM strategy suffers poor performance during episodes of time series momentum reversals, including slumps in an uptrend market, rebounds in a downtrend market, and sideways markets. For a given look-back window, the time series momentum signal is determined by the sign of past cumulative returns. However, the sample mean lacks predictability regarding whether future returns will be positive or negative (Huang et al., 2020). Building on this finding, our primary argument is that predictability of return is weak particularly during episodes of time series momentum reversals, since an unknown number of new observations is needed to update the previous sample. Therefore, we move to explore possible patterns from higher moment that can predict time series momentum reversals.[2] The reversals that cause persistent and deep TSM strategy drawdowns are characterised by consecutive and significant negative (or positive) underlying asset returns in an uptrend (or downtrend) market. Intuitively, we use partial moments, a second-moment measure that weighs positive and negative returns separately, to capture underlying predictable patterns to time series momentum reversals.[3] We find that the asymmetric structure of the tail-distributed upper and lower partial moments can partly predict the reversals. As a result, we propose a nonlinear decision function which enables TSM traders to significantly mitigate losses during periods of reversals. This systematic approach can be seen as a refined version of the TSM strategy, and we refer to it as the managed time series momentum (MTSM) strategy.

[2] Johnson (2002) demonstrated that foreign exchange returns exhibit the consistent property that volatility increases when trends continue and decreases when they reverse.

[3] Partial moments have been proved useful to complement the complete moments whenever only a subset of values of a random variable is of interest (see Winkler et al., 1972; Price et al., 1982).

There is increasing attention being paid to the Chinese commodity futures markets by both academia and practitioners (Yang et al., 2018; Jin et al., 2020). In this paper, we conduct empirical analysis of our proposed MTSM strategy based on 31 futures contracts traded on Chinese commodity futures markets covering metals, energy products, industrial materials, and agriculture products. The 2017 annual summary[4] published by the World Federation of Exchanges (WFE) reported that the three of the Chinese commodity futures exchanges, Shanghai Futures Exchange (SHFE), Dalian Commodity Exchange (DCE), and Zhengzhou Commodity Exchange (ZCE), added together were first in the world in terms of total trading volume. Apart from the large size of the market, we also emphasise the fundamental change in market quality that resulted from the 2013 implementation of night trading (Fan & Zhang, 2020; Jiang et al., 2020). Therefore, we present and check the robustness of our empirical results in two subperiods 2008–2012 and 2013–2019. We also complement our robustness analysis by including the COVID-19 crash period.

Our contribution to the literature is threefold. First, we monitor the concurrent dynamics of both upside and downside risks of TSM losses. We do so by calculating upper and lower partial moments using returns from the last five trading days. Previous studies have discussed the role of risk measurement in terms of the lower partial moment in the field of portfolio optimisation (Bawa & Lindenberg, 1977; Harlow & Rao, 1989; Anthonisz, 2012). In particular, Gao et al. (2017, 2018) documented better performance of the cross-sectional momentum strategy than Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) by remodelling the cross-sectional momentum portfolio risk using upper and lower partial moments, named as partial moment momentum (PMM).[5] Their supportive evidence indicates that partial moments can provide more useful information about measuring the latent risk of the cross-sectional momentum portfolio. We extend

[4]For more information, we refer to the official website of the World Federation of Exchanges: `https://www.world-exchanges.org` (accessed on August 24, 2021).

[5]Regarding the cross-sectional momentum crash, a popular explanation is the time-varying risk (Grundy & Martin, 2001; Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016). From the fact that the very high excess kurtosis of the cross-sectional momentum strategy is more than twice the market portfolio, Barroso & Santa-Clara (2015) explored an estimator of the cross-sectional momentum risk to scale the exposure to the cross-sectional momentum strategy in order to maintain constant risk over time. Guo et al. (2020) evaluated a large number of competing explanations for the cross-sectional momentum anomaly and concluded that all explanations capture 31% of momentum, while 69% of momentum remains unexplained.

the research along this line to explore the role that upper and lower partial moments can play in managing the latent risk of time series momentum strategy.

Second, we analyse the underlying linkage between partial moments and momentum reversals under different scenarios of time series momentum. Daniel & Moskowitz (2016) showed the evidence that the cross-sectional momentum crash is partly predictable since it often occurs under some panic market states, especially for rebounds in a bear market when market volatility is high. Following this idea, we examine the effect of ex-ante upper and lower partial moments on future asset returns under different time series momentum states, namely upward momentum, downward momentum, and momentum reversal. We find that upper and lower partial moments have a more substantial lead–lag effect on future returns under the state of momentum reversals, which fills the gap in examining the return predictability of time series momentum conditional on different states.

Third, we find predictable patterns to time series momentum reversals using information extracted from upper and lower partial moments, which complements the extensive work done on examining return predictability in the sense of time series momentum. The original TSM strategy gives long/short signals simply according to the sign of individual asset cumulative returns over a certain look-back window. However, assuming that asset price follows a continuous-time diffusion process with the stochastic trend, recent studies of the optimal control problem suggest more complicated buy and sell decisions if the goal is maximisation of expected future wealth (see more details in Dayanik & Karatzas, 2003; Di Guilmi et al., 2014; He & Li, 2015; He et al., 2018; Li & Liu, 2019). In our proposed MTSM strategy, we design a set of rule-based actions to adjust the original TSM long/short signals in different scenarios.

The rest of this paper is organised as follows. In Section 2, we describe the dataset of the Chinese commodity futures markets on which our empirical study focused. Section 3 models the effects of conditional upper and lower partial moments on future returns under different time series momentum states and assesses to what extent momentum reversals are predictable. In Section 4, we present how the managed time series momentum portfolio is constructed in different scenarios and evaluate the performance of this rule-based approach in mitigating time series momentum losses. Section 5 concludes our study.

2. Data

Our data sample contains the daily returns of the main contracts of 31 commodity futures on the Chinese commodity futures markets from January 2007 to December 2019.[6] We collect our dataset from the WIND database.[7] All prices are close prices and all returns are daily close-to-close returns. The daily series of the risk-free rate that is used to calculate Sharpe ratio and Sortino ratio is from the CSMAR database.[8] To ensure our empirical results can be tracked and implemented in the assets management industry, we include commodity contracts which have good liquidity in the dataset.[9] The starting dates of each commodity contract in our data sample are reported in Table 1, with the annualised mean, annualised volatility, skewness, and kurtosis.

In the last three decades, the Chinese futures market has experienced significant development. The Chinese government restructured several small commodity futures exchanges in 1998, thereby laying the three-legged pattern of the existing commodity futures exchanges: SHFE, DCE, and ZCE. Due to historical events, all metal contracts including the precious metals (gold and silver) are traded in SHFE. Some of the agricultural and industrial contracts are traded in ZCE. Most of the industrial and energy contracts and other agricultural contracts are traded in DCE. Additionally, the China Financial Futures Exchange (CFFEX) was established in 2006 for the contracts of stock index futures, stock index options, and treasury bond futures.

[6]In Chinese futures markets, the main contract is defined as the contract which has the biggest open interest for a specific future security.

[7]Fore more information about the data source, please visit `https://www.wind.com.cn/en/edb.html`.

[8]We include the risk-free rate in the calculation of Sharpe ratio and Sortino ratio since it is not negligible in China which has relatively high level interest rate than other countries during certain historical periods, even though the empirical analysis is based on daily rebalanced strategies in this study. We can have larger Sharpe ratio and Sortino ratio if setting the daily risk-free rate as zero. Please see more details of the China Stock Market & Accounting Research (CSMAR) Database via `http://us.gtadata.com`.

[9]We exclude the commodity contract which does not meet the minimum requirement of 10,000 open interest on average.

Table 1: Summary statistics.

Exchange	Name	Code	Sector	Data Start Date	Annualized Mean(%)	Annualized Volatility(%)	Skewness	Kurtosis
SHFE	Gold	AU	MET	Jan-08	0.71	17.70	-0.36	7.77
	Silver	AG	MET	May-12	-12.10	21.11	-0.27	8.50
	Copper	CU	MET	Jan-07	0.17	24.19	-0.20	5.32
	Aluminum	AL	MET	Jan-07	-5.73	15.83	-0.29	7.90
	Nickel	NI	MET	Mar-15	-5.10	25.16	-0.13	4.09
	Zinc	ZN	MET	Mar-07	-4.40	24.93	-0.30	4.73
	Rebar	RB	ENG	Mar-09	-2.60	22.20	-0.04	7.29
	Hot Rolled Coil	HC	ENG	Mar-14	7.92	26.40	-0.16	6.01
	Bitumen	BU	IND	Oct-13	-18.22	26.04	-0.45	5.37
	Natural Rubber	RU	IND	Jan-07	-12.95	30.34	-0.21	4.08
ZCE	Cotton	CF	AGI	Jan-07	-1.58	17.53	0.00	8.10
	Sugar	SR	AGI	Jan-07	-1.47	17.21	-0.04	5.94
	Rapeseed Meal	RM	AGI	Dec-12	6.75	20.87	-0.05	4.58
	Rapeseed Oil	OI	AGI	Mar-13	-10.14	14.75	-0.21	5.79
	PTA	TA	IND	Jan-07	-2.89	20.63	-0.14	5.51
	Methyl Alcohol	MA	IND	Jun-14	-1.84	24.31	-0.04	4.06
	Flat Glass	FG	IND	Dec-12	6.31	20.60	0.08	5.06
	Thermal Coal	ZC	IND	May-15	16.62	22.65	-0.05	4.31
DCE	Polypropylene	PP	IND	Feb-14	6.24	21.38	0.08	4.42
	PVC	V	IND	May-09	-3.49	17.45	-0.02	5.86
	LLDPE	L	IND	Jul-07	-1.04	22.56	-0.21	5.01
	Coke	J	ENG	Apr-11	0.27	28.03	-0.13	6.38
	Coking Coal	JM	ENG	Mar-13	2.34	30.09	-0.11	5.91
	Iron Ore	I	ENG	Oct-13	-2.83	33.14	-0.03	4.33
	Corn	C	AGI	Jan-07	-0.43	10.98	-0.07	9.14
	Corn Starch	CS	AGI	Dec-14	1.97	15.93	0.09	5.09
	Soybean 1	A	AGI	Jan-07	1.26	17.72	-0.21	7.08
	Soybean Meal	M	AGI	Jan-07	8.21	20.95	-0.11	4.99
	Soybean Oil	Y	AGI	Jan-07	-4.14	19.90	-0.33	5.69
	Palm Oil	P	AGI	Oct-07	-9.60	22.04	-0.29	4.83
	Egg	JD	AGI	Nov-13	-1.22	19.25	-0.01	5.60

Note: *MET*, *ENG*, *IND*, and *AGI* stand for the market sector of metals, energy products, industrial materials, and agriculture products, respectively.

According to WFE, the Chinese commodity futures markets have the largest trading volume across the world (Yang et al., 2018; Ham et al., 2019). At the end of 2017, SHFE ranked first in the world, with the biggest trading volume among commodity futures exchanges. Meanwhile, DCE and ZCE took third and fourth place, respectively. Previous literature documented the emerging dependence structure between the rapidly growing Chinese commodity industry and the global commodity market (Fung et al., 2013; Li & Hayes, 2017; Jin et al., 2018). Yang et al. (2018) examined the significant cross-sectional momentum and reversal effect on the Chinese commodity futures markets. Based on ten commodity futures on the Chinese markets, Ham et al. (2019) constructed a monthly re-balancing strategy and compared the performance of time-series momentum with cross-sectional momentum.

Moreover, we highlight the importance of the introduction of the night-trading rule as a significant event in the development of the Chinese futures markets. The night-trading policy is one of a series of reformations of the Chinese futures markets undertaken by the China Securities Regulatory Commission (CSRC), aiming to stabilise price shocks from the international market. Since 2013, an increasing number of contracts have been allowed to be traded not only during the business day, but also after hours. As documented in the literature, the night-trading policy led to a fundamental change in the market microstructure and reshaped trading behaviour (Cai et al., 2020; Jiang et al., 2020; Fan & Todorova, 2021). Therefore, we check the robustness of our results on subsamples before 2013 and after 2013.

3. Time series momentum and partial moments

In this section, we review the time series momentum strategy on the Chinese commodity futures markets from January 2008 to December 2019. We suggest that the TSM strategy losses are caused by the wrong trading signals generated from the sign of past cumulative returns. The TSM strategy generates profits by pursuing price momentum. However, failing to avoid momentum reversals can also generate losses. We further explore the underlying link between the tail risks measured by partial moments and the time series momentum reversals. We find that the asymmetric structures of the upper and the lower partial moments can capture future momentum reversals.

3.1. Time series momentum

In accordance with Moskowitz et al. (2012), we construct the one-period-holding time series momentum portfolio based on recent J days' cumulative return of each contract (look-back window: J days). Let $\{r_{i,d_t}\}_{t=1}^{T}$ be the daily returns of asset i and $\{d_t\}_{t=1}^{T}$ be the dates of trading days. The portfolio return that diversifies across all N_t futures contracts available at time t is:

$$r_{p,d_{t+1}}^{tsm} = \frac{1}{N_t}\sum_{i=1}^{N_t} \operatorname{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right)\frac{\sigma_{target}}{\sigma_{i,d_t}} r_{i,d_{t+1}}. \tag{1}$$

We set the annualised target volatility σ_{target} as 40% to scale the ex-ante volatility estimator, σ_{i,d_t}, which is an exponentially weighted moving standard deviation with J-days span on r_{i,d_t}.

As discussed in Section 2, we divide the whole sample into two subperiods, 2008–2012 and 2013–2019. Table 2 reports the performance of the one-day-holding TSM strategy with various look-back windows (J = 20, 30, 40, 60, 90, 120, 250 trading days) during the whole sample in Panel A, the first subsample from January 2008 to December 2012 in Panel B, and the second subsample from January 2013 to December 2019 in Panel C.[10] Statistics evaluating the performance of the strategies include the annual return, Sharpe ratio, maximum drawdown, Sortino ratio, Calmar ratio, percentage of wins, and average profit over average loss. In addition, skewness, kurtosis, and t-statistics of normality test are also tabulated according to different look-back windows.

We observe two stylised facts from Table 2. First, both subsamples witness economically and statistically significant profitability for TSM trading strategies with various look-back windows (J = 20, 30, 40 days). Among the wide range of look-back windows that we examined, the time series momentum pattern over 20 days turns out to be the most robust and most profitable. The strategy yields more than 37% (t-statistic = 3.60) and 16% (t-statistic = 3.04) per year on average from 2008 to 2012 and from 2013 to 2019, respectively.

Moreover, this profitable pattern disappears when expanding the look-back window to longer than 40 trading days in the first subsample (e.g., there is an insignificant annual return of 15.60% (t-statistic = 1.73) using a look-back window of 60 days). However, the result becomes economically and statistically significant, 11.96% (t-statistic = 2.26), during the second subsample. In Panel C of Table 2, similar changes are also presented in cases of look-back windows that are longer than 60 trading days. These changes indicate that the persistence of the time series momentum effect is strengthened during the period from 2013 to 2019.

[10]We are aware of certain contracts are not included in the first subsample. We try to include as much data as possible in this study. In the construction of commodities portfolio, we start adding each commodity into the assets pool only after the data start date tabulated in Table 1.

Table 2: Strategy performance of the time series momentum investment.

	look-back Window (days)						
	20	30	40	60	90	120	250
Panel A: The whole sample from January 2008 to December 2019							
Annual Return (%)	25.16	20.25	20.95	13.48	12.06	12.50	10.77
Sharpe Ratio	1.29	1.05	1.08	0.72	0.67	0.69	0.61
MDD (%)	26.02	28.71	27.24	29.07	28.85	28.32	41.28
Sortino Ratio	2.01	1.58	1.63	1.07	0.99	0.99	0.85
Calmar Ratio	0.97	0.71	0.77	0.46	0.42	0.44	0.26
% of Win	52.62	52.07	52.48	52.14	50.98	52.65	52.99
AP-to-AL	1.16	1.13	1.12	1.06	1.10	1.03	1.01
Skewness	0.60	0.44	0.54	0.40	0.25	0.10	0.16
Kurtosis	8.29	7.80	8.79	8.16	7.32	6.48	7.60
t-statistics	4.70	3.87	3.98	2.76	2.59	2.65	2.38
Panel B: The first subsample from January 2008 to December 2012							
Annual Return (%)	37.28	26.29	29.99	15.60	14.93	12.36	5.56
Sharpe Ratio	1.55	1.10	1.26	0.69	0.69	0.57	0.27
MDD (%)	26.02	28.71	21.76	29.07	28.85	28.32	41.28
Sortino Ratio	2.40	1.65	1.87	1.02	1.05	0.84	0.38
Calmar Ratio	1.43	0.92	1.38	0.54	0.52	0.44	0.13
% of Win	52.91	53.16	54.31	52.34	51.93	52.42	53.31
AP-to-AL	1.20	1.09	1.07	1.05	1.06	1.02	0.93
Skewness	0.46	0.32	0.37	0.43	0.30	0.05	0.12
Kurtosis	6.38	6.15	6.57	7.19	6.36	5.64	5.98
t-statistics	3.60	2.61	2.96	1.73	1.73	1.47	0.80
Panel C: The second subsample from January 2013 to December 2019							
Annual Return (%)	16.48	15.93	14.48	11.96	10.01	12.61	14.48
Sharpe Ratio	1.08	1.04	0.94	0.78	0.66	0.82	0.94
MDD (%)	15.87	18.73	27.24	16.83	18.70	18.29	28.92
Sortino Ratio	1.76	1.68	1.53	1.21	1.00	1.21	1.37
Calmar Ratio	1.04	0.85	0.53	0.71	0.54	0.69	0.50
% of Win	52.41	51.29	51.18	52.00	50.29	52.82	52.76
AP-to-AL	1.12	1.16	1.14	1.07	1.13	1.05	1.08
Skewness	0.66	0.57	0.75	0.24	0.07	0.20	0.23
Kurtosis	8.99	8.01	10.77	6.82	6.79	6.23	9.30
t-statistics	3.04	2.96	2.68	2.26	1.97	2.38	2.70

Notes: *MDD* is short for the maximum drawdown, and *AP-to-AL* stands for the ratio of average profit over average loss. The Sharpe ratio tabulated is the annualized value by setting 250 trading days within a year in the calculation.

3.2. Partial moments

Partial moments were first proposed in Winkler et al. (1972) to refine complete moments when only a subset of the set of values of a random variable is of interest. A measure of the downside risk is computed as the average of the squared deviations below a target return, namely lower partial moment. This measurement is more general than semivariance, which is computed as the average of the squared deviations below the mean return.

For day d_t, we compute the upper partial moment (UPM_{i,d_t}) and lower partial moment (LPM_{i,d_t}) for asset i using daily returns in the previous n days. Then,

$$\mathrm{UPM}_{i,d_t} = \frac{1}{n}\sum_{j=0}^{n-1} r_{i,d_{t-j}}^2 I(r_{i,d_{t-j}} > 0), \tag{2}$$

and

$$\mathrm{LPM}_{i,d_t} = \frac{1}{n}\sum_{j=0}^{n-1} r_{i,d_{t-j}}^2 I(r_{i,d_{t-j}} < 0), \tag{3}$$

where $I(\cdot)$ is the indicator function. These two measurements are the specific version of partial moments with truncation at zero. Unlike long-only portfolios, for which we are concerned only with downside risk, we later use UPM to measure the upside risk for a short position and use LPM to measure the downside risk for a long position in the time series momentum portfolio.

More specifically, we suggest using the UPM and LPM over the last five trading days (weekly horizon) to capture time series momentum losses during momentum reversals. The horizon of five trading days comes from a one-week window on a calendar day, and individual investors with short investment horizons are a feature of the Chinese commodity futures markets (Fan & Zhang, 2020). Empirical evidence shows that upper and lower partial moments can capture the time series momentum reversals, thus reducing false long or short exposure in the TSM strategy. We provide further details in the following subsection.

3.3. Momentum states and partial moments

Supporting evidence for the relevance of higher-moment effects on time series momentum was given by Johnson (2002), who explored the connection between realised trends and changes in volatility and concluded that finite-horizon skewness behaves like a lagged momentum indicator. Moreover, Müller et al. (1997) provided direct evidence of the relationship between long-term returns (trends) and short-term volatility, estimating a volatility specification, dubbed HARCH. Their heterogeneous market hypothesis states that volatilities measured with different time resolutions reflect the perceptions and actions of different market components. In this subsection, we show that future commodity returns are highly correlated with ex-ante risk measures of UPM and LPM over the weekly horizon, particularly during the periods of time series momentum reversals.

We then illustrate in detail with a set of regressions on univariate daily return series of 31 commodity futures contracts. The dependent variable in all regressions is $\widetilde{r}_{i,d_{t+1}}$, the individual commodity return on day d_{t+1}. The independent variables are the combinations of:

- UPM_{i,d_t}, the ex-ante upper partial moment on day d_t;
- LPM_{i,d_t}, the ex-ante lower partial moment on day d_t;
- I_U, an ex-ante upward momentum indicator that equals one if the cumulative return of recent 30 trading days on day d_t is positive (that is, a long signal is derived from time series momentum for d_{t+1}) and is zero otherwise;
- I_D, an ex-ante downward momentum indicator that equals one if the cumulative return of recent 30 trading days on day d_t is negative (that is, a short signal is derived from time series momentum for d_{t+1}) and is zero otherwise;
- $\widetilde{I}_F$, a contemporaneous, i.e., not ex-ante, falling day indicator variable that is one if the asset return is less than zero ($r_{i,d_{t+1}} < 0$) and is zero otherwise;
- $\widetilde{I}_R$, a contemporaneous, i.e., not ex-ante, rising day indicator variable that is one if the asset return is greater than zero ($r_{i,d_{t+1}} > 0$) and is zero otherwise.

We take the look-back window $J = 30$ trading days in the time series momentum formula of Eq. (1) as an example. The ultimate results are consistent for various look-back windows. In Tables 3 and 4, we report regression results of Eq. (4) on different subsamples.

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} = \alpha &+ [(\beta^+_U I_U + \beta^+_{U,F} I_U \cdot \widetilde{I}_F) + (\beta^+_D I_D + \beta^+_{D,R} I_D \cdot \widetilde{I}_R)]\mathrm{UPM}_{i,d_t} \\ &+ [(\beta^-_U I_U + \beta^-_{U,F} I_U \cdot \widetilde{I}_F) + (\beta^-_D I_D + \beta^-_{D,R} I_D \cdot \widetilde{I}_R)]\mathrm{LPM}_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}}.\end{aligned} \tag{4}$$

Our model specification is similar to the one used by Daniel & Moskowitz (2016) to assess market timing results of cross-sectional WML (Winner-minus-Loser) portfolios. The estimated coefficients for each contract are tabulated and classified into four market sectors of metals (MET), energy products (ENG), industrial materials (IND), and agriculture products (AGI). These results allow us to assess the extent to which the UPM and LPM under upward and downward momentum states can capture future momentum reversals with the interaction terms, $I_U \cdot \widetilde{I}_F$ and $I_D \cdot \widetilde{I}_R$. The regression of Eq. (4) is considered as a simultaneous version of following two regressions which consider the states of upward momentum in Eq. (5) and downward momentum in Eq. (6) separately:

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} = \alpha &+ (\beta^+_0 + \beta^+_U I_U + \beta^+_{U,F} I_U \cdot \widetilde{I}_F)\mathrm{UPM}_{i,d_t} \\ &+ (\beta^-_0 + \beta^-_U I_U + \beta^-_{U,F} I_U \cdot \widetilde{I}_F)\mathrm{LPM}_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}},\end{aligned} \tag{5}$$

and

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} = \alpha &+ (\beta^+_0 + \beta^+_D I_D + \beta^+_{D,R} I_D \cdot \widetilde{I}_R)\mathrm{UPM}_{i,d_t} \\ &+ (\beta^-_0 + \beta^-_D I_D + \beta^-_{D,R} I_D \cdot \widetilde{I}_R)\mathrm{LPM}_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}}.\end{aligned} \tag{6}$$

Using the forward equation regression of Eq. (4), we find that the UPM and LPM have a statistically significant relationship on the next period returns for each commodity. From Tables 3 and 4, all coefficients that are conditional on both single indicator terms and interaction terms are statistically significant. The results of each of the 31 commodity futures contracts show a similar pattern. Considering potential heteroscedasticity and serial autocorrelation in the model residuals, we employ a Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard error estimator (West & Newey, 1987), and tabulate the robust t-statistics in the parentheses.

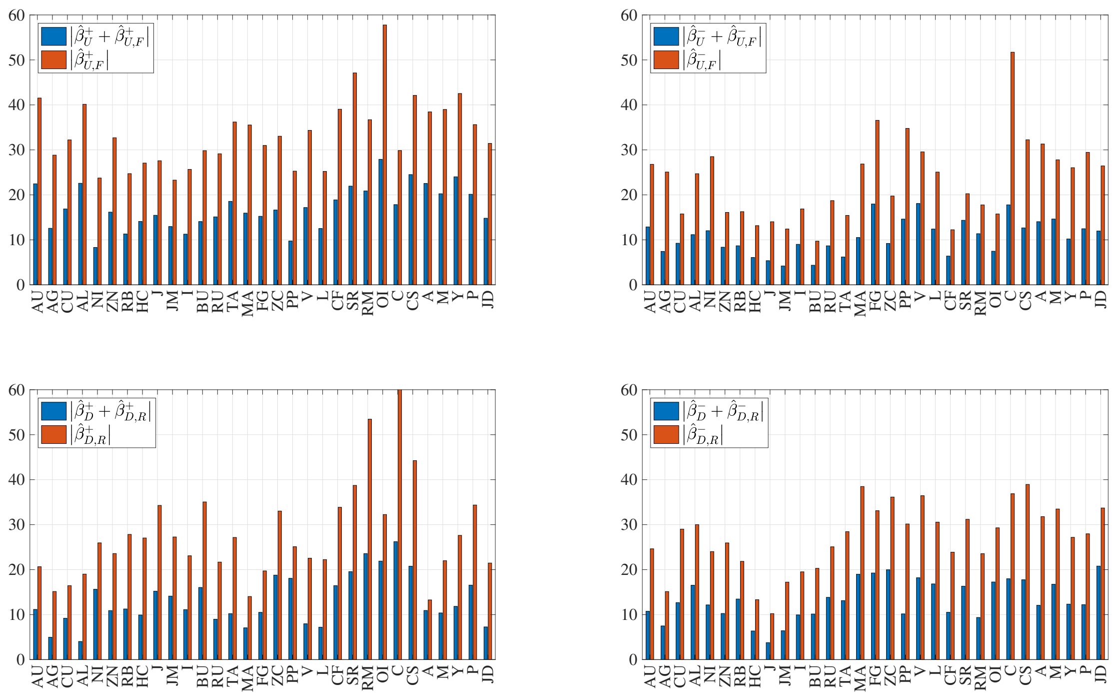

Figure 2: Least square estimates of the model coefficients for each commodity future contract from the start date in the data sample to December 2019. The momentum timing regression fits the next period individual asset daily return $\widetilde{r}_{i,d_{t+1}}$ with the ex-ante upper partial moment and the ex-ante lower partial moment conditional on different momentum indicators:

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} = \alpha &+ [(\beta_U^+ I_U + \beta_{U,F}^+ I_U \cdot \widetilde{I}_F) + (\beta_D^+ I_D + \beta_{D,R}^+ I_D \cdot \widetilde{I}_R)]\mathrm{UPM}_{i,d_t} \\ &+ [(\beta_U^- I_U + \beta_{U,F}^- I_U \cdot \widetilde{I}_F) + (\beta_D^- I_D + \beta_{D,R}^- I_D \cdot \widetilde{I}_R)]\mathrm{LPM}_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}}.\end{aligned}$$

where I_U is the ex-ante upward momentum indicator, I_D is the ex-ante downward momentum indicator, $\widetilde{I}_F$ is the contemporaneous falling day indicator, and $\widetilde{I}_R$ is the contemporaneous rising day indicator. The red bars on the graph depict the absolute values of the coefficients in terms of the incoming falling days in the upward momentum $I_U \cdot \widetilde{I}_F$ and the incoming rising days in the downward momentum $I_D \cdot \widetilde{I}_R$. The blue bars on the graph depict the absolute values of the coefficients in terms of the regular upward momentum and the regular downward momentum.

Table 3: Regression results on the first subsample from January 2008 to December 2012.

Heteroskedasticity and Autocorrelation Consistent Estimator
(t-statistics in parentheses)

Variable	1	$I_U \cdot$ UPM	$I_U \cdot \widetilde{I}_F \cdot$ UPM	$I_D \cdot$ UPM	$I_D \cdot \widetilde{I}_R \cdot$ UPM	$I_U \cdot$ LPM	$I_U \cdot \widetilde{I}_F \cdot$ LPM	$I_D \cdot$ LPM	$I_D \cdot \widetilde{I}_R \cdot$ LPM	R^2_{adj}
Coefficient	$\hat{\alpha}$	$\hat{\beta}^+_U$	$\hat{\beta}^+_{U,F}$	$\hat{\beta}^+_D$	$\hat{\beta}^+_{D,R}$	$\hat{\beta}^-_U$	$\hat{\beta}^-_{U,F}$	$\hat{\beta}^-_D$	$\hat{\beta}^-_{D,R}$	
Panel A: MET sector										
AU	0.0004	17.3901	-39.4611	-7.2529	16.5596	12.5865	-24.4375	-16.0201	27.6817	0.3515
	(0.89)	(5.18)	(-7.02)	(-0.54)	(1.03)	(3.96)	(-5.52)	(-2.78)	(3.94)	
AG	-0.0005	13.9452	-19.6361	-37.9664	72.5657	35.7353	-55.1594	-13.8999	23.7402	0.3537
	(-0.30)	(4.85)	(-5.01)	(-2.69)	(4.73)	(2.26)	(-4.15)	(-1.89)	(3.22)	
CU	0.0004	16.4578	-34.9192	-11.2588	23.7881	5.2291	-13.8903	-14.0722	23.5859	0.4424
	(0.76)	(8.44)	(-11.26)	(-3.52)	(5.73)	(2.57)	(-4.83)	(-6.26)	(7.44)	
AL	-0.0002	17.9793	-37.1923	-11.4129	12.6200	13.3014	-26.5173	-13.4294	30.3736	0.3929
	(-0.73)	(3.34)	(-5.47)	(-2.66)	(1.96)	(3.80)	(-6.02)	(-4.93)	(7.41)	
ZN	-0.0004	18.5130	-31.8100	-10.9783	19.5751	6.5201	-15.9274	-14.8612	25.2714	0.4048
	(-0.55)	(6.54)	(-6.11)	(-2.98)	(4.09)	(2.41)	(-3.05)	(-6.72)	(9.60)	
Panel B: ENG sector										
RB	-0.0004	10.4985	-24.3322	-16.0018	41.5428	19.5798	-41.3957	-11.7301	27.0496	0.2764
	(-1.04)	(2.43)	(-3.47)	(-2.10)	(4.77)	(5.07)	(-6.82)	(-2.92)	(4.23)	
J	-0.0004	37.5158	-60.1895	-21.2427	34.7293	18.9338	-39.3983	-22.1475	30.3626	0.3244
	(-0.57)	(3.46)	(-4.20)	(-2.74)	(3.71)	(2.72)	(-3.51)	(-5.42)	(5.90)	
Panel C: IND sector										
RU	0.0000	15.9216	-32.7142	-8.6789	12.6297	9.9072	-23.5294	-15.3825	32.6178	0.4628
	(-0.06)	(8.16)	(-10.68)	(-3.10)	(2.94)	(6.36)	(-8.75)	(-7.75)	(10.81)	
TA	0.0002	18.0790	-34.8710	-17.5856	25.3623	9.0013	-17.2883	-14.0434	26.6428	0.3651
	(0.33)	(6.91)	(-6.93)	(-3.10)	(3.77)	(2.95)	(-2.26)	(-3.33)	(5.44)	
V	-0.0001	14.5452	-38.5821	-20.5758	28.9607	9.8003	-22.6822	-15.5888	33.4139	0.2952
	(-0.35)	(2.58)	(-3.81)	(-3.36)	(2.89)	(3.37)	(-4.78)	(-3.57)	(5.00)	
L	-0.0003	20.6941	-33.6063	-13.3757	19.1254	9.9414	-22.4229	-13.1186	28.6110	0.4333
	(-0.59)	(8.27)	(-7.72)	(-4.72)	(4.78)	(3.33)	(-5.29)	(-6.42)	(7.47)	
Panel D: AGI sector										
CF	-0.0001	17.4838	-34.3458	-13.6335	26.1589	10.3001	-21.2953	-12.8731	25.4927	0.3643
	(-0.25)	(5.65)	(-6.19)	(-3.36)	(3.51)	(3.05)	(-5.25)	(-4.19)	(5.46)	
SR	-0.0003	26.5245	-50.1925	-15.1175	31.6525	4.4333	-17.5316	-16.4471	33.7188	0.3838
	(-0.62)	(9.79)	(-10.45)	(-3.97)	(5.56)	(2.77)	(-4.01)	(-4.70)	(6.65)	
C	-0.0002	5.1350	-27.5015	-33.1504	75.0920	52.9609	-58.8730	-18.0318	34.7231	0.3053
	(-0.74)	(1.01)	(-4.99)	(-5.25)	(5.73)	(5.36)	(-3.90)	(-4.64)	(3.88)	
A	0.0002	17.1338	-42.6299	-1.2827	11.6458	19.0698	-34.0623	-19.4074	30.5707	0.4331
	(0.39)	(6.19)	(-7.93)	(-0.52)	(2.63)	(5.65)	(-8.02)	(-8.59)	(10.85)	
M	0.0004	20.2560	-43.4203	-8.5072	16.9440	12.4797	-26.9362	-18.2089	35.4580	0.4298
	(0.74)	(8.42)	(-11.06)	(-1.80)	(2.49)	(4.13)	(-6.43)	(-6.65)	(9.20)	
Y	-0.0001	18.0463	-40.1795	-13.4671	23.3827	14.1035	-24.9587	-14.7085	26.4186	0.4641
	(-0.20)	(7.02)	(-9.02)	(-4.20)	(4.53)	(5.99)	(-8.52)	(-5.54)	(7.86)	
P	-0.0002	13.3636	-31.0555	-14.8875	28.3811	15.9715	-30.8212	-15.7411	27.6533	0.4747
	(-0.42)	(5.03)	(-8.43)	(-3.37)	(5.38)	(4.76)	(-8.09)	(-8.97)	(11.41)	

Notes: West & Newey (1987) standard errors are employed, and the bandwidth is set to $\lfloor 4(T/100)^{2/9} \rfloor$. *MET*, *ENG*, *IND*, and *AGI* stand for the market sector of metals, energy products, industrial materials, and agriculture products, respectively.

Table 4: Regression results on the second subsample from January 2013 to December 2019.

Heteroskedasticity and Autocorrelation Consistent Estimator
(t-statistics in parentheses)

Variable	1	$I_U \cdot$ UPM	$I_U \cdot \widetilde{I}_F \cdot$ UPM	$I_D \cdot$ UPM	$I_D \cdot \widetilde{I}_R \cdot$ UPM	$I_U \cdot$ LPM	$I_U \cdot \widetilde{I}_F \cdot$ LPM	$I_D \cdot$ LPM	$I_D \cdot \widetilde{I}_R \cdot$ LPM	R^2_{adj}
Coefficient	$\hat{\alpha}$	$\hat{\beta}^+_U$	$\hat{\beta}^+_{U,F}$	$\hat{\beta}^+_D$	$\hat{\beta}^+_{D,R}$	$\hat{\beta}^-_U$	$\hat{\beta}^-_{U,F}$	$\hat{\beta}^-_D$	$\hat{\beta}^-_{D,R}$	
Panel A: MET sector										
AU	0.0000	22.4760	-46.9642	-9.7992	22.3615	22.6577	-47.3544	-12.1233	21.8037	0.2377
	(-0.20)	(4.03)	(-5.11)	(-2.40)	(2.89)	(2.37)	(-3.72)	(-2.28)	(2.17)	
AG	-0.0003	16.6666	-32.2722	-9.5397	14.0265	16.1464	-22.1770	-7.4710	14.5861	0.2095
	(-0.92)	(6.49)	(-7.17)	(-2.41)	(2.59)	(5.03)	(-5.24)	(-3.86)	(2.97)	
CU	-0.0003	8.6148	-20.9377	0.2788	4.0263	17.9870	-33.0486	-22.6335	45.1566	0.2794
	(-1.06)	(2.48)	(-3.53)	(0.06)	(0.40)	(3.66)	(-3.01)	(-6.35)	(6.85)	
AL	0.0002	17.0039	-45.4401	-31.9868	50.7555	13.5436	-22.3294	-21.6883	40.7762	0.2855
	(0.69)	(3.08)	(-5.38)	(-4.37)	(5.28)	(3.15)	(-3.64)	(-2.64)	(3.26)	
NI	-0.0010	15.4240	-23.7421	-10.3194	25.9584	16.4663	-28.5004	-11.8513	24.0180	0.3034
	(-1.59)	(5.50)	(-6.82)	(-1.99)	(3.20)	(7.21)	(-7.12)	(-2.67)	(2.99)	
ZN	0.0004	13.4976	-35.4893	-16.1390	35.9615	11.1955	-17.9903	-20.8114	31.6891	0.3327
	(1.30)	(5.52)	(-7.29)	(-3.88)	(5.33)	(2.46)	(-2.18)	(-6.19)	(7.03)	
Panel B: ENG sector										
RB	-0.0001	13.6222	-24.8978	-16.6871	25.6334	6.8775	-14.9224	-7.9087	21.2400	0.3338
	(-0.20)	(6.35)	(-7.22)	(-5.02)	(3.43)	(2.89)	(-3.26)	(-2.78)	(4.09)	
HC	0.0007	12.9779	-27.0681	-17.1166	27.0426	7.0825	-13.1605	-6.9511	13.3225	0.3218
	(1.48)	(4.31)	(-6.48)	(-5.71)	(5.74)	(2.41)	(-2.49)	(-2.39)	(2.58)	
J	0.0007	11.7176	-27.4070	-20.0114	35.0851	8.4604	-13.8958	-5.5423	8.8596	0.3516
	(1.33)	(5.92)	(-9.59)	(-6.18)	(7.36)	(4.23)	(-4.77)	(-1.95)	(1.91)	
JM	0.0003	10.3187	-23.2779	-13.1494	27.2711	8.2092	-12.4099	-10.8132	17.2327	0.3607
	(0.70)	(5.20)	(-6.57)	(-3.37)	(6.50)	(3.89)	(-4.15)	(-4.92)	(4.50)	
I	-0.0001	14.3983	-25.6672	-11.9640	23.0851	7.8616	-16.8692	-9.5683	19.5146	0.3870
	(-0.10)	(10.88)	(-10.40)	(-4.51)	(5.35)	(5.14)	(-7.15)	(-6.97)	(7.49)	
Panel C: IND sector										
BU	-0.0006	15.7617	-29.8316	-19.0160	35.0564	5.3535	-9.7120	-10.1499	20.2904	0.3101
	(-1.14)	(6.17)	(-8.28)	(-5.18)	(6.58)	(3.01)	(-1.79)	(-5.08)	(7.97)	
RU	-0.0014	12.2038	-25.4802	-17.2995	32.1330	9.5802	-15.5975	-7.9065	19.8348	0.3029
	(-2.31)	(6.10)	(-7.12)	(-7.73)	(8.91)	(6.32)	(-4.12)	(-5.01)	(8.25)	
TA	-0.0001	17.0142	-37.7375	-17.1301	29.1747	9.2626	-14.0589	-16.7492	31.4498	0.2803
	(-0.19)	(4.78)	(-7.12)	(-3.25)	(2.49)	(1.73)	(-1.49)	(-6.27)	(8.35)	
MA	-0.0007	19.5868	-35.5338	-6.9622	14.0304	16.3437	-26.8591	-19.5122	38.4869	0.3729
	(-1.07)	(8.85)	(-11.84)	(-2.51)	(3.27)	(5.66)	(-6.36)	(-7.21)	(10.96)	
FG	-0.0002	15.8614	-30.9595	-9.1047	19.7276	18.7422	-36.5906	-13.7253	33.1467	0.3182
	(-0.63)	(9.37)	(-10.49)	(-2.02)	(2.98)	(7.68)	(-10.36)	(-5.66)	(7.32)	
ZC	0.0000	16.4045	-33.0398	-14.2392	33.0272	10.5448	-19.7427	-16.1672	36.1442	0.3368
	(-0.01)	(7.06)	(-6.60)	(-2.32)	(4.58)	(3.67)	(-6.11)	(-2.54)	(3.34)	
PP	-0.0001	15.5302	-25.2767	-7.0285	25.1002	20.1580	-34.7732	-19.9904	30.1592	0.3055
	(-0.26)	(5.03)	(-5.97)	(-2.22)	(3.00)	(4.61)	(-6.02)	(-7.15)	(5.65)	
V	0.0002	17.5556	-32.4061	-12.5349	20.2733	14.1583	-36.9850	-19.5704	38.0005	0.2979
	(0.65)	(3.21)	(-3.73)	(-3.02)	(2.38)	(2.71)	(-6.03)	(-4.36)	(5.93)	
L	-0.0002	7.0074	-18.3865	-24.6617	48.0723	16.9312	-28.4130	-14.6945	36.0790	0.3141
	(-0.75)	(1.50)	(-2.42)	(-6.25)	(5.80)	(5.24)	(-6.42)	(-4.65)	(5.31)	

continued on the next page

(continued) Regression results on the second subsample from January 2013 to December 2019.

Heteroskedasticity and Autocorrelation Consistent Estimator
(t-statistics in parentheses)

Variable	1	$I_U \cdot$ UPM	$I_U \cdot \widetilde{I}_F \cdot$ UPM	$I_D \cdot$ UPM	$I_D \cdot \widetilde{I}_R \cdot$ UPM	$I_U \cdot$ LPM	$I_U \cdot \widetilde{I}_F \cdot$ LPM	$I_D \cdot$ LPM	$I_D \cdot \widetilde{I}_R \cdot$ LPM	R^2_{adj}
Coefficient	$\hat{\alpha}$	$\hat{\beta}^+_U$	$\hat{\beta}^+_{U,F}$	$\hat{\beta}^+_D$	$\hat{\beta}^+_{D,R}$	$\hat{\beta}^-_U$	$\hat{\beta}^-_{U,F}$	$\hat{\beta}^-_D$	$\hat{\beta}^-_{D,R}$	
Panel D: AGI sector										
CF	-0.0002	22.9699	-43.8214	-25.8606	46.3595	3.2299	-5.6174	-14.4293	23.3704	0.3241
	(-0.56)	(6.44)	(-6.57)	(-4.24)	(6.53)	(1.14)	(-0.98)	(-4.12)	(5.11)	
SR	-0.0007	17.7157	-35.7700	-33.8176	75.5812	38.5294	-56.7704	-11.0988	26.0367	0.3110
	(-2.29)	(5.13)	(-6.81)	(-5.46)	(6.87)	(5.56)	(-5.18)	(-2.67)	(3.55)	
RM	0.0010	15.8361	-36.7081	-29.8719	53.4471	6.4018	-17.7713	-14.1819	23.5503	0.3329
	(2.35)	(7.86)	(-7.93)	(-7.84)	(8.67)	(2.12)	(-3.17)	(-4.99)	(5.23)	
OI	-0.0006	29.8585	-57.7647	-10.3470	32.2526	8.2762	-15.7506	-12.0413	29.3027	0.2566
	(-2.20)	(5.67)	(-8.02)	(-2.23)	(3.06)	(1.87)	(-2.11)	(-1.79)	(2.53)	
C	0.0001	15.2830	-31.4270	-33.6390	51.8539	26.5134	-48.9134	-20.0854	39.8013	0.2533
	(0.29)	(2.18)	(-3.94)	(-3.30)	(3.70)	(2.99)	(-3.73)	(-4.83)	(5.57)	
CS	0.0002	17.6006	-42.1093	-23.4727	44.2483	19.5899	-32.2519	-21.1937	38.9481	0.3121
	(0.71)	(3.64)	(-6.23)	(-4.98)	(6.32)	(2.39)	(-2.40)	(-5.88)	(6.21)	
A	-0.0001	13.1817	-33.4664	-11.6188	23.1961	13.6806	-24.2012	-23.9709	43.0546	0.2377
	(-0.38)	(4.44)	(-6.44)	(-1.78)	(2.29)	(2.48)	(-3.29)	(-6.84)	(6.75)	
M	0.0003	17.4695	-35.4213	-23.0926	41.5650	13.5935	-28.0909	-14.7315	30.6318	0.3311
	(0.62)	(9.13)	(-11.73)	(-6.35)	(5.32)	(4.12)	(-4.62)	(-4.57)	(5.18)	
Y	-0.0003	19.3586	-50.5268	-29.8915	62.3847	27.3059	-37.0337	-19.8144	35.8645	0.3434
	(-1.10)	(3.40)	(-5.18)	(-6.00)	(7.28)	(3.41)	(-2.87)	(-4.49)	(5.78)	
P	-0.0006	20.4388	-44.2982	-30.2513	65.8882	24.0803	-30.2559	-16.1403	30.1502	0.3738
	(-1.55)	(6.47)	(-8.79)	(-7.45)	(11.18)	(5.37)	(-3.75)	(-4.95)	(6.62)	
JD	-0.0004	16.6285	-31.4371	-14.2033	21.4733	14.4831	-26.4438	-12.9144	33.7089	0.2491
	(-0.97)	(5.04)	(-5.42)	(-3.24)	(2.97)	(2.74)	(-3.44)	(-3.51)	(6.44)	

Notes: West & Newey (1987) standard errors are employed, and the bandwidth is set to $\lfloor 4(T/100)^{2/9} \rfloor$. *MET*, *ENG*, *IND*, and *AGI* stand for the market sector of metals, energy products, industrial materials, and agriculture products, respectively.

Furthermore, this lead–lag effect is significantly stronger (i.e., larger absolute value of estimated coefficient) during the periods of time series momentum reversals. For simplicity, we summarise these featured structures of the coefficients in Figure 2. As illustrated on the graph, the red bars of the $\left|\hat{\beta}^+_{U,F}\right|$ and $\left|\hat{\beta}^-_{U,F}\right|$ are greater than the blue bars of $\left|\hat{\beta}^+_U + \hat{\beta}^+_{U,F}\right|$ and $\left|\hat{\beta}^-_U + \hat{\beta}^-_{U,F}\right|$ for all contracts. More specifically, the effect is stronger in the coming falling days of upward momentum (uptrend market) than in the regular upward momentum market. In a similar way, this pattern also shows up in the coming rising days of downward momentum (downtrend market) when compared with the regular downward momentum market.

More importantly, these results indicate that time series momentum reversal predictions can potentially be made by observing larger increments in UPM or LPM. Thus, we suggest managing the time series momentum signals when the UPM or LPM has a relatively large value. In the next section, we will explore further how the UPM and LPM can predict further time series momentum reversals when they progress into the tail quantile groups.

4. Managed time series momentum

Originated in Moskowitz et al. (2012), the time series momentum strategy based on Eq. (1) shows a well-defined weight-generating function for the volatility scaling. However, the long/short trading signals generated by Eq. (1) are based only on the sign of past cumulative returns, which is debatable (Kim et al., 2016; Huang et al., 2020).[11] A recent study of time series momentum performance also proved that it is the weight allocation not the trading signal, that makes the most significant contribution to time series momentum profits (Jusselin et al., 2017).

Inspired by the relationship between market states and cross-sectional momentum crashes documented by (Daniel & Moskowitz, 2016), we investigate the losses of time series momentum in different market states.[12] We notice that time series momentum losses generally occur when the asset prices slump in uptrend markets, when they rebound in downtrend markets, and in sideways markets.

In this section, based on the lead–lag relationship between partial moments and time series momentum losses, we examine to what extent we can effectively, and in a timely manner, improve the long/short signal to mitigate TSM strategy losses. We construct managed time series momentum (MTSM) portfolios based on the rolling-window approach that of TSM strategy and evaluate their performance in the out-of-sample period. The performance of MTSM strategies reveals that the asymmetric structure of upper and lower partial moments in right-tailed quantiles can help in predicting future momentum reversals.

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[11] Kim et al. (2016) maintained that the time series momentum without scaling by volatility (or the so-called risk parity approach) offer similar cumulative returns with the buy-and-hold strategy. Huang et al. (2020) argued that the time series momentum strategy is virtually the same as a similar strategy based on historical sample mean and does not require predictability.

[12] Daniel & Moskowitz (2016) documented that the cross-sectional momentum crashes occur in panic states, following market declines and when market volatility is high, and are contemporaneous with market rebounds. Cooper et al. (2004) also maintained that the cross-sectional momentum profits depend on the states of market.

4.1. Portfolio construction

The rule-based approach of our managed time series momentum (MTSM) strategy originates from the regression analysis in Section 3. We use the recursive percentile of the historical joint distribution of (UPM, LPM) as the reference point to identify the relatively large values of the UPM and LPM. From the view of market microstructure, this allows us to monitor the behaviour of market participants (e.g., herding traders and contrarian traders), and their tailed risks measured by the upper and lower partial moment. For instance, lower partial moment is used to measure the risk for a herding trader in the upward momentum, and upper partial moment is used to measure the risk for a contrarian trader in this case.

The equal-weight portfolio return of the MTSM strategy is given by:

$$r^{mtsm}_{p,d_{t+1}} = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{sign}^{mtsm}_{i,d_{t+1}} \frac{\sigma_{target}}{\sigma_{i,d_t}} r^{i}_{i,d_{t+1}}, \tag{7}$$

where the long/short decision of the MTSM portfolio is the outcome of a nonlinear function $\mathcal{G}$ of univariate past returns, upper partial moment and lower partial moment:

$$\text{sign}^{mtsm}_{i,d_{t+1}} = \mathcal{G}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}, \text{UPM}_{i,d_t}, \text{LPM}_{i,d_t} \right). \tag{8}$$

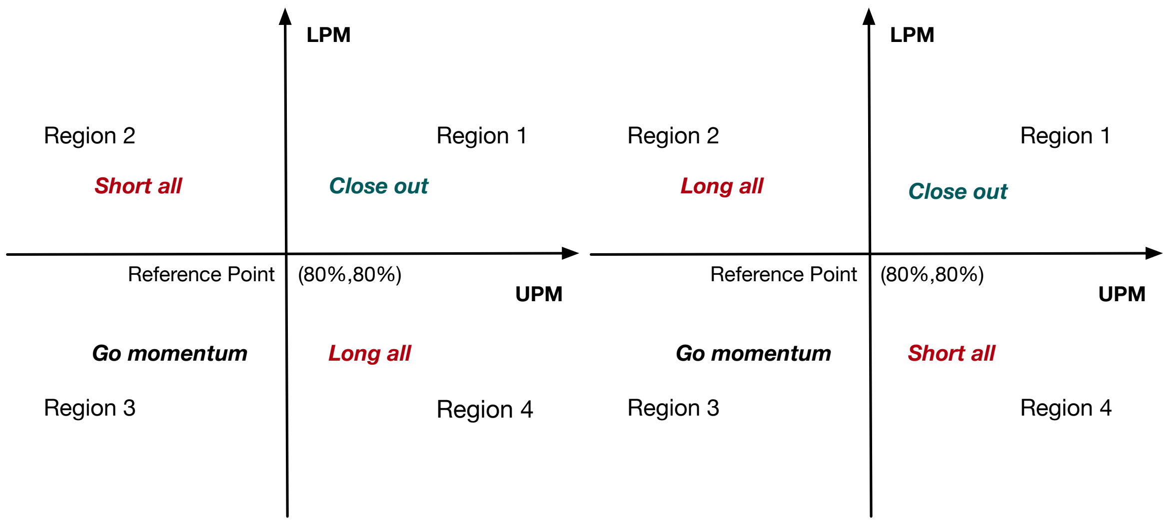
The time series momentum tends to reverse when the UPM or LPM progresses into its tail quantile, as we mentioned in Section 3. We define the recursively generated percentiles (80%, 80%) of the historical joint distribution of the upper partial moment (UPM_{i,d_t}) and the lower partial moment (LPM_{i,d_t}) as the reference point of commodity i in day d_t. As demonstrated in Figure 3, we divide the coordinate plane of UPM and LPM into four regions by the reference point and implement different actions in different regions. It is intuitive to close positions in Region 1 and keep the original TSM in Region 3, but it is less clear what actions should be taken in Regions 2 and 4. As a result, we design two different MTSM strategies, named MTSM-S1 and MTSM-S2, to examine the effectiveness of our proposed rule-based approach.

To assess how the asymmetric pattern of upper or lower partial moments can predict the time series momentum reversals, we investigate individual asset returns in the next period (i.e., time $t + 1$) when the joint distribution of (UPM, LPM) falls into different regions at time t. In Table 5, we report the percentage of contracts for which the individual TSM strategy has an average negative future return under different scenarios. We find from Panel A that the long trades of the TSM strategy have a higher probability (61.11%) of loss in Region 2, and from Panel B that the short trades of the TSM strategy have a higher probability (66.67%) of loss in Region 4 during the first subsample. In Region 2, the LPM is in the tailed quantile while the UPM is not; this asymmetric structure predicts a future price slump in the upward momentum. Similarly in Region 4, the UPM is in the tailed quantile while the LPM is not; this asymmetric pattern predicts a future price rebound in the downward momentum. Thus, in the construction of the MTSM-S1 strategy, we design it to change the long signal to short in Region 2 and to change the short signal to long in Region 4. In addition, we design to close out both long and short positions in Region 1, since the risk measurements of both UPM and LPM are in the tails, and keep the trading signals the same as that of the original time series momentum in Region 3, since the probability of loss is low (16.67% in the upward momentum and 5.56% in the downward momentum). In other scenarios, the trading signal follows that of the original time series momentum (i.e., long position in upward momentum, short position in downward momentum).

Table 5: Percentage of the number of contracts that has an average negative future return in the time series momentum portfolio under different scenarios.

Sample Period	Region 1	Region 2	Region 3	Region 4
Panel A: Under the state of upward momentum				
The first subsample (January 2008 - December 2012)	61.11%	61.11%	16.67%	27.78%
The second subsample (January 2013 - December 2019)	35.48%	29.03%	32.26%	45.16%
Panel B: Under the state of downward momentum				
The first subsample (January 2008 - December 2012)	50.00%	33.33%	5.56%	66.67%
The second subsample (January 2013 - December 2019)	48.39%	67.74%	29.03%	45.16%

Notes: The time series momentum states are classified by the trading signal generated from 30 trading days look-back window. If the sign of the past 30 days cumulative return is positive, then it is an upward momentum state, and otherwise, a downward momentum state. The four regions are on the coordinate plane of upper partial moment (x axis) and lower partial moment (y axis) that divided by their (80%,80%) quantiles of the historical joint distribution.



(a) MTSM-S1 (b) MTSM-S2

Figure 3: Choices of the managed time series momentum strategy in different regions. The coordinate plane of upper partial moment (UPM) and lower partial moment (LPM) is divided into four regions by the reference points that recursively generated from the (80%, 80%) percentiles of the historical joint distribution. Two different managed time series momentum (MTSM) strategies, named *MTSM-S1* and *MTSM-S2*, are designed to take different actions in different regions.

Moreover, we observe a different picture in terms of time series momentum losses during the second subsample from Table 5. Under the state of upward momentum, fewer contracts suffer losses in Region 2, while more contracts lose in Region 4 compared to the first subsample. Similar patterns can also be found in the case of downward momentum, but with more losing contracts in Region 2 than in Region 4. Apart from the MTSM-S1 strategy, we design the MTSM-S2 strategy to incorporate these changes from the first to the second subsample. We change the long signal to short in Region 4 and change the short signal to long in Region 2. Thus, our design of the MTSM-S2 strategy gives opposite trading signals in Region 2 and Region 4 for both upward and downward momentum compared to the MTSM-S1 strategy.

Figure 3 illustrates the details of different actions in the construction of the MTSM-S1 and MTSM-S2 strategies. Following the portfolio return formula of the original TSM strategy in Eq. (1), we note that:

$$r^{tsm}_{p,d_{t+1}} = r^{tsm}_{l,d_{t+1}} - r^{tsm}_{s,d_{t+1}}, \tag{9}$$

where for the long position:

$$r^{tsm}_{l,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\sigma_{target}}{\sigma_{i,d_t}} r^{i}_{i,d_{t+1}} I\left(\text{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right) > 0\right), \tag{10}$$

and for the short position:

$$r^{tsm}_{s,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\sigma_{target}}{\sigma_{i,d_t}} r^{i}_{i,d_{t+1}} I\left(\text{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right) < 0\right). \tag{11}$$

In Table 6, we tabulate different actions and return formulae in the holding period of the MTSM strategy under each of the four regions.

Table 6: Methodologies and results of the construction of the managed time series momentum strategy.

MTSM Strategy	Region 1		Region 2		Region 3		Region 4	
	Action	Return	Action	Return	Action	Return	Action	Return
MTSM-S1	Close out	0	Short all	$-r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	Momentum	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	Long all	$r^{tsm}_{l,d_t} + r^{tsm}_{s,d_t}$
MTSM-S2	Close out	0	Long all	$r^{tsm}_{l,d_t} + r^{tsm}_{s,d_t}$	Momentum	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	Short all	$-r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$

Notes: The time series momentum portfolio return $r^{tsm}_{p,d_{t+1}}$ across N_t securities at the day d_{t+1} can be decomposed into two components:

$$r^{tsm}_{p,d_{t+1}} = r^{tsm}_{l,d_{t+1}} - r^{tsm}_{s,d_{t+1}},$$

where $r^{tsm}_{l,d_{t+1}}$ is for the long positions:

$$r^{tsm}_{l,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\sigma_{target}}{\sigma_{i,d_t}} r_{i,d_{t+1}} I\left(\text{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right) > 0\right),$$

and $r^{tsm}_{s,d_{t+1}}$ is for the short positions:

$$r^{tsm}_{s,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\sigma_{target}}{\sigma_{i,d_t}} r_{i,d_{t+1}} I\left(\text{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right) < 0\right),$$

where the annualized target volatility σ_{target} is set to be 40% to scale the ex-ante volatility estimator σ_{i,d_t}, which is an exponentially weighted moving standard deviation with J-days span on the daily asset returns r_{i,d_t}.

4.2. Strategy performance

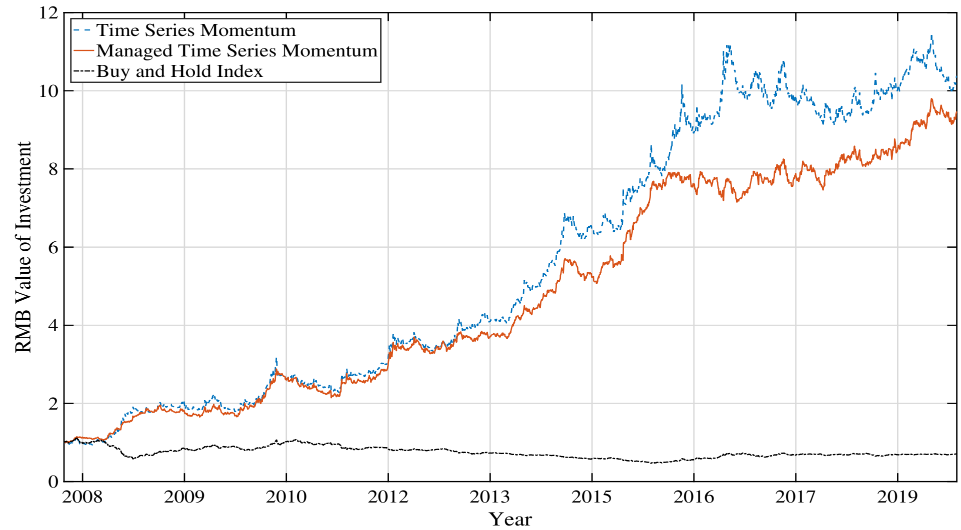
In this subsection, we examine the performance of MTSM strategies on the subperiods. We first investigate the performance of the MTSM strategies with look-back window of 30 trading days as a demonstration. Further studies present consistent results among different look-back windows. Statistics including the annual return, Sharpe ratio, maximum drawdown, Sortino ratio, Calmar ratio, percentage of the win, average profit over average loss, skewness, kurtosis, and t-statistics of normality test are tabulated in Table 7 according to different subsamples (Panel A for the first subsample from January 2008 to December 2012; Panel B for the second subsample from January 2013 to December 2019). The MTSM strategies show better performance than the original TSM strategy, with a higher Sharpe ratio and Sortino ratio in the first subsample as well as in the second one.

Table 7: Performance of the managed time series momentum strategy on the Chinese commodity futures markets.

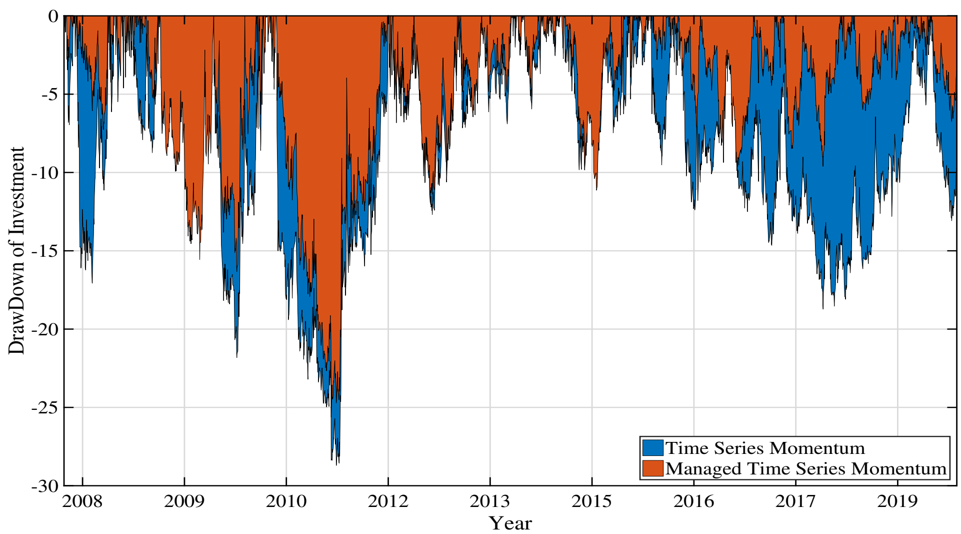
Strategy	Annual Return (%)	Sharpe Ratio	Maximum DrawDown (%)	Sortino Ratio	Calmar Ratio	Percentage of Win (%)	AP-to-AL	Skewness	Kurtosis	t-statistics
Panel A: The first subsample (January 2008 - December 2012)										
BAH	-4.65	-0.28 (0.08)	49.23	-0.37	-0.09	52.09	0.90	-0.46	4.49	-0.34
TSM	26.29	**1.10** (1.00)	28.71	**1.65**	**0.92**	53.16	1.09	0.32	6.15	2.61
MTSM-S1	25.11	**1.25** (0.06)	25.62	**1.91**	**0.98**	52.83	1.14	0.47	7.13	2.98
MTSM-S2	12.47	0.71 (0.07)	23.68	1.05	0.53	51.93	1.08	0.21	6.81	1.83
Panel B: The second subsample (January 2013 - December 2019)										
BAH	-2.82	-0.25 (0.04)	44.80	-0.37	-0.06	51.53	0.92	-0.13	5.18	-0.34
TSM	15.93	**1.04** (1.00)	18.73	**1.68**	**0.85**	51.29	1.16	0.57	8.01	2.96
MTSM-S1	10.63	0.81 (0.05)	22.98	1.28	0.46	50.59	1.15	0.39	8.24	2.38
MTSM-S2	14.30	**1.25** (0.02)	11.13	**2.13**	**1.28**	52.59	1.15	0.79	8.24	3.58

Notes: *BAH* stands for the buy-and-hold strategy. *TSM* stands for the original time series momentum strategy. *MTSM-S1* and *MTSM-S2* stand for two different reconstructed strategies on the original time series momentum according to the asymmetrically tail-distributed upper and lower partial moments. *AP-to-AL* stands for the ratio of average profit over average loss. The Sharpe ratio tabulated is the annualized value by setting 250 trading days within a year in the calculation. The values in parentheses denote the p-value of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the other. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$.

In the first subsample, the MTSM-S1 enhances the original TSM strategy from 1.10 to 1.25 in terms of the Sharpe ratio, while increasing from 1.65 to 1.91 in terms of the Sortino ratio. In the second subsample, the MTSM-S2 shows a significant 20% improvement in the Sharpe ratio of 1.25 (t-statistic = 3.58) compared with 1.04 (t-statistic = 2.96) for the original TSM strategy. At the same time, the Sortino ratio also rises from 1.68 to 2.13, an increase of approximately 27%. Furthermore, higher Calmar ratios are presented by the MTSM-S1 during the first subsample and by of the MTSM-S2 during the second subsample. These results show that the MTSM approach can effectively mitigate time series momentum losses by systematically managing the risk exposure in the scenarios of predicting future time series momentum reversals.



(a) Cumulative gains



(b) Drawdowns

Figure 4: Comparison of the original and managed time series momentum investment on the Chinese commodity futures markets from January 2008 to December 2019.

In Figure 4, we compare the cumulative gains (Panel a) and the drawdowns (Panel b) of the MTSM investment with the original TSM. The MTSM investment shown combines the performance of MTSM-S1 strategy before 2013 and the performance of MTSM-S2 strategy after 2013.

The graph shows that the rule-based MTSM strategy exhibits significantly a lower level of drawdowns than the original TSM strategy, particularly in the case of recent deep drawback from the high-water mark reached in 2016.

Importantly, different MTSM strategies have proven to be effective on different subsamples, supporting our previous argument that fundamental changes have occurred on the Chinese commodity futures markets. According to the MTSM-S1 strategy, one can conclude that the asymmetric tailed structures of the UPM and LPM in Region 2 can partly predict future slumps in the upward momentum from 2008 to 2012. Similarly, one can conclude that the asymmetric tailed structures of the UPM and LPM in Region 4 can partly predict future rebounds in the downward momentum during that same period. With the MTSM-S2 strategy, one can see the contrary predictable pattern between the partial moments and the momentum reversals from 2013 to 2019. The asymmetric structure of high UPM and relatively low LPM in the Region 4 can predict future upward momentum slumps. In a similar way, the asymmetric structure of high LPM and relatively low UPM in the Region 2 can predict future downward momentum rebounds.

We further explain these findings by highlighting potential changes in the behaviour of major market participants on the Chinese commodity futures markets. In 2013, the night-trading rule was introduced to the Chinese futures markets as one of the financial reformation policies. This policy smoothed overnight price shocks, and brought in international institutional investors with longer-term investment horizons, consequently stabilising market fluctuations. Up until then, most investors in the Chinese futures markets were retail investors with a short-term speculative outlook (Fan & Zhang, 2020). Therefore, the time series momentum strategy was less effective because of the frequency of short-term severe shocks before 2013, and momentum was more likely to reverse when resistance momentum was high.

However, with the increased participation of international institutional investors and the increasing market liquidity following 2013, market reaction to new information has become increasingly more efficient. Since 2013, short-term market shocks have not immediately changed time series momentum states during periods of market underreaction. Thus, the next period of upward momentum slump is predicted not by a point in Region 2 of the coordinate plane but by a point in Region 4, which highlights a scenario of overreaction in the upward momentum. We argue that the asymmetric structure of the UPM and LPM works similarly in the case of downward time series momentum. Moreover, in Table 8, we present the annual Sharpe ratio of the BAH, TSM, MTSM-S1, and MTSM-S2 strategies in each year from 2008 to 2019. According to the statistics shown, we suggest shifting to the MTSM-S2 strategy after 2013, when the MTSM-S2 strategy begins significantly outperforming the TSM and MTSM-S1 strategies.

Table 8: Annual Sharpe ratio of the MTSM strategies on the Chinese commodity futures markets.

Strategy	2008	2009	2010	2011	2012	2013
BAH	-2.19	2.29	0.59	-1.49	-0.23	-1.83
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)
TSM	2.24	0.95	0.82	0.17	1.20	1.29
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
MTSM-S1	3.06	0.71	1.42	-0.15	1.47	1.37
	(0.06)	(0.04)	(0.08)	(0.06)	(0.04)	(0.03)
MTSM-S2	0.34	1.02	1.65	-0.50	0.91	0.82
	(0.08)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Strategy	2014	2015	2016	2017	2018	2019
BAH	-2.24	-1.65	2.07	0.17	-0.80	1.09
	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)	(0.02)
TSM	2.43	1.51	1.59	-0.65	0.25	0.28
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
MTSM-S1	1.93	1.22	1.01	-1.41	0.96	0.08
	(0.05)	(0.07)	(0.03)	(0.06)	(0.06)	(0.04)
MTSM-S2	2.48	3.17	-0.20	0.56	0.63	1.07
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)

Notes: *BAH* stands for the buy-and-hold strategy. *TSM* stands for the original time series momentum strategy. *MTSM-S1* and *MTSM-S2* stand for two different reconstructed strategies on the original time series momentum according to the asymmetrically tail-distributed upper and lower partial moments. The values in parentheses denote the p-value of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the others. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$.

We explain the improvements achieved by the MTSM strategy with the following economic explanations. For risk-averse investors, it is rational to manage risk during episodes of momentum reversals. In the MTSM strategy, there is less risk exposure during momentum reversals. As a result, the returns of the MTSM strategy becomes more stable. This is reflected by a significantly higher Sharpe ratio and a less severe maximum drawdown, though we also observe a slight drop in annualised return. Therefore, the MTSM strategy maintains a better trade-off between risk and return. Moreover, we highlight the merits of using a second-moment measure, partial moments, to predict time series momentum reversals. Bollerslev (2021) suggested that all volatilities are not created equal and that partial (co)variation measures are essential for volatility forecasting and asset pricing. Our superior results from the MTSM strategy add empirical findings to support this claim by analysing time series return predictability.

4.3. Different look-back windows

The MTSM strategies with $J = 30$ trading days were demonstrated in the previous subsection to outperform the TSM strategy. If the MTSM approach is indeed a robust systematic nonlinear approach for predicting time series momentum reversals, the enhancement of the MTSM strategies should hold consistently with various look-back windows.

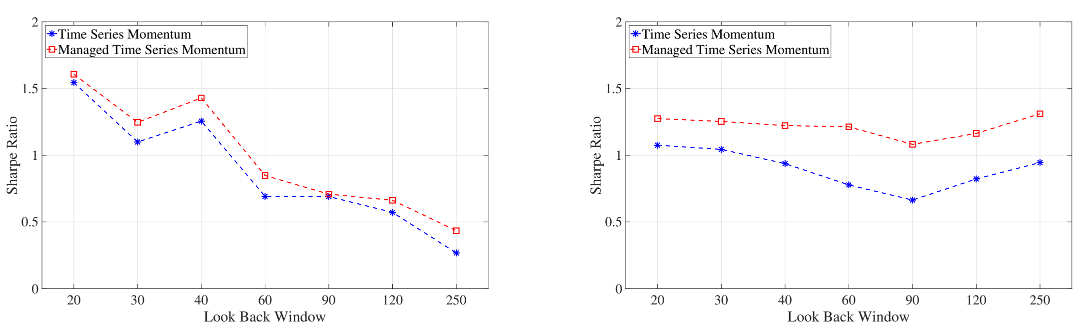
Panels A and B in Table 9 show the evaluation statistics of the time series momentum and the managed time series momentum strategies with varying look-back windows ($J = 20$, 30, 40, 60, 90, 120, 250 trading days) during the first subsample from January 2008 to December 2012 and the second subsample from January 2013 to December 2019, respectively. Statistics including the annual return, Sharpe ratio, maximum drawdown, and t-statistics for the normality test are tabulated with different look-back windows.

We find from Table 9 that MTSM strategies, in which the look-back window range from 20 to 250 trading days, show results consistent with our previous results for 30 trading days. The annual return, Sharpe ratio, and maximum drawdown statistics show consistent improvements in both the first and second subsamples for all look-back windows. In Figure 5, we summarise and depict the Sharpe ratios for various look-back windows during the first and second subsample. The MTSM approach provides a statistically significant improvement in the Sharpe ratio, approximately 20% on average, with respect to the original TSM across different look-back windows and subsamples.

Table 9: Managed time series momentum investment with different look-back windows.

		look-back Window (days)						
		20	30	40	60	90	120	250
Panel A: The first subsample (January 2008 - December 2012)								
TSM	Annual Return (%)	37.28	26.29	29.99	15.60	14.93	12.36	5.56
	Sharpe Ratio	1.55	1.10	1.26	0.69	0.69	0.57	0.27
		(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	MDD (%)	26.02	28.71	21.76	29.07	28.85	28.32	41.28
	t-statistics	3.60	2.61	2.96	1.73	1.73	1.47	0.80
MTSM-S1	Annual Return (%)	34.53	25.11	28.55	15.79	12.53	11.47	7.13
	Sharpe Ratio	1.61	1.25	1.43	0.85	0.71	0.66	0.43
		(0.05)	(0.06)	(0.06)	(0.05)	(0.07)	(0.08)	(0.06)
	MDD (%)	21.12	25.62	14.64	26.15	28.31	23.30	29.43
	t-statistics	3.76	2.98	3.38	2.11	1.82	1.72	1.23
Panel B: The second subsample (January 2013 - December 2019)								
TSM	Annual Return (%)	16.48	15.93	14.48	11.96	10.01	12.61	14.48
	Sharpe Ratio	1.08	1.04	0.94	0.78	0.66	0.82	0.94
		(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	MDD (%)	15.87	18.73	27.24	16.83	18.70	18.29	28.92
	t-statistics	3.04	2.96	2.68	2.26	1.97	2.38	2.70
MTSM-S2	Annual Return (%)	14.42	14.30	14.02	13.91	12.09	13.69	15.63
	Sharpe Ratio	1.27	1.25	1.22	1.21	1.08	1.16	1.31
		(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)	(0.04)
	MDD (%)	11.98	11.13	9.62	12.51	14.43	13.09	25.64
	t-statistics	3.64	3.58	3.50	3.48	3.14	3.34	3.72

Notes: *TSM* stands for the original time series momentum strategy. *MTSM-S1* and *MTSM-S2* indicate two different reconstructed strategies on the original time series momentum according to the asymmetrically tail-distributed upper and lower partial moments. *MDD* is short for the maximum drawdown. The Sharpe ratio tabulated is the annualized value by setting 250 trading days within a year in the calculation. The values in parentheses denote the p-value of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the other. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$.



(a) The first subsample (2008–2012)

(b) The second subsample (2013–2019)

Figure 5: Sharpe ratio of the original and managed time series momentum strategies.

4.4. Performance during COVID-19 Crash Period

As part of our robustness check, we further extend our sample to investigate the performance of our proposed MTSM strategy during the COVID-19 crash period. We focus on the six-month period from December 2019 to May 2020, because major economic activities have significantly recovered in mainland China since April 2020.[13] The dotted black line shown on the upper panel of Figure 6 is the buy-and-hold market index, which is equally weighted on all 31 commodities that are considered in our dataset. The data show the market experienced a crash from January 2020 to March 2020 and enjoyed a rally after that. This severely fluctuating short sample enables us to examine if our proposed MTSM strategy maintains superior performance under extreme scenarios compared to the original TSM strategy.[14]

Table 10: Performance of the managed time series momentum strategy during the COVID-19 crash period from December 2019 to May 2020.

Strategy	Annual Return (%)	Sharpe Ratio	Maximum DrawDown (%)	Sortino Ratio	Calmar Ratio	Percentage of Win (%)	AP-to-AL	Skewness	Kurtosis
BAH	-10.95	-0.77 (0.05)	16.49	-0.82	-0.66	57.14	0.66	-1.41	8.53
TSM	26.26	1.39 (1.00)	8.51	2.12	3.09	53.78	1.12	0.34	4.97
MTSM-S1	22.33	1.32 (0.04)	5.66	2.18	3.95	50.42	1.28	1.21	10.14
MTSM-S2	23.73	**1.79** (0.05)	**4.81**	**3.35**	**4.93**	52.10	1.30	1.35	9.18

Notes: *BAH* stands for the buy-and-hold strategy. *TSM* stands for the original time series momentum strategy. *MTSM-S1* and *MTSM-S2* stand for two different reconstructed strategies on the original time series momentum according to the asymmetrically tail-distributed upper and lower partial moments. *AP-to-AL* stands for the ratio of average profit over average loss. The Sharpe ratio tabulated is the annualized value by setting 250 trading days within a year in the calculation. The values in parentheses denote the p-value of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the other. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$.

In Table 10, we tabulate the evaluation statistics of the proposed MTSM strategies and compare them with the BAH and TSM benchmarks. Following the previous section, a look-back window size of $J = 30$ days is used. The MTSM-S2 strategy continues to outperform the original TSM

[13]The local government of the epicentre of Wuhan City and Hubei Province declared removing previous travel restrictions on April 8, 2020.

[14]Recent works including Liu et al. (2016), Fang & Bessler (2018), and Yousaf & Hassan (2019) also characterized the Chinese stock market crash with the sample period: 2015–2016. However, we do not emphasize on this crash period since we focus on studying the commodity futures markets in this paper.

strategy and MTSM-S1 strategy in the COVID-19 crash period. The Sharpe ratio of MTSM-S2 (1.79) remains statistically significantly higher than the original TSM (1.39). Similar improvements are also observed in the Sortino ratio and Calmar ratio. Also, the maximum drawdown of MTSM-S2 (4.81%) is nearly half of the TSM (8.51%). We note that a smaller drawdown in a crash period has higher practical significance than a larger drawdown for market participants, particularly fund managers.

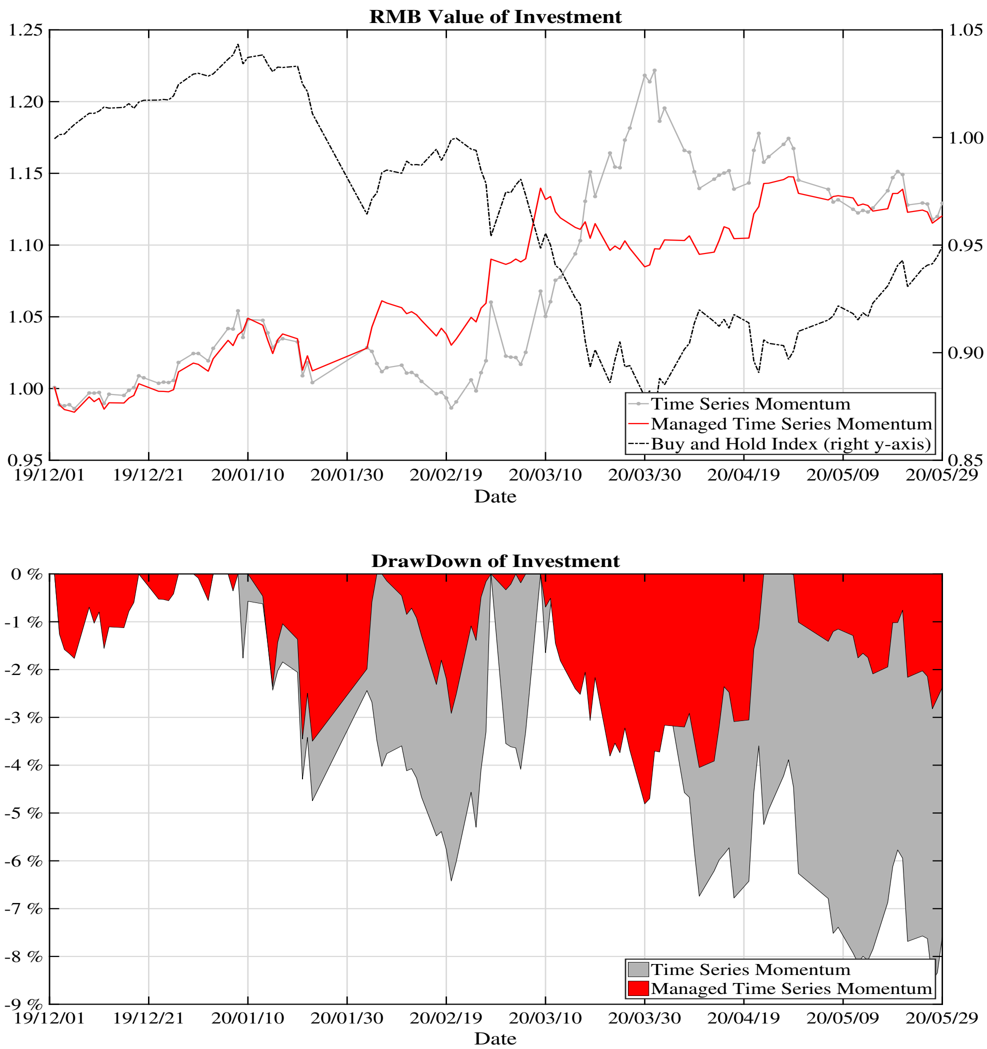


Figure 6: Comparison of the original and managed time series momentum investment on the Chinese commodity futures markets during COVID-19 crash period from December 2019 to May 2020. On the upper panel, the cumulative gains in RMB value are shown on the left y-axis using red line for the managed time series momentum strategy and using grey line with marker for the original time series momentum strategy. The buy and hold investment is shown on the right y-axis using black dotted line to describe the market dynamics during COVID-19 crash period. The drawdowns of both original and managed time series momentum strategies are depicted on the lower panel.

Combining previous results shown in the second subsample, we suggest that time series momentum investors in the Chinese commodity futures markets consider MTSM-S2 strategy as a tool to capture the changing momentum states, thus mitigating time series momentum strategy drawdowns. In Figure 6, the upper panel shows the cumulative gains of the TSM and MTSM-S2 strategies and the lower panel compares the drawdowns of the two strategies during the COVID-19 crash period. Unlike the deep drawdown in the original TSM strategy, the MTSM-S2 strategy illustrates a better control of drawdown throughout the sample.

5. Conclusion

In this paper, we introduce a managed time series momentum (MTSM) strategy based on the upper and lower partial moments. A comprehensive study of 31 commodity futures contracts in the Chinese markets over a decade-long period illustrates the beneficial risk-adjusted return characteristics associated with the MTSM strategies. MTSM provides a set of rules that adjust the original time series momentum signals using the joint distribution of the upper partial moment and the lower partial moment. Various look-back window sizes and two separated subsamples are used to check the robustness, and we also include the COVID-19 crash period to verify the merits of MTSM strategies under this extreme scenario.

We commenced by analysing episodes of time series momentum reversals, in which the TSM strategy suffers losses. In the strand of literature covering the time series return predictability, we further found that the upper and lower partial moments can help to partly predict reversals of time series momentum. Based on such information, we designed rule-based approaches to improve the long/short trading signals of the original time series momentum strategy. We constructed the MTSM strategies and empirically tested this systematic rule-based approach to predicting time series momentum reversals. MTSM is demonstrated to be an effective and robust approach with significantly higher Sharpe ratio, higher Sortino ratio, higher Calmar ratio, and lower maximum drawdown in the out-of-sample period. For investors, MTSM provides an alternative investment stragtegy to TSM, in particular for mitigating the risk during the time series momentum reversals.

For policymakers, the findings of this paper provide further understanding on the characterstics of the Chinese commodity futures markets and the influence of the night-trading policy.

One limitation of this study is that we did not consider the transaction cost, due primarily to the complicated fee structures in the Chinese futures markets. The exchanges also change their fee structures over time. Therefore, we followed Moskowitz et al. (2012) by evaluating the performance of the time series momentum strategy without considering transaction cost. Future research may investigate the role of other variables in improving the time series momentum strategy, such as trading volume, bid–ask spread, and higher moments of returns.

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