Managing Time Series Momentum

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Abstract

Similar with cross-sectional momentum crashes, time series momentum strategy experiences deep and persistent drawdowns in the stressed time of uptrend reversals, downtrend rebounds and long time sideways market. These time series momentum losses are partly forecasted by the upper and lower partial moments which are derived from individual asset daily return over weekly horizon. An implementable systematic rule-based approach is constructed based on Moskowitz et al. (2012), Daniel & Moskowitz (2016), Gulen & Petkova (2015) to manage the risk of wrong trading signals in time series momentum. Its empirical application in the Chinese futures markets documents an improvement in the both Sharpe ratio and maximum drawdown of time series momentum strategy over different looking back periods ranging from 20 to 250 trading days, attributting the recent poor performance of time series momentum to its trading signal component.

Keywords: Time Series Momentum, Momentum Crash, Partial Moments, Quantitative Investing, Trading Strategy

JEL: G11, G13

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Preprint submitted to EFMA2019 Annual Meetings *May 1, 2019*

1. Introduction

A momentum-based investing strategy can be confusing to investors who are often told that "chasing performance" is a massive mistake and "timing the market" is impossible. Yet as a systematized strategy, momentum sits upon 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), later 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). Meanwhile, in assets management industry especially in hedge fund, momentum and particularly time series momentum have already been implemented as their major investment strategy since the day they were founded.

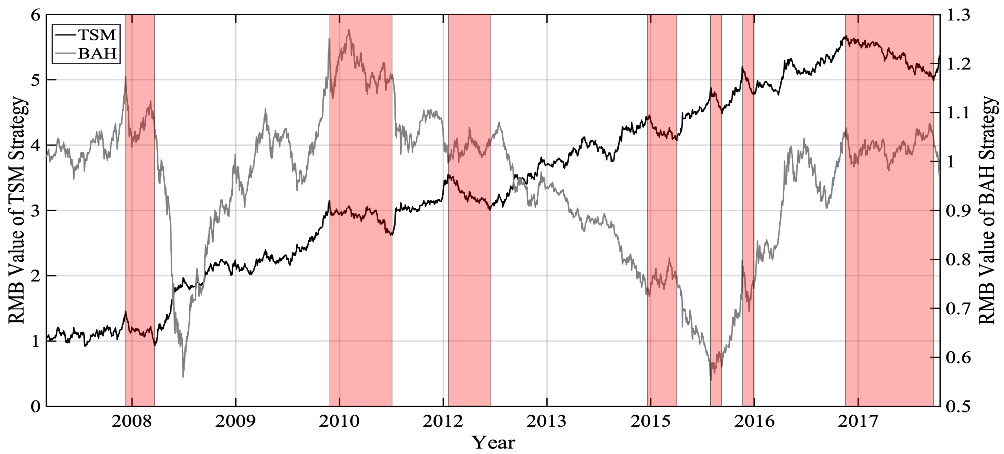
Managed futures funds, also known as Commodity Trading Advisors (CTAs), constitute a significant proportion of the hedge fund industry (Hurst et al., 2010). Using BarclayHedge estimates at the end of 2014, managed futures funds manage a total of $318 billion of assets, which is about 11% of the $2.8 trillion hedge fund industry (Georgopoulou & Wang, 2016). These funds typically trade futures contracts on assets in various asset classes (equity indices, commodities, government bonds and foreign exchange rates) and profit from systematic price trends by means of time series momentum strategies (Baltas & Kosowski, 2015). Simultaneously, hedge fund managers also have experienced severe equity drawdowns of the time series momentum strategy for many times.

Panel A in Figure 1 depicts the cumulative gains of the time series momentum (TSM) strategy with 30 days looking back period and the buy and hold (BAH) strategy investment on the equally weighted index which is constructed from daily return of 31 commodities futures contracts that traded in the Chinese futures markets during Feb. 16, 2007 to Nov. 30, 2018.[1] We use the equity curve of the BAH strategy investment to reveal the price dynamics for continuous main contracts of individual commodity, because the raw price process probably has jumps when the maturity of contemporary main contract changes. It shows that the highest profit that you would achieve nearly 6 RMB if investing 1 RMB on the equally weighted index following TSM

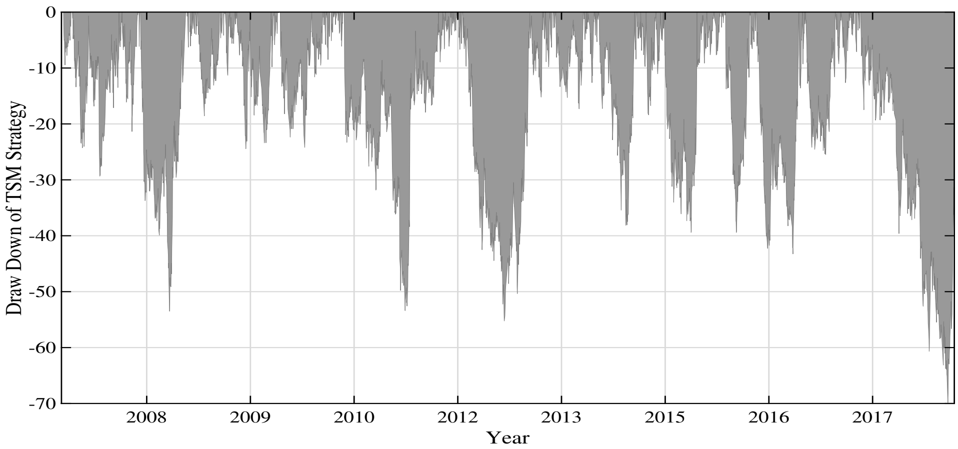
[1]Our data of the constructed equally weighted index starts from 2007, thus we document its performance of time series momentum from Feburary 16, 2007.

strategy since 2007. Simultaneously, there are at least 8 times sharply drawdowns which are over 30% take place during these years. Panel B in Figure 1 gives the drawdowns of TSM strategy investment equity curve on equally weighted index in Panel A. By comparing those two lines in Panel A, we discover that the time series momentum losses occur during the price dynamic states of strong rebounds (e.g., year of 2016) and gradual rebounds (e.g., years of 2012, 2015) following a downtrend market, strong reversals (e.g., years of 2008, 2016) and gradual reversals (e.g., year of 2010) following a uptrend market, and sideways market (e.g., years of 2017 and 2018).

Figure 1: **Time Series Momentum Strategy Investment**



(a) Panel A: Cumulative gains from TSM investment on equally weighted index, Feburary 16, 2007-November 30, 2018



(b) Panel B: Draw Downs of TSM investment on equally weighted index, Feburary 16, 2007-November 30, 2018

Similarly with the cross-sectional momentum crash which has been proposed by Daniel & Moskowitz (2016), time series momentum exhibits deep and persistent drawdowns. As far as we can observe, time series momentum tend to lose during stressed time of reversals in uptrend market, rebounds in downtrend market and sideways market, because of overestimating trend continuation when the trend state of asset price has changed. Recent studies on time series momentum and trend following strategies start to focus on the underperformance of CTAs in asset management industry. Importantly, Baltas & Kosowski (2013) mention that recently poor performance of CTAs are possibly because of capacity constraints. However, their final results demonstrate that there are no significant capacity constraints on time series momentum strategies. Moreover, Georgopoulou & Wang (2016) investigate the correlations across all equity and commodity indices with respect to pre-QE, at-QE and post-QE periods and suggest that it is the market interventions by central banks in recent years challenge the performance of time series momentum portfolios.

From the perspective of endogenous mechanism decomposing time series momentum return as two separated components: trading signal and allocating weight, we maintain that the lack of risk managing in terms of trading signal component is responsible for its poor performance. This paper documents an implementable systematic rule-based approcach which use the upper and lower partial moments of univariate asset return aiming to mitigate the time series momentum losses by controlling risk exposure on wrong trading signals. Our research on the original time series momentum find that the states of reversals in uptrend and rebounds in downtrend can be partly forecasted by the upper and lower partial moments statistics of univarite asset return. Therefore, we suggest a systematic approach which enables time series momentum traders to better capture the trends in assets price and timely avoid huge losses during time series momemtum stressed period by managing original TSM trading signals under different conditions of upper and lower partial moments statistics based on their boundaries. Related definitions about the Upper Partial Moments and Lower Partial Moments statistics are presented later in section 3. This systematic approach can be seen as a more flexible version of TSM (time series momentum) strategy and we simply refer to as an augmented-TSM (ATSM) strategy. Catching all possible profits and avoiding all possible losses of time series momentum in the long run will be the perfect consequence of our ATSM strategy.

Our studies on the time series momentum losses are fundamentally based on the works of Moskowitz et al. (2012), Gulen & Petkova (2015), Daniel & Moskowitz (2016) and Gao et al. (2017). These previous studies inspired us to explore the absolute strength and inferred state of asset price trend when facing recently poor performance of time series momentum strategy. The results and methods that they mentioned in their papers turn out to be helpful and effective in mitigating the time series momentum losses as well.

First of all, we examine the relevance and effectiveness between the risk measurement by partial moments in weekly horizon over daily returns and the trend continuation during time series momentum losses. One possible reason for excess kurtosis is time-varying risk (see, for example, Engle (1982) and Bollerslev (1987)).[2] 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) explore an estimator of momentum risk to scale the exposure to the momentum strategy in order to have constant risk over time. Importantly, partial moments have been proved useful in replacing complete moments whenever only a subset of the set of values of a random variable is of interest, see more in Winkler et al. (1972) and Price et al. (1982). Time series momentum strategy keeps holding the long (short) exposure in an upward (downward) trend. Thererfore, it is of great significance to monitor the concurrent backward side risk of time series momentum long/short positions. Numerous studies have discussed the role of risk measurement of lower partial moments (LPM) in the field of portfolio optimization and asset pricing model (Bawa & Lindenberg, 1977; Harlow & Rao, 1989; Anthonisz, 2012). Liu & O'Neill (2018) suggests lower partial moments (LPM) volatility can better capture potential downside threats and therefore be a better proxy for equity risk than the VIX. Additionally, Gao et al. (2017) document better performance of cross-sectional momentum than Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) by remodeling risk using the method of upper and lower partial moments. This strongly demonstrate that partial moments statistics can deliver more useful information for indicating the latent risk of portfolios.

Secondly, our work use the extreme value of upper and lower partial moments statistics to capture the stressed time of time series momentum strategy. To illustrate the idea behind further, we point out that it must be an strong opposite strength to stop the price momentum continuing its trend and then results in time series momentum lossing.[3] Follow Gulen & Petkova (2015), the ATSM long/short portfolio breakpoints are recursively determined by the historical distribution of weekly realized upper and lower partial moments across time for every individual

[2]Regarding the crashes of cross-sectional momentum, a popular explanation is the time-varying risk (Kothari & Shanken, 1992; Grundy & Martin, 2001; Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016).

[3]From the Newtons First Law of Motion: Every object persists in its state of rest or uniform motion in a straight line unless it is compelled to change that state by forces impressed on it.

future contract. Unsurprisingly, the historical distribution also yields stable breakpoints for the long (short) portfolios in ATSM strategy. We find that extreme value of partial moment statistics can rapidly capture the information of these stressful resistance toward asset price trends, also can be regarded as the winner of a tug of war between strength that pushing price up and strength that pulling price down in market, which contained in very recent asset returns and behave like headwinds of time series momentum losses. Therefore, it turns out to be an indicator of time series momentum life cycle, partly forecasting the state of reversals in the uptrend of assets price and the state of rebounds in the downtrend of assets price.

Last but not the least, we enhance the TSM strategy by using the information of upper and lower partial moments in order to improve the TSM trading signals in different states of price trend. Daniel & Moskowitz (2016) have shown the evidence that the cross-sectional momentum crashes are partly forecastable since they often occur in some panic market states, following market declines and when market volatility is high, and are contemporaneous with market rebounds. As is known to all that the original TSM strategy gives long/short signals simply according to the sign of individual asset cumulative return over certain lookback interval. However, more recently findings of studies on the field of optimal stopping problem which assuming the asset price follows a continuous-time diffusion process with stochastic trend suggest more complicated buy&sell strategy if your goal is maximizing expected future wealth (see more details in Dayanik & Karatzas (2003), Di Guilmi et al. (2014), He & Li (2015), Li & Liu (2017), He et al. (2018)). In section 6, we show that our ATSM strategies which consider the long/short signal in different market states as a function of two ex ante arguments (upper and lower partial moments) which outputs at least four possible signal classifications can outerperform the original TSM strategy.

The rest of this paper is organized as follows. Section 2 describes the data set we used and the Chinese futures market. Section 3 gives some definitions and measures the conditional upper and lower partial moments in time series momentum losses and assesses to what extent these losses are predictable based on these insights. Section 4 compares the performance of original TSM strategy with augmented-TSM strategies and explores the relationship between the time series momentum losses and its trading signals. Section 5 proposes the hypothesis of time series momentum life cycle. Section 6 reports our conclusions.

2. Data

Importantly, according to the report from the World Federation of Exchanges (WFE), the Chinese commodity futures market, which consists of three Exchanges in Shanghai, Dalian and

Zhengzhou, has the largest trading volume across the globel in recent years (Yang et al., 2018). Until year of 2017, the Shanghai Futures Exchange (SHFE) ranked the first place with the biggest trading volume among commodity futures exchanges all over the world. Meanwhile, the Dalian Commodity Exchange (DCE) and the Zhengzhou Commodity Exchange (CZCE) took the third and fourth place, repectively. Therefore, it is of great significance for both financial academics and professional international traders to explore a unique dataset from the Chinese commodity futures markets and fullfill the limitation of research on better understanding of various trading strategies across the global major commodity markets. Previous literatures have documented the emerging dependence structure between the rapidly growing Chinese commodity industry and the global commodity market (Fung et al., 2013; Li & Hayes, 2017). And, Yang et al. (2018) has examined the cross-sectional momentum and reversal strategies at difference trading frequencies for the Chinese commodity futures markets dataset.

2.1. Data Sample

Our data sample for backtesting contains the daily return of the main contract (the contract which has the biggest open interest for each commodity) of 31 commodity futures in the Chinese futures markets from Jan., 2007 to Nov., 2018, constrained by incomplete market trading mechanism. In order to make sure that our empirical results can be tracked and implemented in real assets management industry, the choosen contracts should satisfy some certain conditions which are able to ensure these contracts have better liquidity than others. The starting date of our data sample for individual futures contract are reported in Table 1. More market information for contracts with high trading volume in the Chinese futures market can be found in Yang et al. (2018).

We collect these data with trading information via WIND database. Following convention and availability, all prices are closing prices, and all returns are calculated by taking logarithm from close to close.

2.2. The Chinese Futures Market

The futures market, which acts as a price discovery and risk management center, plays an important role in stabilizing the operation of the market economy. China's futures markets began to sprout as early as the late Qing Dynasty, and experienced a period of rapid development during the Republic of China (see Xing (2018)). Until the year of 1998, the government restructures

Table 1: **Summary Statistics on Futures Contract**

Exchange	Name	Code	Sector	Data Start Date	Annualized Mean(%)	Annualized Volatility(%)	Skewness	Kurtosis
CFFEX	5-years Treasury	TF	FI	Sep-13	0.38	3.19	-0.03	6.38
	10-years Treasury	T	FI	Mar-15	1.24	4.50	0.00	7.26
	SS50 Index Future	IH	EI	Apr-15	-2.19	27.75	-0.53	11.47
	HS300 Index Future	IF	EI	Apr-10	1.46	26.21	-0.38	9.80
	ZZ500 Index Future	IC	EI	Apr-15	2.86	37.99	-0.79	9.10
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	JJR	Mar-09	-2.60	22.20	-0.04	7.29
	Hot Rolled Coil	HC	JJR	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
CZCE	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	JJR	Apr-11	0.27	28.03	-0.13	6.38
	Coking Coal	JM	JJR	Mar-13	2.34	30.09	-0.11	5.91
	Iron Ore	I	JJR	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

several small commodity future exchanges, thereby laying the three-legged pattern of the existing commodity futures exchanges: SHFE, DCE and CZCE.[4]

Due to some historical reasons, all the metal contracts including gold and silver are traded in the SHFE. Some of the agricultural and industrial contracts are traded in the CZCE. Most of the industrial and energy contracts and other agricultural contracts are traded in the DCE. The China Financial Futures Exchange (CFFEX) was established in 2006, trading the contracts of the stock index futures and the treasury futures, and also stock index option contracts. The summary statistics of those contracts which have better liquidity are shown in Table 1 according to different exchanges.

Besides the overall picture of the Chinese futures markets, we claim two iconic events further which should be considered of great significance with the markets. One thing is that an increasing number of contracts were allowed to be traded not only during the day but also during the night following the step of the contracts of gold and silver for the purpose of enhancing the trading volume and reducing the price shocks since 2013. Night-trading policy is one of a series of reformation policies in the Chinese futures markets. What we emphasize here is that the implemented night-trading rule may lead to a strcutual change of the market micro-structure, thus reshaping the market trading behavior. That is why we test the parameter consistency on seperated sample periods later which are divided by the year 2013. The other thing is the listing of new sector including the contacts of coke, coking coal, iron ore, rebar and hotrolled coil (also called “Black Chain” together). It can be easily observed that the new-listed sector brought huge trading volume into the market from historical data. Meanwhile, it is supposed to be leader of market comovements from the perspective of hedge fund managers. Therefore, it is essential to check robustness of the ATSM strategy performance on the subsample.

3. Methodology

3.1. Upper and Lower Partial Moments

It is widely recognized among both finance academics and practitioners that the volatility of financial market is central to the field of asset pricing, asset allocation, and risk management. And importantly, as we know, it varies over time. Most of what we have learned from burgeoning

[4]SHFE, DCE and CZCE are short for the Shanghai Futures Exchange, Dalian Commodity Exchange and Zhengzhou Commodity Exchange, respectively.

literatures is the estimation of parametric GARCH or stochastic volatility models for the underlying returns depends on specific distributional assumptions. However, the realized volatility approach which based on squared returns over relevant horizon can provide model-free unbiased ex post estimates of actual volatility. More properties of RV and related measures can be found in Andersen et al. (2001), Barndorff-Nielsen & Shephard (2002), and Gao et al. (2017).

For each day, we compute the realized volatility RV_{i,d_t} from daily returns in the previous n trading 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. Then the realized volatility of asset i over day t with horizon n is:

$$\mathrm{RV}_{i,d_t}^{n} = \sum_{j=0}^{n-1} r_{i,d_{t-j}}^{2} \tag{1}$$

Then, we define two statistics: UPM (Upper Partial Moments) and LPM (Lower Partial Moments)

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

and

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

where $I(\cdot)$ is the indicator function.

A widely used measure of downside risk is computed as the average of the squared deviations below a target return. This measure of downside risk is more general than semi-variance which is computed as the average of the squared deviations below the mean return. These two statistics above can be seen as a decomposition of sample realized volatility into upper and lower partial moments of order 2 with truncation at zero in both cases, which we later use for measuring the level of upside risk of a short position and downside risk of a long position in the time series momentum strategy. Naturally, then we have:

$$\mathrm{RV}_{i,d_t}^{n} = \mathrm{UPM}_{i,d_t}^{n} + \mathrm{LPM}_{i,d_t}^{n}$$

Besides the lower partial moments, we propose an effective risk predictor with both UPM and LPM statistics over recent 5 trading days (weekly horizon) to capture time series momentum losses during stressed time of uptrend reversals, downtrend rebounds and sideways market, thus reducing false long or short signal exposure in fluctuant markets. We suggest that the Upper Partial moments should be equally weighted with the lower partial moments in risk management of TSM strategy, in order to manage the risk of a short and long position simultaneously. The horizon of 5 trading days comes from one week window in calendar day which is high-valued among investment practitioners, not only in terms of institutional investors, but also individual investors.

Since the long/short signal in time series momentum only depends on individual asset return regardless of other assets within portfolio, therefore, the results we reported in this section and following section are based on the equally weighted index (EWI) which is constructed based on the more than 10 years daily returns of 31 commodities futures contracts that traded in the Chinese futures markets. Table 2 presents the discriptive statistics about RV, UPM and LPM of equally weighted index logarithm return data in the case of n = 5. It can be seen from Table 2 that the distribution of UPM and LPM statistics when n = 5 are both positive skewed (UPM, 2.98; LPM, 4.85) and have excess kurtosis (UPM, 14.11; LPM, 37.34).

Table 2: **Descriptive Statistics of RV, UPM and LPM of Equal Weighted Index**

Variables	Mean	Median	Max	10th Percentile	25th Percentile	75th Percentile	90th Percentile	Standard Deviation	Skewness	Kurtosis	Numer of Observations
RV	3.96	2.44	52.98	0.65	1.29	4.55	8.84	4.87	3.48	20.35	2894
UPM	1.80	0.95	18.47	0.07	0.32	2.23	4.41	2.50	2.98	14.11	2894
LPM	2.16	0.95	52.98	0.06	0.31	2.29	5.33	3.84	4.85	37.34	2894

This table presents the distributions of daily realized volatility (RV), upper and lower partial moments (UPM, LPM) over 5 days horizon throughout the whole sample period from January 2007 to November 2018. Mean, median, max, standard deviation, skewness, kurtosis, number of observations and every 10th percentile value are reported. Values of all percentiles, medians, means, and standard deviations are in 0.0001.

3.2. Time Series Momentum Losses

In this subsection, we pick out and list the 34 worst daily TSM strategy returns in Table 3. Statistics shown in Table 3 present detailed data behind time series momentum losses. Firstly, these 34 worst returns cover all trading days that TSM strategy on EWI loses over 6% per day. Secondly, the time series momentum losses are in an uptrend signal with proportion of nearly 2/3 and a downtrend signal with more than 1/3 by counting $Sign_{d_t}^{tsm}$ on these listed lossing dates. However, more negative TSM strategy returns draw a half and half up-down signals picture when relaxing the benchmark to -4%, as shown in Figure 3. This is consistent with previous observations from Figure 2 that time series momentum losses in both uptrend market and downtrend market without significant preference owing to the stochastic property of long/short signal that generated from past returns. Thirdly, the 5-days cumulative returns that following the lossing date show an opposite tendency when compared with the holding position on lossing date in most cases, regardless of the size of these following 5-days cumulative returns. Big size implies following strong market reversals or rebounds, while small size implies gradual market reversals or rebounds and potential sideways market. Until this, we intuitively and statistically show that the time series momentum losses tend to occur in the stressed state of uptrend reversals, downtrend rebounds and sideways market.

Table 3: **Worst Daily Time Series Momentum Return**

Date	$\mathrm{Sign}^{\mathrm{tsm}}_{\mathrm{d_t}}$	$\mathrm{Ret}^{\mathrm{tsm}}_{\mathrm{d_t}}$	$\mathrm{Ret}_{\mathrm{d_{t+1}},\mathrm{d_{t+5}}}$	Date	$\mathrm{Sign}^{\mathrm{tsm}}_{\mathrm{d_t}}$	$\mathrm{Ret}^{\mathrm{tsm}}_{\mathrm{d_t}}$	$\mathrm{Ret}_{\mathrm{d_{t+1}},\mathrm{d_{t+5}}}$
19-Jun-2018	1	-11.62	0.46	22-Oct-2007	1	-7.07	1.45
05-Aug-2011	1	-10.40	0.53	21-Jun-2010	-1	-6.99	-1.68
14-Nov-2016	1	-9.11	1.93	19-Apr-2010	1	-6.93	0.29
13-Dec-2013	1	-8.92	-1.01	08-Oct-2018	-1	-6.80	0.35
09-Jul-2015	-1	-8.59	-0.11	08-Mar-2011	1	-6.62	-2.41
07-Dec-2017	1	-8.30	0.78	24-Nov-2015	-1	-6.59	2.00
27-Nov-2009	1	-8.30	3.87	13-May-2011	-1	-6.31	-1.06
22-Jan-2008	1	-8.23	2.82	20-May-2015	1	-6.28	0.71
12-Nov-2010	1	-8.17	-5.52	20-Jul-2007	-1	-6.24	0.66
17-Aug-2007	1	-8.15	2.35	17-Nov-2010	1	-6.23	-0.04
13-Jan-2010	1	-7.98	0.85	18-Aug-2008	-1	-6.18	-0.32
18-Feb-2013	1	-7.88	-2.91	26-Feb-2008	1	-6.15	3.07
20-Jun-2014	-1	-7.63	0.33	13-Jul-2011	-1	-6.12	0.59
21-Feb-2013	1	-7.52	-1.54	22-Apr-2016	1	-6.08	-0.72
17-Aug-2009	1	-7.46	0.63	27-Jun-2011	1	-6.07	2.66
23-Jul-2012	1	-7.40	0.32	20-Aug-2010	1	-6.03	1.92
18-Mar-2008	1	-7.35	-0.87	23-May-2016	1	-6.02	2.07

This table lists the 34 worst daily returns to the original TSM strategy ($Ret^{tsm}_{d_t}$) with 30 days looking back period of equally weighted index over Feburary 16, 2007 to November 30, 2018. Also tabulated are $Sign^{tsm}_{d_t}$, the sign of position (1 for long and -1 for short) that the TSM strategy holds in the same date, and $Ret_{d_{t+1},d_{t+5}}$, the 5-days cumulative return of individual asset following the lossing date. All numbers in the table are in percent.

Consider the time series momentum return in Moskowitz et al. (2012), constructing a one-period holding time series momentum portfolio on the basis of recently J days (looking back period: J; holding period: $K = 1$), the cumulative return for each univarite sucurity i:

$$r^{tsm}_{i,d_{t+1}} = sign\Big(\sum_{j=0}^{J} r_{i,d_{t-j}}\Big)\frac{\sigma_{target}}{\sigma_{i,d_t}} r^{i}_{i,d_{t+1}} \tag{4}$$

Decomposing time series momentum return into two separated components: trading signal

$sign\Big(\sum_{j=0}^{J} r_{i,d_{t-j}}\Big)$ and allocating weight $\frac{\sigma_{target}}{\sigma_{i,d_t}}$, Table 4 reports related statistics of the two components for each group that sorted by time series momentum return on the equally weighted index with different looking back periods. For every looking back periods, the average allocating weight of P1 group which has the largest TSM returns and P10 group which has the samllest TSM returns do not show any significant difference. Therefore, we have the hypothesis that it is the wrong trading signals that probably result in time series momentum losses.

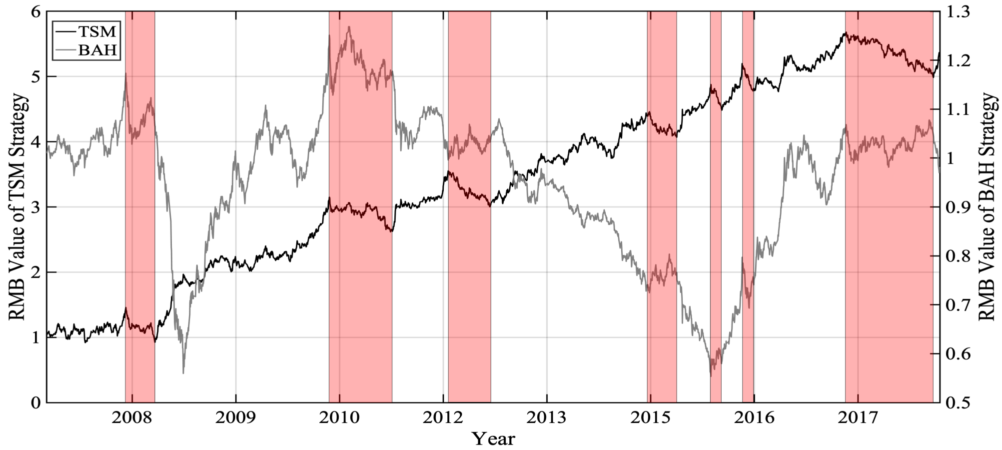
Moreover, the bar chart of Panel B in Figure 2 describes the changes of time-varying UPM and LPM statistics from Feburary 16, 2007-November 30, 2018. The UPM and LPM are calculated in every day d_t over weekly window (recent 5 trading day returns including day d_t) from Eq. 2 and Eq. 3. When putting Panel A and B together, it is not hard to observe that the relative difference between UPM and LPM are probably correlated to the time series momentum losses. Furthermore, we find that both UPM and LPM statistics during losses not only show volatility-clustering-like property in time series from Panel B of Figure 2, but also are clustering distributed in quantile level from Figure 4. Figure 5 shows a overall picture of joint distribution of UPM and LPM in the lossing period with respect to whole sample. Interestingly, the joint-distribution of UPM and LPM during losses printed in Figure 6 show that most lossing points with a long/short position (uptrend/downtrend signal) are located in the northwestern/southeastern part if we divide all points into four parts according to the 70^{th} quantile of UPM and the 80^{th} quantile of LPM.

Table 4: **Ten groups sorted by daily time series momentum return of equally weighted index**

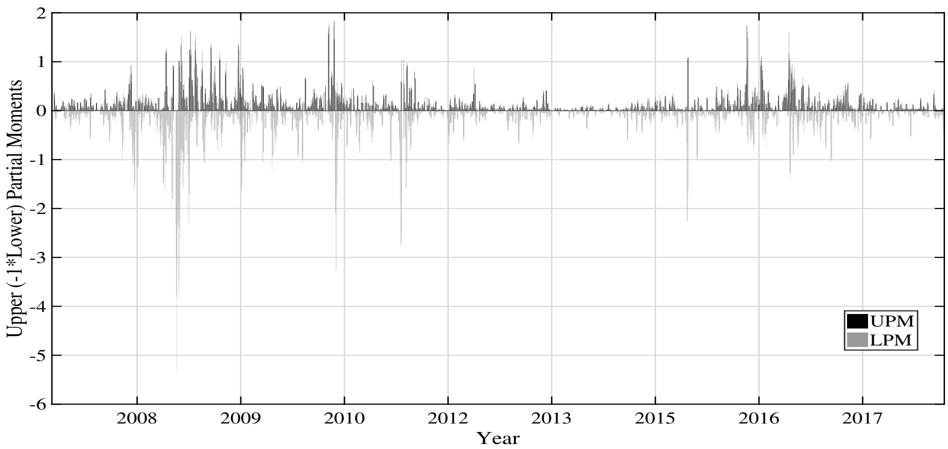
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
					Looking Back Period: 20 (days)					
AR	0.0534	0.0288	0.0185	0.0108	0.0041	-0.0021	-0.0083	-0.0153	-0.0249	-0.0455
AW	3.75	3.59	3.64	3.45	3.64	3.68	3.38	3.59	3.58	3.70
CS-Ratio	1	1	1	1	1	0.11	0	0	0	0
					Looking Back Period: 30 (days)					
	0.0516	0.0278	0.0176	0.0103	0.0041	-0.0019	-0.0081	-0.0151	-0.0245	-0.0447
AW	3.63	3.42	3.50	3.34	3.47	3.60	3.34	3.40	3.52	3.53
CS-Ratio	1	1	1	1	1	0.16	0	0	0	0
					Looking Back Period: 40 (days)					
AR	0.0506	0.0272	0.0175	0.0106	0.0046	-0.0014	-0.0074	-0.0145	-0.0242	-0.0444
AW	3.53	3.42	3.34	3.29	3.33	3.53	3.39	3.33	3.40	3.46
CS-Ratio	1	1	1	1	1	0.22	0	0	0	0
					Looking Back Period: 60 (days)					
AR	0.0496	0.0261	0.0162	0.0093	0.0034	-0.0023	-0.0084	-0.0153	-0.0244	-0.0442
AW	3.41	3.37	3.27	3.24	3.31	3.42	3.28	3.21	3.33	3.30
CS-Ratio	1	1	1	1	1	0.06	0	0	0	0
					Looking Back Period: 90 (days)					
AR	0.0494	0.0258	0.0164	0.0097	0.0040	-0.0018	-0.0074	-0.0144	-0.0237	-0.0436
AW	3.31	3.24	3.13	3.23	3.15	3.39	3.17	3.20	3.26	3.26
CS-Ratio	1	1	1	1	1	0.12	0	0	0	0
					Looking Back Period: 120 (days)					
AR	0.0486	0.0254	0.0163	0.0093	0.0034	-0.0022	-0.0077	-0.0142	-0.0234	-0.0442
AW	3.31	3.18	3.09	3.18	3.11	3.30	3.19	3.10	3.18	3.15
CS-Ratio	1	1	1	1	1	0.03	0	0	0	0
					Looking Back Period: 250 (days)					
AR	0.0470	0.0245	0.0157	0.0095	0.0041	-0.0013	-0.0067	-0.0136	-0.0228	-0.0461
AW	3.11	3.06	3.02	3.02	3.02	3.15	3.06	3.01	2.99	3.02
CS-Ratio	1	1	1	1	1	0.24	0	0	0	0

Note: Statistics including Average Return (AR) of TSM strategy, Allocating Weight (AW, taking average value over allocating weight componet: $\frac{\sigma_{target}}{\sigma_{i,d_t}}$) and Correct Signal Ratio (CS-Ratio, the ratio of number of days which has correct trading signals and total days) for each group are tabulated.

Figure 2: **Time Series Momentum Losses and Partial Moments**



(a) Panel A: Cumulative gains from TSM investment on equally weighted index, Feburary 16, 2007-November 30, 2018



(b) Panel B: Dynamics of UPM and LPM from daily return of equally weighted index, Feburary 16, 2007-November 30, 2018

Figure 3: **Daily TSM Return vs. Raw Return of Equally Weighted Index in Whole Sample and Lossing Period**

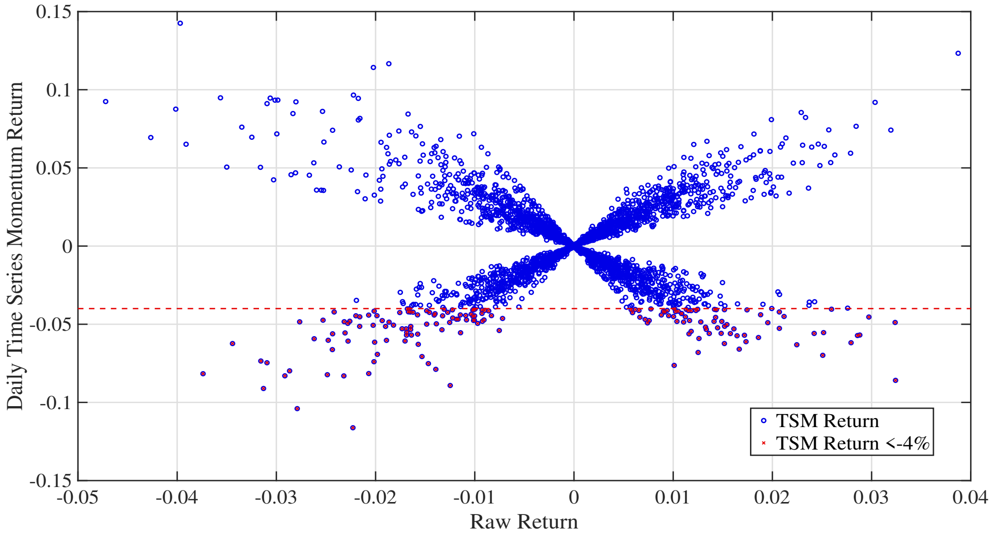
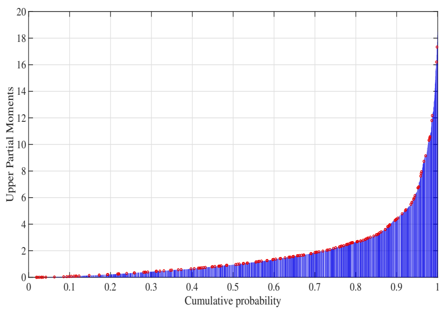
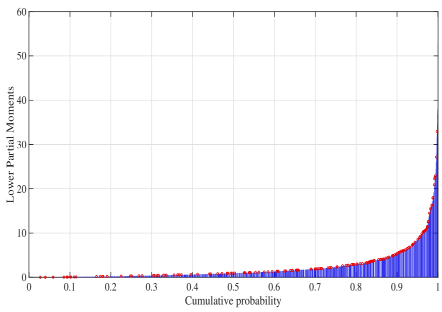


Figure 4: **The Location of Lossing Points (Daily TSM Return $< -4\%$) in Cumulative Distribution of UPM and LPM**



(a) UPM



(b) LPM

Figure 5: **The Joint Distribution of UPM vs. LPM in Whole Sample and Lossing Period (Daily TSM Return $< -4\%$)**

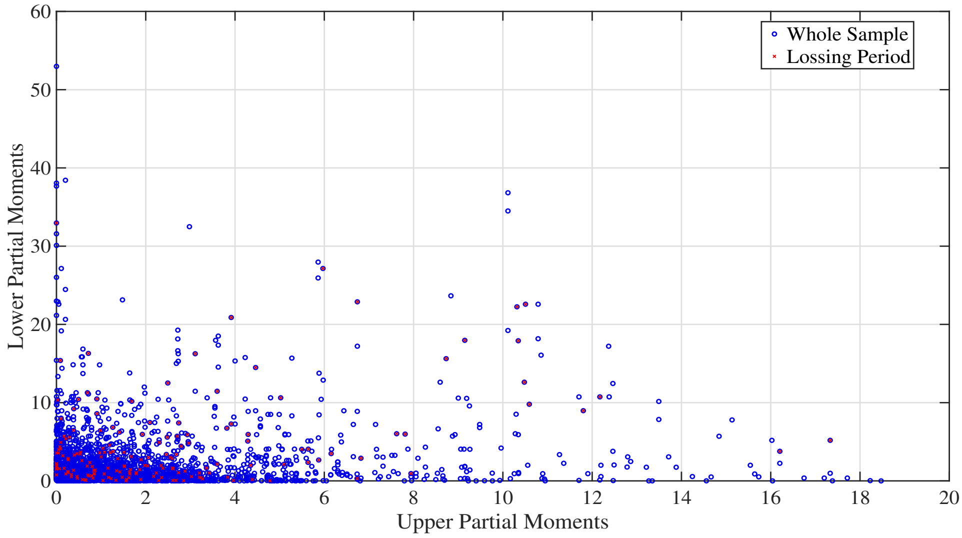
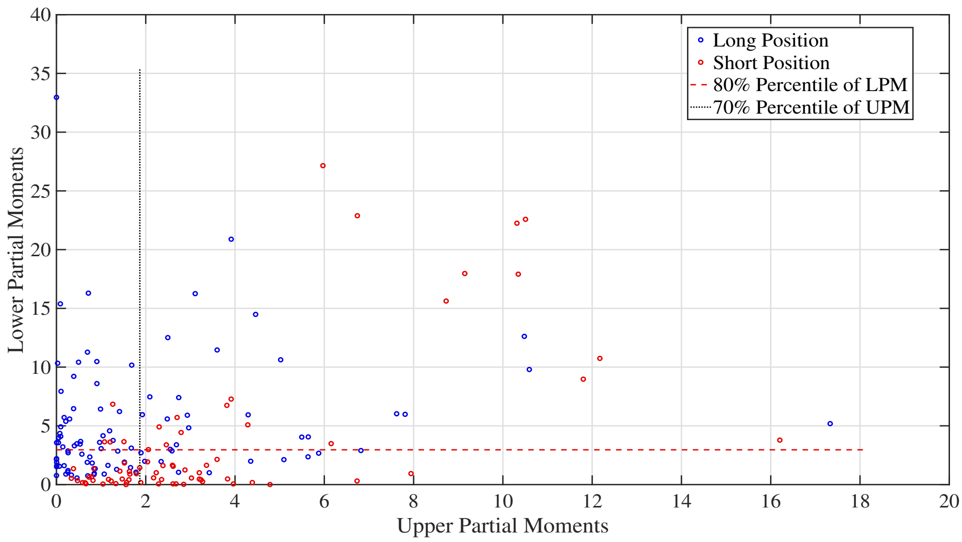


Figure 6: **The Joint Distribution of UPM vs. LPM for Long and Short Position in Losses (Daily TSM Return $< -4\%$)**



3.3. Price Trend States and Partial Moments

Supporting evidence for the relevance of higher-moment effects on time series momentum is given by Johnson (2002), who explore the connection between realized trends and changes in volatility and conclude that finite-horizon skewness behaves like a lagged momentum indicator.[5] Moreover, Müller et al. (1997) provide 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. On the basis of these studies, we build our frequency changing analytical approach aiming to investigate the implied dynamics of higher-moments in univariate asset return series and model the implied states structure of time series momentum.

In this subsection, we show that the return of univariate asset is highly correlated with its weekly horizon estimated risk characteristics (i.e., ex ante UPM and LPM) in varing price trend states that derived from time series momentum. Using a set of forward equation regressions (Eq. 5), we first find that the UPM and LPM statistics have statistically significant predictable pattern with next period univariate return for not only the equally weighted index but also each commodity future contracts. Furthermore, this lead-lag effect relationship is significantly stronger (larger absolute value of estimated coefficient) for both a next period falling day in uptrend market than the normal days which has upward trend signal and a next period rising day in downtrend market than the normal days which has downward trend signal. In addition, this lead-lag effect show asymmetric property for UPM and LPM under different price trend processes. The UPM contributes more in downward price trend than in upward trend ($|\beta_D^+ + \beta_{D,R}^+| > |\beta_U^+ + \beta_{U,F}^+|$). However, the LPM contributes more in upward price trend than in downward trend ($|\beta_U^- + \beta_{U,F}^-| > |\beta_D^- + \beta_{D,R}^-|$). Both of these results indicate that, it is of great importance to managing the risk of time series momentum portfolio when the UPM (LPM) statistics of individual asset is relatively high in downward (upward) trend. Especially, the larger absolute value of estimated coefficients for the interaction terms require additional attention on UPM and LPM statistics in these price trend states.

We then illustrate these issues with a set of daily time series regressions on univariate return series of 31 commodities futures contracts and an equally weighted index that constructed based

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

on those commodities futures contracts returns, the results of which are presented in Table 5 for the index (EWI) and commodities that classified into sectors of Met and JJR, and in Table 6 for commodities that classified into sectors of IND and AGI.[6] The dependent variable in all regressions is $\widetilde{r}_{i,d_{t+1}}$, the individual asset return in day d_{t+1}. The independent variables are combinations of:

- UPM_{i,d_t}, the ex ante upper partial moments statistics in day d_t;
- LPM_{i,d_t}, the ex ante lower partial moments statistics in day d_t;
- I_U, an ex ante uptrend market indicator that equals one if the cumulative return of recent 30 days (including day d_t) is positive (that is, long signal for d_{t+1} which is derived from time series momentum) and is zero otherwise.
- I_D, an ex ante downtrend market indicator that equals one if the cumulative return of recent 30 days (including day d_t) is negative (that is, short signal for d_{t+1} which is derived from time series momentum) and is zero otherwise.
- $\widetilde{I}_F$, a contemporaneous, i.e., not ex ante, falling day indicator variable that is one if the individual 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 individual asset return is greater than zero ($r_{i,d_{t+1}} \geq 0$), and is zero otherwise.

Regressions results in Table 5 and Table 6 fit a conditional model (Eq. 5) that allows us to assess the extent to which the predictable pattern of both UPM and LPM statistics on individual asset return differs simultaneously under uptrend and downtrend market conditions, with the upward and downward trend indicators, I_U and I_D, as instruments. Furthermore, using the falling and rising day indicators, $\widetilde{I}_F$ and $\widetilde{I}_R$, allows us to examine the effectiveness under the price trend states of falling days in upward trend and rising days in downward trend, with the interaction terms, $I_U \cdot \widetilde{I}_F$ and $I_D \cdot \widetilde{I}_R$, as instruments. Our model specification are similar to that used by Daniel & Moskowitz (2016) to assess market timing results of cross-sectional WML

[6]Give the related literature of sector classification.

portfolios.

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} &= \alpha + \left[(\beta_U^+ I_U + \beta_{U,F}^+ I_U \cdot \widetilde{I}_F) + (\beta_D^+ I_D + \beta_{D,R}^+ I_D \cdot \widetilde{I}_R)\right] UPM_{i,d_t} \\ &+ \left[(\beta_U^- I_U + \beta_{U,F}^- I_U \cdot \widetilde{I}_F) + (\beta_D^- I_D + \beta_{D,R}^- I_D \cdot \widetilde{I}_R)\right] LPM_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}}\end{aligned} \tag{5}$$

Acturally, the conditional model above (Eq. 5) can be regarded as a combined simultaneous version of following two regressions which consider the situation of upward trend (Eq. 6) and downward trend (Eq. 7) seperately:

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} &= \alpha + (\beta_0^+ + \beta_U^+ I_U + \beta_{U,F}^+ I_U \cdot \widetilde{I}_F) UPM_{i,d_t} \\ &+ (\beta_0^- + \beta_U^- I_U + \beta_{U,F}^- I_U \cdot \widetilde{I}_F) LPM_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}}\end{aligned} \tag{6}$$

and

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} &= \alpha + (\beta_0^+ + \beta_D^+ I_D + \beta_{D,R}^+ I_D \cdot \widetilde{I}_R) UPM_{i,d_t} \\ &+ (\beta_0^- + \beta_D^- I_D + \beta_{D,R}^- I_D \cdot \widetilde{I}_R) LPM_{i,d_t} + \widetilde{\epsilon}_{i,d_{t+1}}\end{aligned} \tag{7}$$

Interestingly, all coefficients which are conditional on single indicator terms and interaction terms that shown in Table 5 and Table 6 are statistically significant. Although there exists low signal-to-noise ratio issue in asset return which has been widely accepted by both academics and practioners, our results tabulated not only give significant t-statistics in terms of coefficient estimating but also report high adjusted R^2 in terms of model fitting (i.e., 0.4184 of R^2_{adj} for the case of EWI). To make sure the fitted residuals from our time-series regression do not have heteroscedasticity and serial autocorrelation, we use the approach of Newey-West estimation, which is known as an heteroscedasticity-autocorrelation-consistent (HAC) estimator, for our fitted time-series models. See more details in (White, 1980; MacKinnon & White, 1985; West & Newey, 1987).

To illustrate our regression results in detail, we take the case of EWI (Panel A in Table 5) as an example. The fitted results from each of the 31 commodities futures cantracts returns have the similar pattern. On the one hand, estimated $\hat{\beta}_{U,F}^+$ of -24.4899 and $\hat{\beta}_{U,F}^-$ of -17.2539 for UPM and LPM is larger than estimated $\hat{\beta}_U^+ + \hat{\beta}_{U,F}^+$ = -10.5397 and $\hat{\beta}_U^- + \hat{\beta}_{U,F}^-$ = -9.7551 in absolute value, repectively. Meanwhile, the estimated coefficients of interaction terms ($\hat{\beta}_{D,R}^+ =$ 20.2007, $\hat{\beta}_{D,R}^- = 14.7061$) show similar results with repect to ($\hat{\beta}_D^+ + \hat{\beta}_{D,R}^+ = 9.3770$, $\hat{\beta}_D^- + \hat{\beta}_{D,R}^- =$ 7.8941). These results imply that larger increment in UPM or LPM will potentially contribute more negative future time series momentum return, i.e., future negative asset return in uptrend and future positive return in downtrend. That is one of the reasons why we choose to implement risk management measures on time series momentum when the UPM or LPM has large values.

On the other hand, larger absolute value of estimated coefficients for LPM under uptrend state ($\hat{\beta}_U^- + \hat{\beta}_{U,F}^-$ = -9.7551) than under downtrend state ($\hat{\beta}_D^- + \hat{\beta}_{D,R}^-$ = 7.8941) demonstrates the importance of monitoring the change of LPM in upward trend. However, for UPM, the case of EWI seems like an exception. Nevertheless, in the cases of most individual commodities, the absolute value of estimated coefficients for UPM under downtrend state ($\left|\hat{\beta}_D^+ + \hat{\beta}_{D,R}^+\right|$) is larger than under uptrend state ($\left|\hat{\beta}_U^+ + \hat{\beta}_{U,F}^+\right|$), indicating that increments in UPM are a larger potential threat towards time series momentum profits in downward trend.

To summarize briefly, it is of great significance to protect the time series momentum profits by implementing risk managment measures when the value of UPM or LPM statistics of individual asset is in relative high level and especially when the UPM (LPM) is relatively high in downward (upward) trend.

Table 5: **Trend Timing Regression Results**

Heteroskedasticity and Autocorrelation Consistent Estimator

(t-statistics in parentheses)

Variable	1	$I_U \cdot UPM_{i,d_t}$	$I_U \cdot \widetilde{I}_F \cdot UPM_{i,d_t}$	$I_D \cdot UPM_{i,d_t}$	$I_D \cdot \widetilde{I}_R \cdot UPM_{i,d_t}$	$I_U \cdot LPM_{i,d_t}$	$I_U \cdot \widetilde{I}_F \cdot LPM_{i,d_t}$	$I_D \cdot LPM_{i,d_t}$	$I_D \cdot \widetilde{I}_R \cdot LPM_{i,d_t}$	R^2_{adj}
Coeff.	$\hat{\alpha}$	$\hat{\beta}_U^+$	$\hat{\beta}_{U,F}^+$	$\hat{\beta}_D^+$	$\hat{\beta}_{D,R}^+$	$\hat{\beta}_U^-$	$\hat{\beta}_{U,F}^-$	$\hat{\beta}_D^-$	$\hat{\beta}_{D,R}^-$	
Panel A: Index										
EWI	-0.0003	13.9502	-24.4899	-10.8237	20.2007	7.4988	-17.2539	-6.8120	14.7061	0.4184
	(-1.46)	(9.82)	(-13.23)	(-5.64)	(6.23)	(5.38)	(-9.24)	(-7.33)	(9.61)	
Panel B: Met Sector										
AU	0.0001	6.7568	-13.5593	-5.2113	10.7469	5.8412	-12.9653	-5.0402	8.6365	0.3165
	(0.53)	(6.11)	(-7.80)	(-2.78)	(3.77)	(4.13)	(-6.16)	(-4.54)	(4.85)	
AG	-0.0007	6.1873	-10.5592	-6.0566	9.2473	6.9430	-11.4556	-2.6017	6.3379	0.2380
	(-2.00)	(7.93)	(-12.12)	(-4.26)	(3.69)	(5.73)	(-6.69)	(-4.20)	(4.65)	
CU	-0.0001	5.6091	-10.5817	-4.4649	10.5009	4.4880	-9.8178	-5.4582	9.7108	0.4180
	(-0.53)	(7.91)	(-13.29)	(-3.99)	(6.18)	(6.55)	(-9.16)	(-10.81)	(10.26)	
AL	-0.0001	8.0032	-16.2955	-4.8924	9.2494	5.2500	-10.6708	-7.1500	11.9455	0.3693
	(-0.50)	(7.36)	(-10.56)	(-3.42)	(3.93)	(4.61)	(-5.99)	(-8.68)	(9.65)	
NI	-0.0006	7.1479	-12.8180	-4.1721	12.3751	5.9642	-11.3349	-6.2931	10.9176	0.3469
	(-0.66)	(4.92)	(-7.43)	(-2.02)	(4.59)	(5.85)	(-6.32)	(-6.65)	(7.61)	
ZN	0.0001	6.2484	-12.1776	-6.6664	12.2638	4.1360	-9.5809	-5.4955	9.6156	0.4067
	(0.23)	(8.74)	(-14.28)	(-5.20)	(7.68)	(5.41)	(-8.11)	(-11.28)	(12.77)	
Panel C: JJR Sector										
RB	-0.0005	6.2821	-10.6272	-6.5395	13.2106	2.7646	-6.3417	-4.2460	9.1185	0.3501
	(-1.50)	(9.36)	(-13.83)	(-5.32)	(5.34)	(3.43)	(-4.38)	(-4.50)	(6.83)	
HC	0.0002	5.5927	-10.8271	-7.0563	12.1015	3.1192	-5.7682	-4.1400	8.4555	0.3712
	(0.28)	(4.76)	(-7.83)	(-4.25)	(5.54)	(4.04)	(-4.78)	(-3.60)	(5.00)	
J	0.0001	5.0746	-9.9234	-6.7742	12.8236	3.2494	-6.6094	-3.6379	6.2039	0.3738
	(0.20)	(7.04)	(-11.62)	(-5.22)	(6.12)	(5.47)	(-6.19)	(-4.51)	(5.81)	
JM	0.0008	4.3939	-9.5243	-6.8584	12.4244	2.9444	-5.0427	-4.3331	6.8463	0.3981
	(1.41)	(4.53)	(-7.31)	(-5.40)	(7.61)	(3.79)	(-5.16)	(-7.80)	(7.23)	
I	-0.0007	5.0555	-8.6248	-5.5747	11.6078	4.0000	-8.7014	-3.4540	6.8794	0.4064
	(-0.85)	(9.63)	(-14.01)	(-5.36)	(7.80)	(5.50)	(-7.40)	(-5.47)	(7.07)	

Notes: West & Newey (1987) standard errors are employed. The coefficient estimation and R-square are reported, the statistical significance is documented in terms of t-Value.

Table 6: **Trend Timing Regression Results (Table 5 continued)**

Heteroskedasticity and Autocorrelation Consistent Estimator

(t-statistics in parentheses)

Variable	1	$I_U \cdot UPM_{i,d_t}$	$I_U \cdot I_F \cdot UPM_{i,d_t}$	$I_D \cdot UPM_{i,d_t}$	$I_D \cdot \widetilde{I}_R \cdot UPM_{i,d_t}$	$I_U \cdot LPM_{i,d_t}$	$I_U \cdot I_F \cdot LPM_{i,d_t}$	$I_D \cdot LPM_{i,d_t}$	$I_D \cdot \widetilde{I}_R \cdot LPM_{i,d_t}$	R^2_{adj}
Coeff.	$\hat{\alpha}$	$\hat{\beta}^+_U$	$\hat{\beta}^+_{U,F}$	$\hat{\beta}^+_D$	$\hat{\beta}^+_{D,R}$	$\hat{\beta}^-_U$	$\hat{\beta}^-_{U,F}$	$\hat{\beta}^-_D$	$\hat{\beta}^-_{D,R}$	
Panel A: IND Sector										
BU	-0.0004	5.8917	-11.5532	-8.3355	15.3931	3.8547	-6.8739	-4.4716	7.4595	0.3367
	(-0.69)	(4.97)	(-7.23)	(-6.01)	(7.06)	(4.02)	(-2.68)	(-6.73)	(8.90)	
RU	-0.0007	5.2872	-10.2651	-6.2107	11.8034	4.7350	-10.2296	-4.2844	8.2371	0.3964
	(-1.40)	(13.06)	(-15.28)	(-8.41)	(9.90)	(10.35)	(-11.00)	(-12.48)	(14.56)	
TA	-0.0001	7.1634	-13.0617	-8.4770	13.4608	4.2583	-8.1343	-6.1134	11.0564	0.3602
	(-0.23)	(11.78)	(-12.55)	(-6.01)	(6.24)	(3.89)	(-3.00)	(-9.54)	(12.89)	
MA	-0.0006	6.6416	-12.0693	-3.5145	9.6344	8.4068	-13.4418	-6.3045	11.9772	0.3820
	(-0.96)	(8.42)	(-10.76)	(-2.30)	(3.89)	(7.35)	(-8.39)	(-5.97)	(10.50)	
FG	-0.0004	5.5524	-10.9550	-6.7028	13.7390	8.7805	-16.3168	-5.2166	11.8924	0.3261
	(-0.85)	(7.50)	(-9.42)	(-3.81)	(5.33)	(8.58)	(-10.03)	(-6.46)	(8.67)	
ZC	-0.0002	7.1955	-13.5835	-5.0123	12.9999	4.5068	-9.6826	-6.7155	14.5821	0.3820
	(-0.37)	(9.21)	(-10.25)	(-2.41)	(5.68)	(3.59)	(-6.51)	(-2.89)	(3.53)	
PP	-0.0005	7.1331	-12.3234	-3.8326	13.3066	9.9714	-15.6874	-7.4896	13.1729	0.3658
	(-0.84)	(7.23)	(-10.72)	(-2.60)	(5.46)	(7.15)	(-9.40)	(-7.83)	(8.22)	
V	-0.0001	7.7319	-14.2769	-6.4925	12.2071	4.4838	-11.5430	-7.4055	13.5508	0.3306
	(-0.40)	(7.12)	(-8.42)	(-4.33)	(4.56)	(4.24)	(-7.68)	(-9.27)	(12.02)	
L	-0.0002	6.8633	-12.7753	-6.5977	12.0818	5.6844	-10.8819	-4.8476	10.4498	0.4155
	(-0.73)	(9.03)	(-10.62)	(-9.16)	(9.39)	(6.34)	(-8.09)	(-9.99)	(13.64)	
Panel B: AGI Sector										
CF	-0.0001	6.6122	-11.5208	-7.4127	13.7813	3.2066	-8.4787	-6.5463	12.1741	0.3715
	(-0.42)	(10.50)	(-10.56)	(-4.77)	(6.31)	(3.88)	(-5.98)	(-8.22)	(11.93)	
SR	-0.0002	8.7749	-15.7679	-7.1067	15.9450	3.0607	-9.4264	-9.1552	16.3732	0.3764
	(-0.70)	(10.40)	(-15.08)	(-4.01)	(5.73)	(3.25)	(-4.52)	(-10.21)	(12.91)	
RM	0.0008	5.7092	-14.1088	-9.1114	19.7677	4.3109	-9.9016	-8.0509	12.6271	0.3653
	(1.57)	(7.91)	(-12.20)	(-5.75)	(8.29)	(4.14)	(-4.17)	(-6.54)	(8.64)	
OI	-0.0008	10.5184	-18.6033	-9.2691	22.9131	5.6295	-10.4207	-5.8694	13.0673	0.2986
	(-2.71)	(6.72)	(-7.46)	(-3.70)	(6.16)	(2.73)	(-3.00)	(-3.64)	(4.50)	
C	0.0001	7.2307	-15.1111	-14.8738	26.9881	11.4865	-18.1367	-8.3571	14.5066	0.2879
	(0.36)	(4.42)	(-6.99)	(-5.92)	(6.64)	(3.47)	(-4.04)	(-7.95)	(6.57)	
CS	0.0001	7.1615	-14.8108	-9.5015	20.7638	8.3316	-15.6190	-7.7161	13.7799	0.3342
	(0.36)	(4.63)	(-8.34)	(-4.24)	(6.52)	(3.49)	(-5.00)	(-4.15)	(3.91)	
A	0.0001	7.7625	-15.0582	-1.8444	8.5909	6.1432	-15.6562	-7.5074	11.2346	0.3711
	(0.59)	(9.76)	(-13.50)	(-1.07)	(3.97)	(6.25)	(-10.84)	(-12.56)	(10.36)	
M	0.0003	7.3168	-14.3577	-5.2378	10.8364	5.6082	-13.4655	-5.5857	10.9767	0.4010
	(0.98)	(11.59)	(-18.31)	(-3.57)	(4.41)	(6.59)	(-11.24)	(-7.16)	(10.20)	
Y	0.0000	7.2389	-16.3940	-5.6732	11.1155	6.9272	-12.1742	-6.1124	10.5922	0.4294
	(-0.13)	(12.23)	(-17.15)	(-4.25)	(4.67)	(10.17)	(-11.27)	(-7.06)	(9.23)	
P	-0.0003	6.5067	-13.3744	-6.6948	14.4315	6.8161	-12.7023	-6.0551	10.0000	0.4327
	(-1.01)	(9.33)	(-14.61)	(-5.27)	(6.50)	(9.29)	(-12.06)	(-8.89)	(10.02)	
JD	-0.0005	7.6110	-14.4548	-4.9585	9.1023	6.0524	-9.8579	-6.2587	12.8912	0.2786
	(-1.03)	(7.62)	(-11.89)	(-2.51)	(2.65)	(4.21)	(-4.51)	(-6.39)	(7.42)	

4. Augmented Time Series Momentum Strategy

Although the original time series momentum in Moskowitz et al. (2012) show a well-defined weight generating function based on the volatility scaling and risk parity approach in terms of portfolio optimization, the given long/short signals what are regarded as an overhasty choice for individual asset in the portfolio (Kim et al., 2016).[7] Recent study of time series momentum performance prove that it is the changing weight within portfolio not the sign of signals contributes the major part of time series momentum profits (Jusselin et al., 2017).

In previous section, we point out that our ATSM strategy which based on the relationship of trend states and the time series momentum losses can effectively and timely adjust the long/short position on TSM strategy to mitigate huge losses in time series momentum strategy. Seminal work of Daniel & Moskowitz (2016) has examined the relationship between the market states and the cross-sectional momentum crashes. Cooper et al. (2004) have already proved that cross-sectional momentum profits depend on the states of market. Owing to the fundamental difference between cross-sectional momentum and time series momentum, we naturally move our concentration from portfolio asset allocation to the time-series states of univariate asset price process. Interestingly and endogenously, we notice that time series momentum losses occur generally when univariate asset price exhibits dramatic reversals in up-trend market, strong rebounds in down-trend market and sideways market with wrong trading signals. At the mean time, empirical evidence from the Chinese futures markets have reported that the upper and lower partial moments can generate predictable pattern about these trend states. We design a set of systematic rules that changing the original TSM trading signals accroding to different conditions under the joint distribution of UPM and LPM to demonstrate that controlling the risk exposure that originated from high probability of wrong trading signals can mitigate time series momentum losses.

4.1. TSM Strategy Performance

In the front of testing the performance of ATSM approach, we examine the performance of time series momentum strategy in the Chinese futures markets at first using 31 commodities futures contract data from Jan, 2008 to Nov., 2018. According to Moskowitz et al. (2012), we firstly construct a one-period holding time series momentum portfolio on the basis of recently J days (looking back period: J; holding period: $K = 1$) cumulative return of each sucurities. The overall return of the strategy that diversifies across all the securities in S_t that are available at time t is:

$$r^{tsm}_{p,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t} sign\Big(\sum_{j=0}^{J} r_{i,d_{t-j}}\Big)\frac{\sigma_{target}}{\sigma_{i,d_t}} r^{i}_{i,d_{t+1}} \tag{8}$$

[7]Kim et al. (2016) maintain that the time series momentum and a buy-and-hold strategy offer similar cumulative returns without scaling by volatility (or the socalled risk parity approach to asset allocation).

where N_t is the total number of securities in set S_t.

As we mentioned in previous subsection, the change of fundamental market trading rule requires separated tests on subsamples that divided by the year of 2013. Panel A and B of Table 10 reports the performance of varying look-back windows and one-day holding time series momentum strstegy (J = 20, 30, 40, 60, 90, 120, 250 trading days; K = 1 trading day) during the subsample period of Jan., 2008 to Dec., 2012 and Jan., 2013 to Nov., 2018, respectively. Results including statistics of annual return, Sharpe ratio, maximum drawdown and t-statistics for normality test are tabulated with different looking back periods.

Consistent with Moskowitz et al. (2012), the Chinese commodity futures markets show significant time series momentum pattern on daily frequency. There are two stylized facts that can be observed from Table 7. For one thing, concurrently, both two subperiods witness economically and statistically significant profitability of the TSM trading strategies with different looking back periods (J = 20, 30, 40 days). With a wide range of looking back windows that we test, the 20 days[8] looking back time series momentum pattern turns out to be the most strong and profitable strategy achieving more than 36% (3.56) and 19% (3.19) return per year in average during 2008:2012 and 2013:2018, respectively.

For another thing, the existing time series momentum effect disappears when expanding look back window to longer than 40 trading days (roughly 2 calendar months) from Panel A in Table 7, e.g., the annual return of 15.29% by looking back 60 days is not statistically significant with t-statistics 1.72. While the average profit per year with same looking back window of 60 trading days (around a quarter) after 2013 which presented in Panel B is economically and statistically significant positive with 12.72% (2.14). Similar pattern of other looking back periods that longer than 60 are reported, either.

As we mentioned in section 2, assuming that the microstructure of Chinese Futures Market changed after the issue of Night-trading policy, therefore, we examine the existence of time series effect on different subperiods. These two facts observed above confirm previous assumptions. Due to the disappearing of TSM effect over longer horizons, the TSM losses are results proportionally from long time risk exposure with wrong trading signals more than dynamic allocation weights. Moreover, the increasing significant average returns over longer looking back periods indicate that the persistence of price trend is strenghtend over 2013 to 2018. Thus, if we try to capture potential lifecycle of the time series momentum, things are different before and after 2013 which

[8] 20 trading days = almost 1 calendar month.

we illustrate later in section 5.

Table 7: **Time Series Momentum Strategy Performance for Chinese Commodity Futures Markets**

	Looking Back Period (days)						
	20	30	40	60	90	120	250
Panel A: 2008-2012							
Annual Return (%)	36.24	25.71	28.80	15.29	14.45	11.60	4.54
Sharpe Ratio	1.51	1.08	1.22	0.68	0.67	0.54	0.22
MDD (%)	26.75	28.73	21.68	28.38	29.15	30.59	44.26
t-statistics	3.56	2.61	2.91	1.72	1.71	1.41	0.70
Panel B: 2013-2018							
Annual Return (%)	19.47	17.34	16.11	12.72	11.61	13.77	16.22
Sharpe Ratio	1.22	1.09	1.00	0.79	0.74	0.85	1.00
MDD (%)	15.09	19.73	28.35	17.08	18.95	17.97	30.45
t-statistics	3.19	2.88	2.65	2.14	2.00	2.29	2.64

4.2. ATSM Portfolio Construction

Our rule-based approach of ATSM strategy comes from the analysis of different time series momentum lossing scenarios. We suggest to change the original TSM strategy long/short signals in certain conditions, e.g., change the long signal to short signal in a uptrend market when the lower partial moments (LPM) is in a relative high level with respect to the concurrent upper partial moments (UPM). Following the method in Gulen & Petkova (2015), we use the recursive percentile of historical disbution of UPM and LPM as breakpoints to capture the absolute strength of price trend that driven by group of traders who pushing price up and traders who pulling price down. Under the hypothesis, relative high LPM with repect to UPM indicates that future falling in a uptrend market, and relative high UPM with respect to LPM indicates that future rising in a downtrend market.

Figure 7 shows four classifications of upper and lower partial moments based on their quantile related boundaries in the coordinate plane. The corresponding strategies that available during holding period under each of these four conditions are listed. The original point represents the breakpoints ($Breakpoint_{i,d_t}(UPM_{i,d_1:d_t}, LPM_{i,d_1:d_t})$) for both upper partial moments (UPM_{i,d_t}) and lower partial moments (LPM_{i,d_t}) of asset i in day d_t. We suggest that the breakpoints should recursively generate from the (70%, 80%) percentiles of historical distribution of (UPM, LPM) with increasing rolling window, repectively.

Figure 7: **ATSM Strategy Choices under Different Classifications**

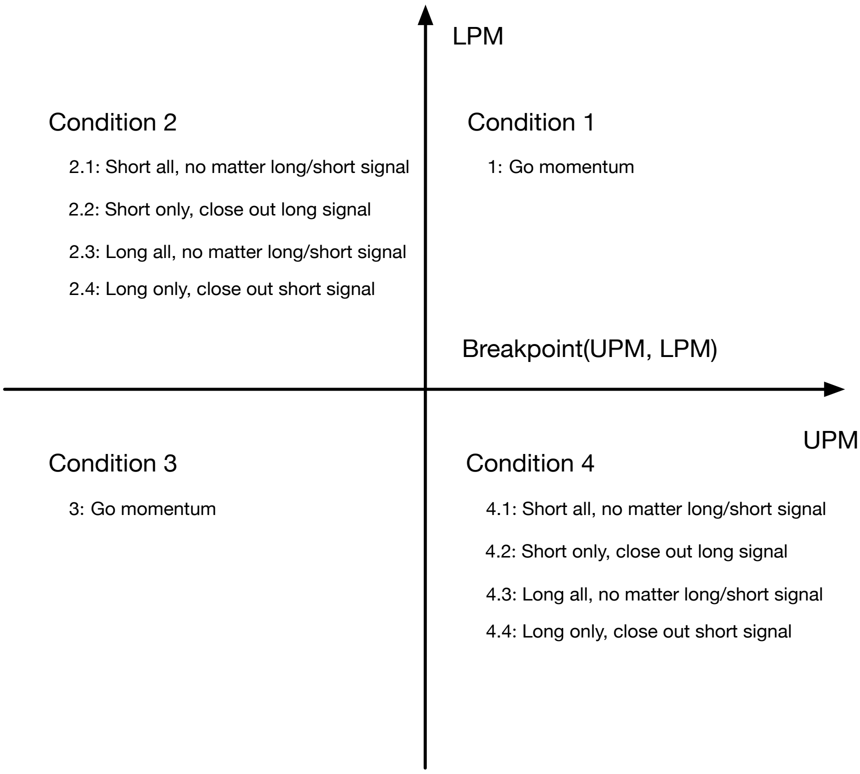


Table 8 reports different actions and returns in holding periods of the ATSM portfolio under each of the four conditions presented in Figure 7 of our 4 ATSM strategies, which was represented by ATSM_S1 to ATSM_ S4. The behind ideas of optimal portfolio choices for long/short signals from original TSM strategy are explained as follow:

- ATSM_S1: Changing long (short) signal to short (long) signal to avoid losses in uptrend (downtrend) market and keeping short (long) signal to increase profits in downtrend (uptrend) market under condition 2 (4), if relative high LPM (UPM) in condition 2 (4) is an indicator for future reversals (rebounds) in a upward (downward) trend, and meanwhile, is not an indicator for downward (upward) trend ending.

- ATSM_S2: Closing out long (short) signal to clear risk exposure in uptrend (downtrend) market and keeping short (long) signal to increase profits in downtrend (uptrend) market under condition 2 (4), if relative high LPM (UPM) in condition 2 (4) is an indicator for future reversals (rebounds) in a upward (downward) trend, and meanwhile, is not an indicator for downward (upward) trend ending.
- ATSM_S3: Changing short (long) signal to long (short) signal to avoid losses in downtrend (uptrend) market and keeping long (short) signal to increase profits in uptrend (downtrend) market under condition 2 (4), if relative high LPM (UPM) in condition 2 (4) is not only an indicator for future rebounds (reversals) in a downward (upward) trend but also an indicator for continuing upward (downward) trend with a future new higher (lower) price.
- ATSM_S4: Closing out short (long) signal to clear risk exposure in downtrend (uptrend) market and keeping long (short) signal to increase profits in uptrend (downtrend) market under condition 2 (4), if relative high LPM (UPM) in condition 2 (4) is not only an indicator for future rebounds (reversals) in a downward (upward) trend but also an indicator for continuing upward (downward) trend with a future new higher (lower) price.

From the Eq. 8 which we shown to state the portfolio return of original TSM strategy (Moskowitz et al., 2012), we decomposite the TSM portfolio return into two components: long position return and short position return.

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

where for long positions:

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

and for short positions:

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

Then, we construct our ATSM portfolios based on the original time series momentum signals:

$$r^{atsm}_{p,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t} sign^{atsm}_{i,d_{t+1}}\frac{\sigma_{target}}{\sigma_{i,d_t}} r^i_{i,d_{t+1}} \tag{12}$$

where the long/short decisions of ATSM portfolios is a function of univariate past returns, upper partial moments and lower partial moments:

$$sign^{atsm}_{i,d_{t+1}} = F\Big(\sum_{j=0}^{J} r_{i,d_{t-j}},\ UPM_{i,d_t},\ LPM_{i,d_t}\Big) \tag{13}$$

which we present in Figure 7 for different choices. Table 8 gives detailed methodologies and results of our ATSM strategies.

Table 8: **Methodologies and Results of ATSM Strategies Construction**

ATSM Strategies	Condition 1		Condition 2		Condition 3		Condition 4	
	Method	Return	Method	Return	Method	Return	Method	Return
ATSM_S1	1	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	2.1	$-r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	3	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	4.3	$r^{tsm}_{l,d_t} + r^{tsm}_{s,d_t}$
ATSM_S2	1	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	2.2	$0 - r^{tsm}_{s,d_t}$	3	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	4.4	$r^{tsm}_{l,d_t} - 0$
ATSM_S3	1	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	2.3	$r^{tsm}_{l,d_t} + r^{tsm}_{s,d_t}$	3	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	4.1	$-r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$
ATSM_S4	1	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	2.4	$r^{tsm}_{l,d_t} - 0$	3	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	4.2	$0 - r^{tsm}_{s,d_t}$

4.3. ATSM Strategy Performance

The performance of ATSM approach is examined on the basis of original TSM strategy with 30 trading days (nearly half a quarter in calendar) looking back period as an example. Our later results show the consistency among different looking back periods. Results including statistics of annual return, Sharpe ratio, maximum drawdown and t-statistics for normality test are tabulated in Table 8 according to different subsamples (Panel A for 2008:2012; Panel B for 2013:2018). The ATSM strategies show better performance than original TSM strategy in both subsamples with higher Sharpe ratio and lower maximum drawdown.

During 2008 to 2012, the ATSM_S1 enhances original TSM strategy with a rise of 20% (1.08 to 1.31) in Sharpe ratio and a drop of 28% (28.73% to 20.78%) in maximum drawdown. Meanwhile, ATSM_S3 shows an significant improvement by 30% in Sharpe ratio of 1.42 (3.72) compared with original TSM strategy of 1.09 (2.88) during subsample from 2013 to 2018. The maximum drawdown decreases from 19.73% to 14.95% with proportion of 24% at the same time. These evidence prove that the ATSM approach can effectively mitigate the time series momentum losses by systematically reducing risk exposure during the stressed time of individual asset price trend that generated by time series momentum signals, as we proposed in Figure 7.

Coincidently, previous poorly performed ATSM_S3 appears to be effective on subsample of 2013:2018, however ATSM_S1 can not continue. Further analysis behind data reveals more information about the implied changing pattern of trends in price series. At first, as we proposed in Figure 7, the ATSM_S1 strategy choose to switch the long signals to short and keep short position in condition 2, meanwhile choose to switch the short signals to long and keep long position in condition 4. There exists changed position and unchanged position under both condition 2 and 4. On one hand, the changed part means that weekly horizon measured downside (upside) risk for price trend will lead to the discontinuation of trend in the following days, thus switching from long (short) position to short (long) position under condition 2 (4) can protect original time series momentum profits from opposite risk exposure. On the other hand, the unchanged part means that accelerated rising and falling of price will strengthen previous trends.

However, the ATSM_S3 strategy which has completely different choices under condition 2 and 4 reveals another picture of pattern in price trends after 2013. For the case of ATSM_S3, changed trading signals keep previous long (short) signal under condition 2 (4) which means previous price trends are able to proceed eventhough current downside (upside) risk measured by LPM (UPM) is relatively high, and transfer previous short (long) signal under condition 2 (4) to long (short) signal which means previous price trends discontinue after excessive and positive self-accelerated feedback that measured by relative high LPM (UPM) for short (long) signals under condition 2 (4). Significantly improved sharpe ratio of ATSM_S3 from original TSM is consistent with our observed facts in TSM strategies that the persistent of price trend is strenghtend over 2013 to 2018.

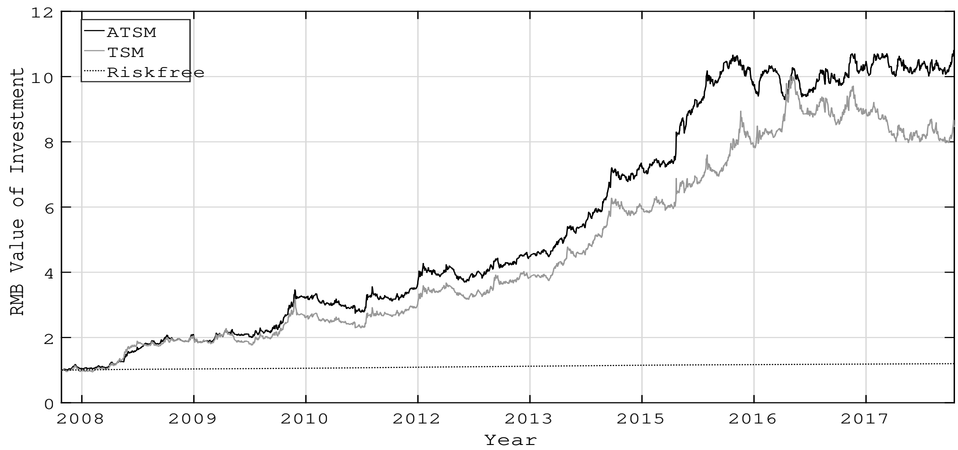
These findings provide the evidence of micro-structure changes in the Chinese commodity futures markets since 2013. For one thing, the year of 2013 witnessed the announcement of night-trading rule in futures markets as one of the financial reformation policies. For the other thing, a more open and international domestic futures market of China becomes more attractive for both international intitutional investors and individual investors to hedge risks from emerging markets, thus potentially pushing longer and longer trends by implementing trend following strategy in the Chinese futures markets.

The comparison between the ATSM approach, which combines ATSM_S1 and ATSM_S3, and the original TSM atrategy are plotted in Figure 8, Panel A for cumulative gains and Panel B for drawdown. From Panel A in the graph, we can see that the rule-based ATSM strategy reports a better performance than original TSM strategy investment, especially when compared with the most recent deep drawdown from high water-level benchmark of original TSM strategy. The enhanced performance confirms our hypothesis about time series momentum losses that they are consequencies of the absence of risk managing measures when the probability of wrong trading signals is high.

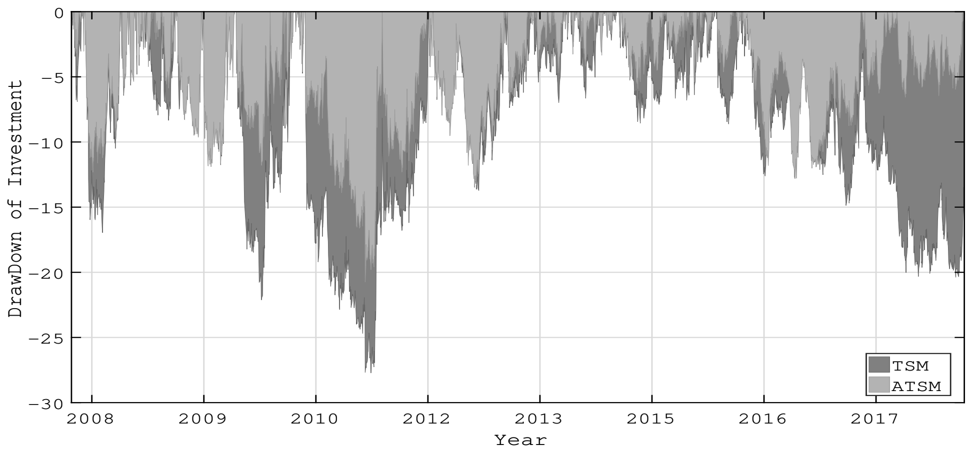
Table 9: **ATSM Strategies Performance for Chinese Commodity Futures Markets**

Strategy	Annual Return (%)	Sharpe Ratio	Maximum DrawDown (%)	t-statistics
Panle A: 2008 - 2012				
BAH	-1.88	-0.11	46.92	0.01
TSM	25.71	**1.08**	**28.73**	**2.61**
ATSM_S1	30.37	**1.31**	**20.78**	**3.13**
ATSM_S2	29.03	1.22	24.64	2.94
ATSM_S3	8.17	0.36	24.72	1.06
ATSM_S4	17.92	0.90	21.40	2.26
Panle B: 2013 - 2018				
BAH	-2.50	-0.22	41.76	-0.24
TSM	17.34	**1.09**	**19.73**	**2.88**
ATSM_S1	11.77	0.71	24.89	1.96
ATSM_S2	15.25	0.93	22.13	2.48
ATSM_S3	19.45	**1.42**	**14.95**	**3.72**
ATSM_S4	19.09	1.35	10.81	3.55

Figure 8: **Augmented and Original Time Series Momemtum Investment**



(a) Panel A: Cumulative gains on the commodities futures in the Chinese futures markets with time series momentum (TSM) and augmented time series momentum (ATSM) strategy, from Jan., 2008 to Nov, 2018.



(b) Panel B: Drawdowns of investment on the commodities futures in the Chinese futures markets with time series momentum (TSM) and augmented time series momentum (ATSM) strategy, from Jan., 2008 to Nov, 2018.

4.4. Different Looking Back Periods

The ATSM strategy with $J = 30$ trading days has been demonstrated outperforming the TSM strategy in previous subsection. Definitely, the effectiveness of the ATSM approach should be proved coincident with various looking back windows of original time series momentum, if the ATSM strategy is indeed a robust systematic rule-based choice for mitigating the time series momentum losses. We report the result of consistency test concerning different length of looking back window in Table 10.

From data in the table, it is not hard to find that the performance of ATSM strategies which looking back from 20 to 250 trading days show consistent result with our tests of $J = 30$ trading days, not only in terms of annual return, Sharpe ratio and maximum drawdown but also in terms of different subsamples (see Panel A for sample 2008:2012; Panel B for sample 2013:2018). The ATSM approach reports an improvment in Sharpe ratio by almost 30% on average and stronger t-statistics of nomarlity test with respect to the original time series momentum across different looking back periods and subsamples. Especially during 2008:2012, the results of ATSM approach with $J = 60$ and 90 trading days report significant positive average yearly returns by 17.78% (2.17) and 15.66% (2.04), rather than insignificant return in the original time series momentum.

Table 10: **Parameter Consistency Check for Different Looking Back Periods**

		Looking Back Period (days)						
		20	30	40	60	90	120	250
Panel A:	2008-2012							
TSM	Annual Return (%)	36.24	25.71	28.80	15.29	14.45	11.60	4.54
	Sharpe Ratio	1.51	1.08	1.22	0.68	0.67	0.54	0.22
	MDD (%)	26.75	28.73	21.68	28.38	29.15	30.59	44.26
	t-statistics	3.56	2.61	2.91	1.72	1.71	1.41	0.70
ATSM_S1	Annual Return (%)	36.31	28.41	30.05	17.78	15.66	15.00	12.90
	Sharpe Ratio	1.59	1.31	1.40	0.87	0.81	0.78	0.67
	MDD (%)	23.77	20.78	16.40	26.70	31.26	22.04	27.19
	t-statistics	3.76	3.13	3.34	2.17	2.04	1.97	1.73
Panel B:	2013-2018							
TSM	Annual Return (%)	19.47	17.34	16.11	12.72	11.61	13.77	16.22
	Sharpe Ratio	1.22	1.09	1.00	0.79	0.74	0.85	1.00
	MDD (%)	15.09	19.73	28.35	17.08	18.95	17.97	30.45
	t-statistics	3.19	2.88	2.65	2.14	2.00	2.29	2.64
ATSM_S3	Annual Return (%)	21.83	18.07	17.78	13.34	13.72	15.50	18.88
	Sharpe Ratio	1.72	1.42	1.37	1.04	1.06	1.16	1.39
	MDD (%)	16.48	14.95	12.15	11.34	13.37	15.36	31.52
	t-statistics	4.45	3.72	3.59	2.78	2.84	3.07	3.61

4.5. Different Breakpoints

Follow the method in Gulen & Petkova (2015), we use the percentiles of historical distribution of upper and lower partial moments as breakpoints to change portfolio signals that from original time series momentum under different conditions. Our previous choice of combination: 70^{th} percentile for UPM and 80^{th} percentile for LPM, has been proved to be useful and effective in ATSM method for mitigating the time series momentum losses. Importantly, what we show following demonstrates that the success of $(70\%, 80\%)$ percentile breakpoints is not just a coincidence and a result of data-mining.

Table 11: **Parameter Consistency Check for Different Breakpoints**

	Panel A: 2008-2012						Panel B: 2013-2018					
	ATSM_S1			ATSM_S2			ATSM_S3			ATSM_S4		
UPM\LPM	60	70	80	60	70	80	60	70	80	60	70	80
60	0.90	0.99	1.19	1.03	1.07	1.17	1.29	1.40	1.35	1.26	1.31	1.34
70	0.89	1.06	1.31	1.03	1.10	1.22	1.26	1.44	1.42	1.26	1.33	1.35
80	0.78	1.03	1.23	0.98	1.09	1.18	1.12	1.26	1.36	1.24	1.27	1.32

Table 11 reports the results measured by the Sharpe ratio of ATSM strategies that using other combinations of breakpoints, range from 60% to 80% for UPM and LPM respectively. The statistics tabulated do not show significant difference as breakpoints changing. Specifically, the ATSM_S3 strategy, that switching the short signal to long signal in condition 2 and switching the long signal to short signal in condition 4 presented in Figure 7, can significantly profit better than original TSM strategy under all breakpoints, by an improvement of around 20% in Sharpe ratio.

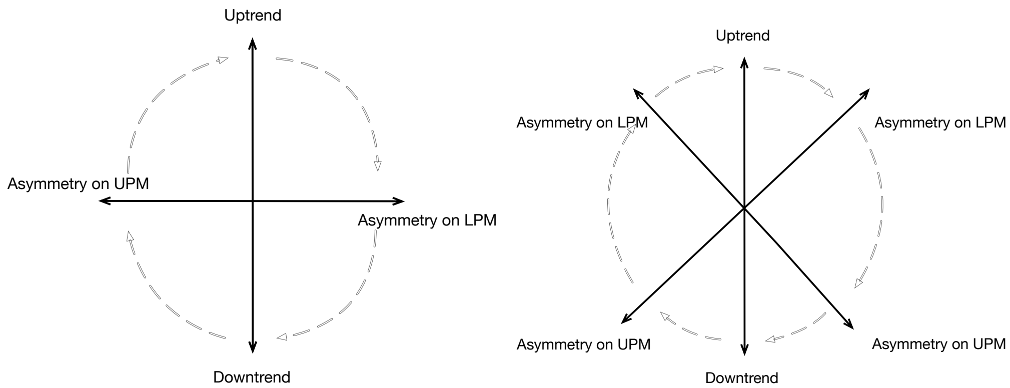
5. Time Series Momentum Life Cycle

An intriguing explanation for the better performance of ATSM strategy compared with original TSM strategy is depicted in Figure 9. This figure presents a simple conceptual diagram that helps to integrate the evidence in this paper. We refer to this diagram as the time series momentum life cycle (TSMLC) hypothesis, a similar concept with momentum life cycle (MLC) hypothesis (Lee & Swaminathan, 2000).

Before the year of 2013, we depict the logic of managing trading signals in ATSM_S1 as a relatively simple dynamic structure combining trend states and asymmetrically distributed pattern of UPM and LPM which is shown in Panel (a) in Figure 9. After the joint distribution exhibiting asymmetric property on LPM with reversals in uptrend, the states of price trend transfer from upward trend to downward trend. Meanwhile, the ATSM_S1 strategy adjust long trading signal to short signal timely to mitigate TSM losses. And vice versa. Therefore describing the time series momentum as a dynamic cyclic process.

However, owing to some unnegligible reason as we disscussed before, its dynamic cyclic patterns show alternation of asymmetric property on LPM and UPM in joint distribution between uptrend and downtrend in Panel (b) of Fingure 9 for the period from 2013 to 2018. Enhanced trend persistence brings additional profitability of original trading signals, thus keeping the long trading signal eventhough there is asymmetric property on LPM with reversals in uptrend. Until the trend is excessive self-accelerated with positive feedback trading, showing that asymmetric property on UPM with quickly rises in uptrend, the upward trend start to be unsustainable and transfer to downtrend. At the same time, the ATSM_S3 strategy which transfers the original TSM long signal to short signal is demonstrated to be an effective choice on reducing risk exposure of wrong trading signals. And also vice versa.

Figure 9: **Time Series Momentum Lifecycle**



(a) Befor 2013: (b) After 2013

6. Conclusion

After the seminal work of Moskowitz et al. (2012), time series momentum, also known as trend following strategy, has made an huge influence among financial academics and practioners. Meanwhile, its poor formance in recent years are also valued by an increasing number of studies. Georgopoulou & Wang (2016) suggest that it is the market interventions by central banks in recent years challenge the performance of time series momentum portfolios. Time series momentum profits with significant trend and loses with sideways market. The significantly increased market uncertainty that resulted by global economic recovery might be one possible reason. Therefore, it is important to explore the relavance of stressed trend states that caused by market uncertainty to time series momentum losses.

Based on the work of Daniel & Moskowitz (2016), Gulen & Petkova (2015) and Gao et al. (2017), we extended our studies on, to what the extent, the upper and lower partial moments of univariate return series were able to predict the stressed states of its price trend, i.e., reversals in uptrend market, rebounds in downtrend market and sideways market. After extensive empirical analysis, we discovered that the dynamics of upper and lower partial moments over weekly horizon can generate predictable pattern with stressed time of price trend. Specifically, the method of using the extreme value of upper and lower partial moments that filtered by its historical distribution breakpoints to capture those stressed price trend states and managing the risk of original time series momentum wrong trading signals has been proved effective for mitigating time series momentum losses by our robust results.

By constructing an augmented time series momentum (ATSM) strategy and examining its performance on the basis of 31 commodities futures contracts returns in the Chinese futures markets, we tested the feasibility of this systematic rule-based approach in actural empirical application. It turned out to be an effective and robust approach to mitigate time series momentum losses with higher Sharpe ratio and lower maximum drawdown for different looking back periods. Choosing different upper and lower partial moments breakpoints can not overthrow our results.

Acknowledgement

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