Time series momentum and reversal: intraday information from realized semivariance

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Abstract

The presence of time series momentum has been widely documented in financial markets across asset classes and countries. In this study, we find a predictable pattern of the realized semivariance estimators for the returns of commodity futures, particularly during the reversals of time series momentum. Based on this finding, we propose a rule-based time series momentum strategy that has a statistically significant higher Sharpe ratio compared to the benchmark of the original time series momentum strategy in the out-of-sample data. The results are robust to different subsamples, lookback windows, volatility scaling, execution lag, and transaction cost.

Keywords: Commodity Futures Pricing, Time Series Momentum, Momentum Reversal, Realized Semivariance, High-frequency Data

JEL: G12, G17

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⋆⋆Declarations of interest: none.

1. Introduction

Since the seminal work of Moskowitz et al. (2012), the time series momentum effect has been widely discussed in financial markets across various assets classes and countries (Baltas & Kosowski, 2013; Hurst et al., 2013, 2017; Lempérière et al., 2014). As the analogue of cross-sectional momentum (Jegadeesh & Titman, 1993), time series momentum directly corresponds to prominent rational and behavioral asset pricing theories, which claim that past returns have direct implications for time series predictability. However, the literature has often questioned its return predictability due to its poor performance in the post-2008 financial crisis period, thereby leaving a gap in the investigation into the impact of time series momentum reversals (Satchell & Grant, 2020; Huang et al., 2020).

Owing to a number of behavioral tendencies and market frictions, the life cycle of time series momentum has been known as a stylized trend of market prices, from the initial under-reaction to the delayed over-reaction toward an incoming shift in the fundamental value of a single asset (Hurst et al., 2013). At the end of the cycle, momentum reverses as the market prices reverse to fundamentals following the over-reaction. As a consequence, momentum reversals result in investment losses owing to the time series momentum strategy. Garg et al. (2021) recognize such a reversal in trends as "momentum turning points" and utilize the information embedded in slow and fast speed strategies to detect the market turning points in the global equity markets. The existing literature also investigates the relationship between the poor performance of the time series momentum strategy and a selection of exogenous factors, such as market capacity constraint and central bank policy (Baltas & Kosowski, 2013; Georgopoulou & Wang, 2016). In this paper, we aim to identify predictor variables, which are endogenously driven by the historical price trajectory of the underlying risky asset. We aim to identify these variables in order to provide a bridge to characterize the dynamics of the time series momentum life cycle and to predict time series momentum reversals in the context of Chinese commodity futures.

We focus on the Chinese commodity futures markets for several reasons. First, the retail–dominance characteristics documented by Fan & Zhang (2020) provide us with a unique dataset for investigating the life cycle of time series momentum from under-reaction to over-reaction, and eventually, to momentum reversal.[1] As an unfavourable consequence of retail–dominance, excessive speculation causes behavioral biases, such as herding and feedback trading, disposition effect, overconfidence, and representativeness to be more significant in China's markets than in others (Wang et al., 2006; Chen et al., 2007; Fan & Zhang, 2020). Second, despite the Chinese commodity futures markets being the largest in the world, this emerging market is still poorly understood due to a series of reformations made by the China Securities Regulatory Commission (CSRC). We consider one of these reformations, the implementation of the night-trading policy, as a major event to test our findings over separated subsamples. Third, due to the tremendous efforts made by the CSRC to eliminate "barriers-to-entry" mentioned in Fan & Zhang (2020) and Bianchi et al. (2021), more internationalized Chinese commodity futures markets have attracted attentions from both academics and practitioners. Providing an innovative understanding of the time series momentum life cycle is not only crucial to academic concerns of time series return predictability, but also to international institutions in the CTA (Commodity Trading Advisor) industry who have established their Chinese divisions.[2]

Some research has dedicated its efforts to revealing the momentum anomaly of commodity futures pricing in China. While Kang & Kwon (2017) focus only on the cross-sectional momentum effect, Yang et al. (2018) extend their study to investigate the cross-sectional momentum and reversal effect. Ham et al. (2019) compare time series momentum with cross-sectional momentum based on ten commodity futures. Liu et al. (2020) investigate the impact of tail risk measured by partial moments to time series momentum reversal broadly over 31 commodity futures. Jin et al. (2020) document the intraday time-series momentum pattern that exists in the copper, steel, soybean, and

[1] Unlike the U.S. market, which is dominated by institutional investors, more than 86% of open interest was held by individual investors in China by the end of 2016 (Fan & Zhang, 2020). In terms of the trading volume, institutions contributed only 9.8%.

[2] Commodity Trading Advisor (CTA), also known as managed futures, is one of the most crucial investment classes in the asset management industry. They 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 time series momentum strategy (Baltas & Kosowski, 2015).

soybean meal futures contracts.[3] Although both time series momentum reversal and intraday returns have been involved in the study of China's commodity futures, the linkage between them is yet to be established.

Moreover, some studies follow conventions in exploring the developed markets to investigate the anomalies of commodity futures pricing in China on a monthly basis (Ham et al., 2019; Bianchi et al., 2021).[4] Yang et al. (2018) also document evidence of cross-sectional momentum on both a daily basis and even the intraday high-frequency basis for the Chinese commodity futures markets. To further explore these areas, we are interested in investigating time series momentum and reversal in China on a daily basis. Our choice to use a daily frequency is also motivated by Huang et al. (2020), who have questioned the time series predictability of monthly returns and suggest developing a new trading strategy with a different horizon. In addition, the retail–dominance makes the Chinese markets behave more speculatively as they are driven by traders with shorter horizons than the developed markets. This provides a unique market environment focusing on daily returns to re-examine the return predictability of time series momentum.

Our study contributes to the literature in the following four ways. First, we are among the first researchers to explore the linkage between the time series momentum life cycle and realized semivariance. Literature on time series momentum has focused on its implementation by traders (Hurst et al., 2013; Baltas & Kosowski, 2015), on its relationship with volatility states (Pettersson, 2014) and the volatility scaling approach (Kim et al., 2016), and on the impact of applying alternative trading rules (Dudler et al., 2015; Levine & Pedersen, 2016; Liu et al., 2020). Besides Garg et al. (2021), few studies have further investigated the details of the reversal episodes of its life cycle. Meanwhile, the realized variance is advocated as an unbiased model-free estimator for the latent volatility of financial assets when the high-frequency (intra-daily) information is employed

[3] The intraday time-series momentum pattern here refers to the asset pricing anomaly that the first half-hour return predicts the last half-hour return as documented by Gao et al. (2018).

[4] Bianchi et al. (2021) reveal significant investable premia of Momentum, Carry, and Basis-momentum strategies and examine its risk exposures to a set of factors, including a three-factor model suggested by Bakshi et al. (2019), a five-factor model discussed in Fan & Zhang (2020), and two political-policy-related risk factors.

(Andersen et al., 2001; Barndorff-Nielsen & Shephard, 2002; Andersen et al., 2003).[5] More importantly, Patton & Sheppard (2015) and Bollerslev (2021) propose that volatilities are not created equal and that partial (co)variation measures are essential for volatility forecasting and asset pricing. Therefore, we are interested in establishing the predictability that realized semivariance has upon time series momentum reversals.

Second, we design a set of robust rules that tunes the original time series momentum signals based on the asymmetric structure of positive and negative realized semivariance, with the aim of empirically examining how the time series momentum life cycle is connected with realized semivariance. Decomposing the sign of past cumulative returns, we further identify the time series momentum as a process between an upward momentum state (past cumulative return is positive) and a downward momentum state (past cumulative return is negative). We then employ positive and negative realized semivariance to capture the intraday behavior of herding and contrarian investors when an upward momentum is experiencing an over-reaction. In general, rational informed investors stabilize prices by taking positions when prices deviate from their fundamentals (Avramov et al., 2006). In this case, the herding investors can be recognized as non-informational, while the contrarian investors are informational.[6] As the number of informed contrarian investors increases, their impact on price increases leads to a decrease in the deviation of a price from its fundamental value, thus causing an upward momentum reversal. When a downward momentum is experiencing an over-reaction, positive realized semivariance captures the behavior of the informed contrarian investors to predict a downward momentum reversal. By monitoring the asymmetric structure of positive and negative realized semivariance, we find a robust predictable pattern for time series momentum reversals.

Third, we evidence that the predictable pattern of realized semivariance toward time series

[5] For more properties of realized volatility (RV) and related measures, such as bipower variation (BV) and truncated variance (TV), we refer to Barndorff-Nielsen & Shephard (2006), Andersen et al. (2013), and Aït-Sahalia & Jacod (2014).

[6] As Avramov et al. (2006) highlight, the caveat in classifying trades on a given day as informed or uninformed is that not all the trades on a given day are the same. We assume that informed or uninformed (herding or contrarian) traders *dominate* on a given intraday sampling interval.

momentum reversals has been consistent before and after the night-trading reformation in China. CSRC has made remarkable efforts to smooth and stabilize price shocks from the international markets. Following the example of the Gold and Silver contracts, an increasing number of contracts were allowed to be traded, not only during the daytime, but also during the night since 2013. Previous studies emphasized that the implementation of the night-trading policy has improved the market quality and have suggested subsample testing for the markets (Fan & Todorova, 2021; Jiang et al., 2020; Cai et al., 2020; Liu et al., 2020). Chordia et al. (2011) and Chordia et al. (2014) suggested that the enhanced market liquidity should have stimulated greater anomaly-based arbitrage and, thus, attenuated capital market anomalies. Our empirical results show that the predictability of the asymmetric structure regarding positive and negative realized semivariance remains unchanged in the subsamples 2008–2012 and 2013–2018.

Fourth, we explain the predictability of positive and negative semivariance by proposing a time series momentum life cycle (TSMLC) hypothesis. We propose that the asymmetry of positive and negative realized semivariance can characterize the life cycle of time series momentum, alternating it between an upward and a downward momentum. Similar to the momentum life cycle (MLC) hypothesis proposed by Lee & Swaminathan (2000), we link the TSMLC hypothesis to the dynamics of intra-daily realized semivariance estimators, which are endogenous variables defined by the intraday high-frequency returns of individual assets.

The rest of this paper is organized as follows. In Section 2 we describe the dataset of the Chinese commodity futures markets and provide definitions and explanations of the positive and negative realized semivariance that we employed in the empirical studies. We further illustrate the relationship between future commodity returns and realized semivariance under different episodes of time series momentum in Section 3. Section 4 explains the rule-based function of tuning decisions on the original time series momentum, and shows its robust out-of-sample performance across different subsamples with the added consideration of the transaction cost. In addition, we introduce the hypothesis of the time series momentum life cycle related to the realized semivariance and explore the sources of risk premia of the original and tuning strategies in this section.

Section 5 extends the robustness checks to volatility scaling, various lookback windows, and a one–day execution lag. The conclusion of our research is presented in Section 6.

2. Data and preliminaries

2.1. Data

Our data sample contains both the daily returns and the 5-min high-frequency intraday returns[7] for the *main contract* of 31 commodity futures in China.[8] Following convention, all prices are closing prices, and returns are calculated by taking the first-order difference of the logarithm of closing prices.[9] The *main contract* here refers to the contract which has the largest open interest out of all the futures contracts of a certain commodity. When there is a roll-over, we update the *main contract* according to the open interest at day t, and start to collect the return data of the new *main contract* on day $t + 1$, and then concatenate it with the return data of the previous *main contract*. More specifically, we undertake the following three steps: i) We download the open interest of all active contracts of a given commodity at the end of trading. ii) We check whether the open interest of the current *main contract* is surpassed by any contracts that follow along the futures curve. If any do surpass it, we roll to the next contract with the largest open interest and this becomes the new *main contract*. Otherwise, there is no roll-over. iii) We append the daily return (rather than price) of the *main contract* to the return data series whenever a roll-over occurs.[10]

We choose to incorporate 31 commodity futures in our analysis because they have adequate liquidity. Our sample period is from January 2007 to December 2018, and the start date of each

[7] We use the intraday returns at a 5-minute frequency to maintain the trade-off between utilizing informative intra-daily signals and the effect of market microstructure noises (Barndorff-Nielsen & Shephard, 2002).

[8] We exclude the Chinese financial futures in this study, mainly due to the following three reasons: i) They are not subjected to the influence of the night-trading policy. All financial futures contracts only have daytime trading sessions. ii) They have a shorter sample period compared to the commodity futures. The first stock index futures and the first treasury futures were listed on the China Financial Futures Exchange in 2010 and 2013, respectively. iii) They were affected by various policy interventions, such as margins and commissions being raised significantly and the pushing down of the limits of opening and closing positions in 2015. The study of such characteristics of financial futures in China is left for future research.

[9] We rebalance the portfolio on a daily basis in this study. Thus, the returns calculated at daily closing prices, rather than settlement prices, are used to evaluate portfolio performance.

[10] We calculate the daily return based on the closing prices of a given contract, which is never computed based on the prices of different contracts.

commodity futures contract is reported in Table 1. The 31 commodity futures are categorized into four sectors: metals (MET), energy products (ENG), industrial materials (IND), and agriculture products (AGI). More summary statistics, including the annualized mean, annualized volatility, skewness, and kurtosis, are also shown in Table 1. We obtain the commodity data from the Wind[11] database and the daily series of the risk-free rate is taken from the CSMAR database, which is transformed from the fixed one-year savings interest rate.

Meanwhile, due to the night-trading policy introduced in 2013, we later implement our empirical analysis by segmenting our whole sample into two subsamples: these being before and after 2013. The night-trading policy was among a series of reformations within the Chinese futures markets, made by the China Securities Regulatory Commission (CSRC). This policy is considered to have triggered fundamental changes in the behavior of market participants (Jin et al., 2018; Fan & Todorova, 2021; Jiang et al., 2020; Cai et al., 2020). As stated by Jiang et al. (2020), the introduction of the night trading session increased liquidity and trading activity measured by volume, turnover, and open interest.

[11] Wind is a leading provider of financial information services in China. For more information about the data source, please visit `https://www.wind.com.cn/en/edb.html` (October 1, 2022).

Table 1: Summary statistics of the daily return series of each commodity futures contracts on the Chinese commodity futures markets

Exchange	Name	Code	Sector	Data Sample Start Date	Annualized Mean(%)	Annualized Volatility(%)	Skewness	Kurtosis
SHFE	Gold	AU	MET	Jan-08	0.97	17.64	-0.36	7.81
	Silver	AG	MET	May-12	-11.25	21.00	-0.28	8.58
	Copper	CU	MET	Jan-07	-0.06	24.12	-0.20	5.34
	Aluminium	AL	MET	Jan-07	-5.69	15.79	-0.29	7.92
	Nickel	NI	MET	Mar-15	-5.86	24.96	-0.13	4.14
	Zinc	ZN	MET	Mar-07	-4.12	24.90	-0.30	4.73
	Rebar	RB	ENG	Mar-09	-2.13	22.21	-0.04	7.24
	Hot Rolled Coil	HC	ENG	Mar-14	8.88	26.36	-0.15	5.99
	Bitumen	BU	IND	Oct-13	-19.17	26.15	-0.46	5.33
	Natural Rubber	RU	IND	Jan-07	-12.78	30.27	-0.21	4.09
CZCE	Cotton	CF	AGI	Jan-07	-1.69	17.50	-0.01	8.11
	Sugar	SR	AGI	Jan-07	-1.82	17.19	-0.04	5.94
	Rapeseed Meal	RM	AGI	Dec-12	5.97	20.81	-0.05	4.60
	Rapeseed Oil	OI	AGI	Mar-13	-10.42	14.69	-0.21	5.81
	PTA	TA	IND	Jan-07	-3.17	20.66	-0.13	5.47
	Methyl Alcohol	MA	IND	Jun-14	-1.72	24.55	0.01	4.28
	Flat Glass	FG	IND	Dec-12	6.80	20.51	0.08	5.09
	Thermal Coal	ZC	IND	May-15	16.39	22.47	-0.05	4.35
DCE	Polypropylene	PP	IND	Feb-14	6.90	21.38	0.07	4.38
	PVC	V	IND	May-09	-3.12	17.44	-0.03	5.84
	LLDPE	L	IND	Jul-07	-0.77	22.51	-0.21	5.03
	Coke	J	ENG	Apr-11	1.07	28.21	-0.10	6.32
	Coking Coal	JM	ENG	Mar-13	3.51	30.03	-0.11	5.90
	Iron Ore	I	ENG	Oct-13	-1.19	32.95	-0.04	4.37
	Corn	C	AGI	Jan-07	-0.79	11.01	-0.08	9.05
	Corn Starch	CS	AGI	Dec-14	0.90	15.89	0.07	5.14
	Soybean 1	A	AGI	Jan-07	0.71	17.69	-0.20	7.09
	Soybean Meal	M	AGI	Jan-07	7.87	20.90	-0.11	5.01
	Soybean Oil	Y	AGI	Jan-07	-4.39	19.85	-0.33	5.71
	Palm Oil	P	AGI	Oct-07	-9.61	21.97	-0.29	4.85
	Egg	JD	AGI	Nov-13	-1.28	19.14	-0.01	5.64

Notes: The raw data involved is from its start date shown in the fifth column to December 2018 for each commodity futures contracts. The exchanges SHFE, DCE, and CZCE are short for the Shanghai Futures Exchange, the Dalian Commodity Exchange, and the China Zhengzhou Commodity Exchange, respectively. The code of each futures contract is the one given by the exchange. The sectors MET, ENG, IND and AGI stand for the market sector of metals, energy products, industrial materials, and agriculture products, respectively.

2.2. Definitions of positive and negative realized semivariance

For simplicity, let $\{d_t\}_{t=1}^{T}$ be the dates of trading days and $\{r_{i,d_t}\}_{t=1}^{T}$ be the daily return sequence of individual asset i, Δ be the sampling interval for high-frequency data and $\{r_{i,t,\Delta}\}_{t=1}^{T/\Delta}$ be the Δ-period intraday high-frequency return sequence of the individual asset i. Due to there being different trading times across various commodity futures in China, the intraday sampling interval Δ is not the same for all contracts. For example, as the length of the intraday trading time for the Gold contract is 555 minutes in a day in total, then the sampling interval $\Delta = 1/111$ in this case, since the 5-min high-frequency intraday data is involved.[12] While in the case of the Egg contract, the trading time is 225 minutes in total and the sampling interval $\Delta = 1/45$.[13]

For each day, we compute the weekly aggregation of realized variance $\text{RV}_{i,t}$ from 5-min intraday high-frequency returns within the latest five trading days. The aggregation of realized variance of individual asset i in day d_t over weekly horizons is then

$$\text{RV}_{i,t}(\Delta) = \sum_{k=1}^{W} r^2_{i,t-(k-1)\Delta,\Delta}, \tag{1}$$

where $W = 5/\Delta$, and $r_{i,t,\Delta} \equiv log(P_i(t)) - log(P_i(t-\Delta))$, $P_i(t)$ indicates the intraday price series. Hence, the aggregations of positive realized semivariance $\text{RS}^+_{i,t}$ and negative realized semivariance $\text{RS}^-_{i,t}$ over weekly horizons are

$$\text{RS}^+_{i,t}(\Delta) = \sum_{k=1}^{W} r^2_{i,t-(k-1)\Delta,\Delta} I(r_{i,t-(k-1)\Delta,\Delta} > 0), \tag{2}$$

and

$$\text{RS}^-_{i,t}(\Delta) = \sum_{k=1}^{W} r^2_{i,t-(k-1)\Delta,\Delta} I(r_{i,t-(k-1)\Delta,\Delta} < 0), \tag{3}$$

where $I(\cdot)$ is the indicator function. Naturally, $\text{RV}_{i,t}(\Delta) = \text{RS}^+_{i,t}(\Delta) + \text{RS}^-_{i,t}(\Delta)$. In order to allow for a direct comparison between the quantities defined over various time horizons, the multiperiod realized volatilities are normalized sums of the one-period realized volatilities, i.e., a simple average of the daily quantities (Corsi, 2009; Patton & Sheppard, 2015; Bollerslev et al., 2016). We note that our empirical results do not change, irrespective of whether we are using the summation or the average of daily quantities, because the summation is a linear transformation of the average.

[12]The futures contracts of Gold are listed on the Shanghai Futures Exchange (SHFE). Its intraday trading time covers the day-trading and night-trading periods. The day-trading periods consist of 09:00 – 10:15, 10:30 – 11:30, and 13:30 – 15:00. And the night-trading period is 21:00 – 02:30 (T+1, i.e., the next day).

[13]The futures contracts of Egg are listed on the Dalian Commodity Exchange (DCE). Its intraday trading time only contains the day-trading periods, which are 09:00 – 10:15, 10:30 – 11:30, and 13:30 – 15:00.

We choose to use the weekly horizon due to the characteristics of investors in the Chinese commodity futures markets. As Corsi (2009) points out, one can identify three primary volatility components: the short-term traders with a daily or intra-daily trading frequency, the medium-term investors who typically rebalance their positions weekly, and the long-term agents with a characteristic trading frequency of one or more months. According to Fan & Zhang (2020), retail investors are known to be the dominant market participants in the Chinese commodity futures markets. Typically, retail investors have perceptions relating to short-term and medium-term investing horizons. Thus, we decide to consider the weekly aggregated realized semivariance in our study.[14]

2.3. Why use realized semivariance?

As a measure of downside risk, semivariance has a long history in financial applications. The positive and negative realized semivariance relate the realized variance to positive and negative high-frequency returns. They were named by Patton & Sheppard (2015) as "good volatility" and "bad volatility", since positive jumps lead to significantly lower future volatility and negative jumps lead to significantly higher volatility. The time series momentum portfolio contains both long and short positions. Thus, "good" and "bad" volatility does not strictly refer to positive and negative realized semivariance, and they should be interpreted in our context as follows: positive realized semivariance is "good" for the long positions, but "bad" for the short, and vice versa for the negative realized semivariance.

By using the intraday information, realized variance is a superior risk measurement when compared to those based on daily returns (Andersen et al., 2001; Barndorff-Nielsen & Shephard, 2002; Andersen et al., 2003). Furthermore, positive and negative realized semivariance can capture the behavior of the market participants in a higher level of detail that cannot generally be captured by the daily returns. Therefore, we use the positive (negative) realized semivariance as an indicator of information flow to monitor the herding (contrarian) traders in a period of upward momentum.

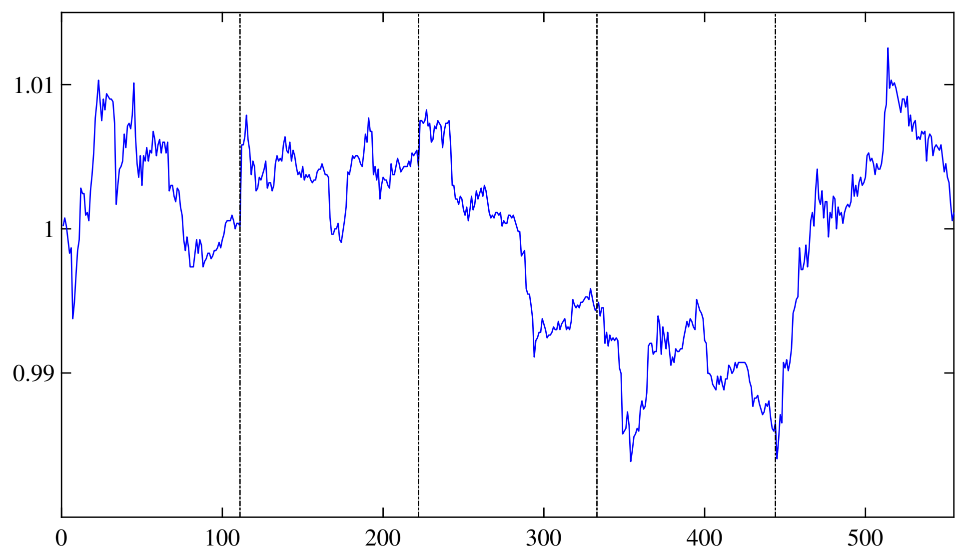
[14]Corsi (2009), Patton & Sheppard (2015), and Bollerslev et al. (2016) also advocate making use of a monthly aggregation of daily realized volatility. One can incorporate the monthly aggregation period when considering the long-term market participants with an investing horizon of one or more months for the developed financial markets.

Contrarily, the involved negative (positive) realized semivariance monitors the herding (contrarian) traders in a period of downward momentum.

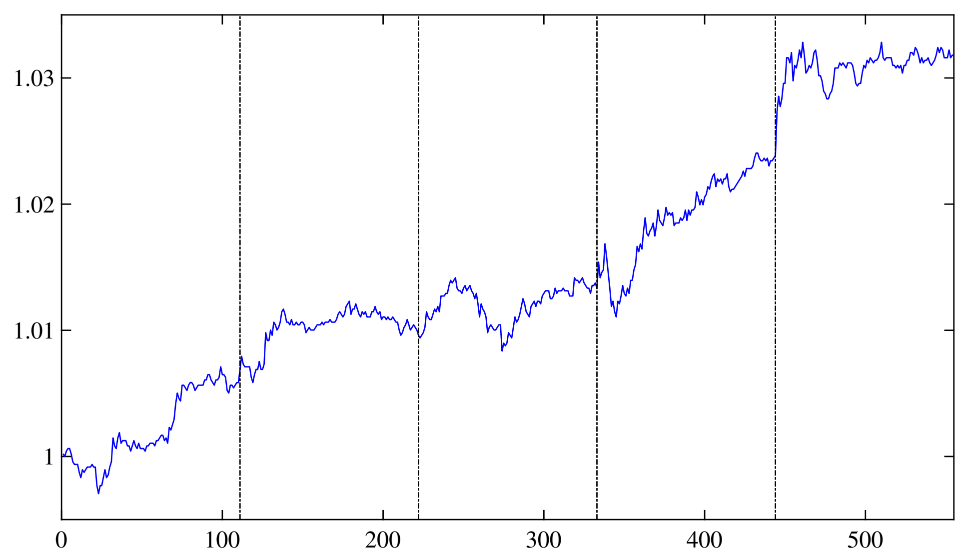
In Figure 1, we demonstrate the realized semivariance over five trading days under two different market scenarios: a sideways market in Panel (a) and an uptrending market in Panel (b). The 5-min high-frequency intraday returns of the Gold future contract is presented here as an example. In Panel (a) we observe that, although the five-day cumulative return is almost zero (= 0.11%), the upside risk measured by the positive realized semivariance and the downside risk measured by the negative realized semivariance are not actually low ($RS^+ = 0.0313\%$, $RS^- = 0.0336\%$). As shown in Panel (b), there is a strong upward one-sided market, of which the cumulative return is 3.18%. Nevertheless, both the upside risk (RS^+) and the downside risk (RS^-) turn out to be lower than those in Panel (a). This shows the merit of the realized semivariance, considering that the downside risk for the long position holder is indeed much lower in fact on the strong uptrending market in Panel (b), than on the volatile sideways market in Panel (a).

Table 2 presents the descriptive statistics in relation to the realized variance RV defined in (1), the positive realized semivariance RS^+ defined in (2), and the negative realized semivariance RS^- defined in (3) for each of the 31 commodity futures contracts from January 2007 to December 2018. For a given commodity, the median of its RS^+ and RS^- are comparable. By comparing different sectors, RS^+ and RS^- in the ENG and IND sectors are generally larger than the ones in the MET and AGI sectors.

Figure 1: Intraday price dynamics over five trading days of the Gold future contract. The intraday price dynamics are plotted with the solid blue line, and different trading days are divided by the dashed vertical black line. Panel (a) is for the period from March 7^{th}, 2016 to March 11^{th}, 2016, which depicts severe fluctuation. Panel (b) is for the period from Feburary 1^{st}, 2016 to Feburary 5^{th}, 2016, which depicts a strong upward one-side market. CR is the cumulative return over the five trading days interval. RS^+ and RS^- are the positive and negative realized semivariance calculated over this interval using 5-min high-frequency intraday returns.



(a) CR = 0.11%, RS^+ = 0.0313%, RS^- = 0.0336%



(b) CR = 3.18%, RS^+ = 0.0109%, RS^- = 0.0067%

Table 2: Descriptive statistics of the realized variance (RV), the positive realized semivariance (RS^+), and the negative realized semivariance (RS^-) for each commodity futures contracts on the Chinese commodity futures markets

Code	RV (%)			RS^+ (%)			RS^- (%)			Number
	Min	Median	Max	Min	Median	Max	Min	Median	Max	of Obs.
Panel A: MET sector										
AU	0.0019	0.0315	1.4619	0.0007	0.0132	0.7854	0.0006	0.0138	1.0709	2660
AG	0.0069	0.0508	1.6144	0.0021	0.0225	0.6262	0.0027	0.0236	1.5368	1608
CU	0.0073	0.0576	1.2345	0.0008	0.0272	0.6874	0.0024	0.0270	1.0805	2902
AL	0.0017	0.0292	0.8916	0.0008	0.0138	0.4170	0.0008	0.0138	0.7598	2902
ZN	0.0040	0.0788	2.1254	0.0011	0.0364	0.5316	0.0010	0.0371	1.6645	2855
NI	0.0378	0.1018	0.9843	0.0133	0.0498	0.4065	0.0174	0.0513	0.6795	920
Panel B: ENG sector										
RB	0.0056	0.0522	1.0996	0.0025	0.0248	0.6047	0.0022	0.0250	0.4949	2365
HC	0.0102	0.0877	1.1592	0.0036	0.0449	0.6730	0.0052	0.0457	0.6216	1157
J	0.0041	0.0994	1.4792	0.0022	0.0490	0.6045	0.0015	0.0494	0.8747	1867
JM	0.0156	0.1352	1.7904	0.0087	0.0666	0.7858	0.0062	0.0680	1.0047	1396
I	0.0135	0.1918	1.5721	0.0042	0.0946	0.9613	0.0091	0.0935	0.8642	1261
Panel C: IND sector										
BU	0.0025	0.1379	2.1508	0.0000	0.0665	1.0445	0.0011	0.0669	1.3203	1260
RU	0.0142	0.1412	1.7451	0.0000	0.0658	0.7443	0.0072	0.0672	1.3730	2902
TA	0.0051	0.0583	1.8903	0.0022	0.0282	0.7830	0.0007	0.0282	1.1632	2902
MA	0.0122	0.1135	0.6077	0.0064	0.0546	0.3286	0.0034	0.0547	0.3719	1099
FG	0.0076	0.0812	0.8345	0.0037	0.0422	0.4186	0.0034	0.0395	0.4159	1467
ZC	0.0029	0.0868	1.0785	0.0013	0.0427	0.5521	0.0015	0.0414	0.5337	886
PP	0.0097	0.0821	0.5394	0.0015	0.0398	0.3504	0.0029	0.0386	0.2933	1172
V	0.0055	0.0526	0.8523	0.0023	0.0250	0.3952	0.0032	0.0247	0.4807	2326
L	0.0058	0.0730	1.4636	0.0022	0.0344	0.6736	0.0024	0.0345	0.9912	2769
Panel D: AGI sector										
CF	0.0021	0.0304	1.5430	0.0008	0.0152	0.6335	0.0009	0.0146	1.2233	2902
SR	0.0048	0.0378	1.3024	0.0020	0.0183	0.4273	0.0020	0.0182	1.0640	2902
RM	0.0108	0.0664	0.7348	0.0040	0.0317	0.3438	0.0066	0.0317	0.4702	1448
OI	0.0006	0.0377	0.4297	0.0004	0.0182	0.2478	0.0002	0.0179	0.2919	1394
C	0.0007	0.0168	0.4284	0.0003	0.0086	0.1963	0.0004	0.0080	0.4053	2902
CS	0.0013	0.0410	0.3593	0.0006	0.0210	0.2077	0.0007	0.0202	0.2014	972
A	0.0035	0.0401	1.2796	0.0015	0.0191	0.6966	0.0016	0.0182	0.9661	2902
M	0.0082	0.0532	1.3848	0.0022	0.0249	0.6468	0.0026	0.0240	1.1074	2902
Y	0.0061	0.0456	1.4262	0.0028	0.0225	0.4982	0.0025	0.0205	1.1717	2902
P	0.0058	0.0655	1.4279	0.0030	0.0308	0.6424	0.0028	0.0299	1.1038	2710
JD	0.0064	0.0526	0.4558	0.0027	0.0256	0.1697	0.0037	0.0266	0.3279	1246

Notes: The sectors MET, ENG, IND and AGI stand for the market sector of metals, energy products, industrial materials, and agriculture products, respectively. The RV, RS^+, and RS^- are calculated by the partial sum of the squared 5-min high-frequency intraday returns over five trading days window from the start date in the data sample to December 2018 for each commodity futures contracts.

3. Realized semivariance and time series momentum

The heterogeneous market hypothesis (Müller et al., 1997) highlights that volatilities measured with different time resolutions reflect the perceptions and actions of different market components. Daniel & Moskowitz (2016) investigate the phenomenon of cross-sectional momentum crashes under different market states by segmenting the bull market and bear market. These studies demonstrate that capturing the implied dynamic features of both the realized semivariance and the price trends simultaneously over different windows is helpful for investigating the life cycle of time series momentum. Garg et al. (2021) also use SLOW (the trailing 12-month return) and FAST (the trailing 1-month return) momentum signals to define the four stock market cycles (or states): Bull, Correction, Bear, and Rebound.

In this section, we use the model-free risk estimators $\mathrm{RS}^{+}_{i,t}$ and $\mathrm{RS}^{-}_{i,t}$ over the latest five trading days (weekly horizon) to characterize the scenarios of time series momentum losses. One key aspect of using time series momentum is the potential to suffer losses during episodes of uptrend slumps, downtrend rebounds, and a sideways market. As mentioned earlier, we differentiate between the positive realized semivariance and the negative realized semivariance in order to monitor the "bad" side risk simultaneously for both the short and long positions in a time series momentum portfolio.

3.1. Time series momentum formula

Following Moskowitz et al. (2012), we construct the one-period-holding time series momentum portfolio based on recent J days cumulative return of each contract, where J is referred to as the length of the lookback window.[15] Since our empirical study is based on the Chinese markets,

[15] As stated in Moskowitz et al. (2012), the portfolio return of time series momentum strategy with 12-months look-back period and 1-month holding period across S_t securities from time t to $t+1$ is given by:

$$r^{\mathrm{TSM}}_{t,t+1} = \frac{1}{S_t}\sum_{s=1}^{S_t} \mathrm{sign}\left(r^s_{t-12,t}\right)\frac{40\%}{\sigma^s_t} r^s_{t,t+1},$$

where S_t is the number of securities available at time t, and the ex-ante volatility estimator σ^s_t is an exponentially weighted moving standard deviation with 60 days span.

we consider a relatively short length of lookback window for the time series momentum strategy, as opposed to concentrating on past months. Recall that the main proportion of investors on the Chinese market are retail investors, and they maintain a relatively short investing horizon. Yang et al. (2018) also document the evidence of cross-sectional momentum on both the daily basis and even the intraday high-frequency basis for the Chinese commodity futures markets, which was typically discussed on the monthly basis for the international markets. One can choose to use the monthly lookback window when examining the corresponding empirical evidence for other international markets. The overall return of a time series momentum portfolio that diversifies across all the N_t contracts that are available at time t is

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

We follow Moskowitz et al. (2012) to set the annualized 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}.[16]

More specifically, since there are long positions and short positions in a time series momentum portfolio, the portfolio return $r^{tsm}_{p,d_{t+1}}$ can be decomposed into two components:

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

for the long positions, and

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

[16] We note that the choice of a 40% annual target volatility follows the definition of Moskowitz et al. (2012), and this quantity of target volatility only matters if one intends to amplify or shrink the whole sequence of time series momentum portfolio returns using the same scale. Changing the value of this parameter does not change the crucial results of this study.

for the short positions, where $I(\cdot)$ is the indicator function. In this case, we naturally have

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

Considering the portfolio return formula in (4), we interpret its economic intuition through three endogenous components: (i) momentum indicator, identifying the momentum signal for a single risky asset by using the cumulative return over the lookback window; (ii) constant risk parity, scaling the time-varying volatility of each risky asset using a consistent target volatility; (iii) equally weighted portfolio, distributing an equal amount of funds to each risky asset within the portfolio, which follows the "naive 1/N rule". This decomposition allows us to identify the properties of time series momentum portfolio construction that contribute to the distribution of time series momentum portfolio returns. We consider the momentum indicator component as being the most significant element in the construction of the time series momentum strategy when compared to the two other components. The momentum indicator is defined by the sign of an individual asset cumulative return over certain lookback windows. Indeed, this momentum indicator (+1/-1) gives the right holding period signal (long/short) for the time series momentum strategy when there exists a persistent (upward/downward) episode of momentum in the time series of single asset returns. We argue that it provides an adverse holding period signal during the reversal episode of momentum and the episode of ambiguous momentum signals in a volatile sideways market.

3.2. Realized semivariance under different episodes of momentum

In this subsection, we show that the returns of single contracts in the subsequent period are highly correlated with the ex-ante intraday risk estimators over weekly horizons (i.e., the ex-ante aggregation of positive realized semivariance $\mathrm{RS}^{+}_{i,t}$ and negative realized semivariance $\mathrm{RS}^{-}_{i,t}$) under various price trends that are generated by time series momentum. Moreover, this lead-lag effect is significantly stronger (larger absolute value of the estimated coefficient) during the reversal episodes of time series momentum, than during periods of persistent upward momentum and downward momentum.

We then illustrate these issues with three sets of daily time series regressions on each contract of the 31 commodity futures from January 2007 to December 2018, the results of which are presented in Tables 3 and 4. In the tables, we categorize all contracts into four sectors, which are MET, ENG, IND, and AGI. The dependent variable in all regressions is the individual contract return in day d_{t+1}, i.e., $\widetilde{r}_{i,d_{t+1}}$. The independent variables are combinations of

(i). $\text{RS}^{+}_{i,t}$, the ex-ante weekly aggregated positive realized semivariance in day d_t.

(ii). $\text{RS}^{-}_{i,t}$, the ex-ante weekly aggregated negative realized semivariance in day d_t.

(iii). I_U, an ex-ante upward momentum indicator that equals one if the cumulative return of the latest 20 trading days in d_t is positive (that is, a long signal is derived from time series momentum for d_{t+1}) and is zero otherwise.

(iv). I_D, an ex-ante downward momentum indicator that equals one if the cumulative return of the latest 20 trading days in d_t is negative (that is, a short signal is derived from time series momentum for d_{t+1}) and is zero otherwise.

(v). $\widetilde{I}_F$, a contemporaneous, i.e., not ex-ante, falling day indicator variable that is one if the individual contract return is less than zero ($\widetilde{r}_{i,d_{t+1}} < 0$), and is zero otherwise.

(vi). $\widetilde{I}_R$, a contemporaneous, i.e., not ex-ante, rising day indicator variable that is one if the individual contract return is greater than zero ($\widetilde{r}_{i,d_{t+1}} > 0$), and is zero otherwise.

Our model specifications follow the study of Daniel & Moskowitz (2016) which assessed the results of market timing regressions for the cross-sectional winner-minus-loser (WML) portfolio. Such specifications allow us to assess the predictability of the pattern in terms of $\text{RS}^{+}_{i,t}$ and $\text{RS}^{-}_{i,t}$ on individual commodity futures returns, and how this pattern differs when considering the upward momentum and the downward momentum simultaneously, with the indicators I_U and I_D as instruments. In addition, using the falling and rising day indicators $\widetilde{I}_F$ and $\widetilde{I}_R$, we exploit this further under the reversals of momentum, i.e., subsequent falling days in the upward momentum episode and subsequent rising days in the downward momentum episode, with the interaction terms $I_U \cdot \widetilde{I}_F$ and $I_D \cdot \widetilde{I}_R$ as instruments.

We start with the regression which focuses on the ex-ante realized semivariance estimators. This regression fits the future daily return of individual commodity futures $\widetilde{r}_{i,d_{t+1}}$ unconditionally on the ex-ante positive realized semivariance $\mathrm{RS}^+_{i,t}$ and the ex-ante negative realized semivariance $\mathrm{RS}^-_{i,t}$

$$\widetilde{r}_{i,d_{t+1}} = \alpha_1 + \beta^+ \mathrm{RS}^+_{i,t} + \beta^- \mathrm{RS}^-_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}}. \tag{5}$$

The regression results of (5) are tabulated in column (1) of Table 3. Based on the *t*-statistics, we find that the ex-ante realized semivariance estimators have no significant, direct explanatory power on the next period's returns of commodity futures.[17] The estimated coefficients are not statistically significant and the adjusted R-square is also low. These observations hold for all commodities.

To demonstrate the feature of commodity futures returns under different episodes of momentum, we run the second regression which fits the future daily return of individual commodity futures $\widetilde{r}_{i,d_{t+1}}$ conditionally on the dummy variables:

$$\widetilde{r}_{i,d_{t+1}} = \alpha_2 + \beta_U I_U + \beta_{U,F}\left(I_U \cdot \widetilde{I}_F\right) + \beta_D I_D + \beta_{D,R}\left(I_D \cdot \widetilde{I}_R\right) + \widetilde{\epsilon}_{i,d_{t+1}}. \tag{6}$$

The estimated coefficients of regression in (6) are tabulated in column (2) of Table 3. As expected, the next period's returns of commodity futures are well characterized by the momentum indicators with high adjusted R^2. We observe that each commodity futures has economically and statistically significant negative expected returns in the reversal episodes of upward momentum. Additionally, the absolute value of this negative expected return is larger than the positive expected return when considering the upward momentum only. This means that the economic gains obtained in a period

[17]Considering potential heteroscedasticity and serial autocorrelation in the residuals, we use the Newey-West heteroscedasticity-autocorrelation-consistent (HAC) standard errors to adjust the t-statistics of model coefficient estimates for all time series regressions in this study (see more details in White, 1980; MacKinnon & White, 1985; West & Newey, 1987).

of persistent upward momentum can be offset by the losses that occur in the reversals of upward momentum in the sense of the simple long-only (buy and hold) strategy. A similar pattern is also observed for the returns of each commodity futures during episodes of downward momentum and in the reversal periods of downward momentum. This evidence reveals the necessity of modelling the relationship between the next period's returns of individual commodity futures and the ex-ante risk estimators under different episodes of time series momentum.

We then run the momentum timing regression that fits the next period's daily returns of commodity futures $\widetilde{r}_{i,d_{t+1}}$ with the ex-ante positive realized semivariance $\mathrm{RS}^+_{i,t}$ and the ex-ante negative realized semivariance $\mathrm{RS}^-_{i,t}$ conditional on different momentum indicators:

$$\begin{aligned} \widetilde{r}_{i,d_{t+1}} = \gamma_0 &+ \left[\left(\gamma^+_U I_U + \gamma^+_{U,F} I_U \cdot \widetilde{I}_F\right) + \left(\gamma^+_D I_D + \gamma^+_{D,R} I_D \cdot \widetilde{I}_R\right)\right] \mathrm{RS}^+_{i,t} \\ &+ \left[\left(\gamma^-_U I_U + \gamma^-_{U,F} I_U \cdot \widetilde{I}_F\right) + \left(\gamma^-_D I_D + \gamma^-_{D,R} I_D \cdot \widetilde{I}_R\right)\right] \mathrm{RS}^-_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}}. \end{aligned} \tag{7}$$

The conditional model above in (7) can, in fact, be seen as a simultaneous version following two regressions which consider the episode of upward momentum alone:

$$\begin{aligned} \widetilde{r}_{i,d_{t+1}} = \gamma_0 &+ \left(\gamma^+_U I_U + \gamma^+_{U,F} I_U \cdot \widetilde{I}_F\right) \mathrm{RS}^+_{i,t} \\ &+ \left(\gamma^-_U I_U + \gamma^-_{U,F} I_U \cdot \widetilde{I}_F\right) \mathrm{RS}^-_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}}, \end{aligned}$$

and consider the episode of downward momentum alone:

$$\begin{aligned} \widetilde{r}_{i,d_{t+1}} = \gamma_0 &+ \left(\gamma^+_D I_D + \gamma^+_{D,R} I_D \cdot \widetilde{I}_R\right) \mathrm{RS}^+_{i,t} \\ &+ \left(\gamma^-_D I_D + \gamma^-_{D,R} I_D \cdot \widetilde{I}_R\right) \mathrm{RS}^-_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}}. \end{aligned}$$

Table 4 shows the regression results of the conditional model (7). The estimated coefficients, which are conditional on the single indicator terms and the interaction terms, are statistically significant for most commodity futures. Our results tabulate significant t-statistics in terms of coefficient estimating and also report high adjusted R^2 in terms of model fitting (ranging from 30% to 50% approximately).

Table 3: Results of regression on realized semivariance and momentum indicators separately from January 2007 to December 2018.

	Heteroskedasticity and Autocorrelation Consistent Estimator									
	(1)				(2)					
Variable Coefficient	Intercept $\hat{\alpha}_1$	$RS^+_{i,t}$ $\hat{\beta}^+$	$RS^-_{i,t}$ $\hat{\beta}^-$	R^2	Intercept $\hat{\alpha}_2$	I_U $\hat{\beta}_U$	$I_U \cdot \widetilde{I}_F$ $\hat{\beta}_{U,F}$	I_D $\hat{\beta}_D$	$I_D \cdot \widetilde{I}_R$ $\hat{\beta}_{D,R}$	R^2_{adj}
Panel A: Met sector										
AU	0.0001	-0.3708	0.1835	0.0003	-0.0026	0.0101	-0.0155	-0.0053	0.0154	0.4611
	(0.30)	(-0.58)	(0.43)		(-1.10)	(4.29)	(-24.48)	(-2.23)	(20.34)	
AG	-0.0004	0.7178	-0.6800	0.0027	-0.0004	0.0099	-0.0189	-0.0083	0.0165	0.4174
	(-1.25)	(1.48)	(-2.12)		(-0.12)	(2.90)	(-17.43)	(-2.42)	(18.33)	
CU	0.0003	-0.0731	-0.3096	0.0005	-0.0006	0.0114	-0.0211	-0.0116	0.0224	0.4937
	(0.76)	(-0.14)	(-0.53)		(-0.29)	(5.03)	(-24.07)	(-5.02)	(22.36)	
AL	-0.0001	-1.3604	0.7251	0.0017	-0.0010	0.0085	-0.0152	-0.0058	0.0124	0.4502
	(-0.54)	(-1.29)	(0.94)		(-1.06)	(8.63)	(-21.62)	(-6.02)	(19.68)	
NI	-0.0006	-0.6977	1.1835	0.0014	0.0002	0.0123	-0.0252	-0.0128	0.0233	0.5597
	(-0.70)	(-0.48)	(1.53)		(0.05)	(2.77)	(-22.46)	(-2.83)	(21.72)	
ZN	-0.0001	-0.4015	0.1674	0.0002	0.0058	0.0051	-0.0223	-0.0190	0.0239	0.5171
	(-0.16)	(-0.59)	(0.28)		(1.85)	(1.59)	(-26.43)	(-5.89)	(24.66)	
Panel B: ENG sector										
RB	0.0000	-1.7723	1.6417	0.0018	-0.0009	0.0113	-0.0207	-0.0087	0.0182	0.4613
	(-0.09)	(-1.24)	(1.00)		(-0.44)	(5.32)	(-17.53)	(-4.26)	(25.62)	
HC	0.0008	-1.9277	1.3967	0.0024	0.0002	0.0134	-0.0271	-0.0105	0.0207	0.4988
	(1.05)	(-0.96)	(0.63)		(0.12)	(6.27)	(-15.58)	(-5.14)	(16.87)	
J	-0.0006	1.6272	-0.7632	0.0019	0.0007	0.0149	-0.0293	-0.0125	0.0218	0.4809
	(-1.28)	(1.03)	(-0.59)		(0.30)	(5.72)	(-18.89)	(-4.91)	(20.96)	
JM	0.0000	-1.5808	1.6233	0.0013	-0.0056	0.0217	-0.0314	-0.0069	0.0240	0.5096
	(0.08)	(-1.03)	(1.33)		(-5.40)	(13.91)	(-16.87)	(-5.20)	(19.44)	
I	-0.0001	-1.3333	1.3147	0.0018	-0.0056	0.0231	-0.0339	-0.0100	0.0290	0.5422
	(-0.07)	(-1.10)	(0.95)		(-1.55)	(6.07)	(-18.64)	(-2.64)	(21.20)	
Panel C: IND sector										
BU	0.0002	-2.3087	1.1440	0.0053	-0.0025	0.0140	-0.0234	-0.0111	0.0232	0.4734
	(0.25)	(-1.80)	(1.32)		(-2.59)	(10.17)	(-15.80)	(-8.36)	(18.61)	
RU	-0.0009	1.7650	-1.1566	0.0043	0.0064	0.0084	-0.0295	-0.0222	0.0284	0.5528
	(-1.67)	(2.45)	(-1.82)		(3.39)	(4.30)	(-35.32)	(-11.13)	(33.24)	
TA	0.0002	-1.0824	0.3837	0.0013	-0.0022	0.0124	-0.0196	-0.0078	0.0182	0.5061
	(0.49)	(-1.03)	(0.55)		(-1.15)	(6.31)	(-26.69)	(-3.96)	(25.58)	
MA	-0.0004	1.5724	-1.0944	0.0010	0.0010	0.0120	-0.0237	-0.0140	0.0236	0.5558
	(-0.47)	(1.04)	(-0.72)		(0.46)	(5.13)	(-22.86)	(-5.85)	(18.66)	
FG	0.0003	-0.2160	0.1409	0.0000	0.0000	0.0095	-0.0191	-0.0096	0.0188	0.5073
	(0.63)	(-0.14)	(0.12)		(0.01)	(4.88)	(-23.93)	(-4.88)	(25.99)	
ZC	0.0007	-1.5488	1.5474	0.0009	0.0005	0.0109	-0.0230	-0.0093	0.0189	0.5302
	(1.01)	(-0.92)	(0.85)		(0.24)	(5.12)	(-17.92)	(-4.46)	(16.85)	
PP	0.0003	-1.3306	1.2572	0.0009	0.0012	0.0098	-0.0200	-0.0119	0.0202	0.5300
	(0.42)	(-0.98)	(1.01)		(0.65)	(4.95)	(-21.52)	(-6.05)	(21.33)	
V	0.0001	-1.9184	1.1842	0.0019	0.0000	0.0082	-0.0167	-0.0080	0.0150	0.4858
	(0.37)	(-1.68)	(1.39)		(-0.02)	(3.63)	(-22.61)	(-3.57)	(23.63)	
L	0.0006	-0.3830	-0.8272	0.0040	-0.0006	0.0105	-0.0205	-0.0108	0.0215	0.5209
	(1.42)	(-0.35)	(-0.82)		(-0.30)	(5.25)	(-29.99)	(-5.09)	(21.19)	

continued on the next page

(Continued) Results of regression on realized semivariance and momentum indicators separately from January 2007 to December 2018

	Heteroskedasticity and Autocorrelation Consistent Estimator									
	(1)				(2)					
Variable	Intercept	$RS^+_{i,t}$	$RS^-_{i,t}$	R^2	Intercept	I_U	$I_U \cdot \widetilde{I}_F$	I_D	$I_D \cdot \widetilde{I}_R$	R^2_{adj}
Coefficient	$\hat{\alpha}_1$	$\hat{\beta}^+$	$\hat{\beta}^-$		$\hat{\alpha}_2$	$\hat{\beta}_U$	$\hat{\beta}_{U,F}$	$\hat{\beta}_D$	$\hat{\beta}_{D,R}$	
Panel D: AGI sector										
CF	-0.0001	1.1136	-0.8300	0.0018	0.0000	0.0084	-0.0166	-0.0071	0.0135	0.4374
	(-0.59)	(1.38)	(-1.14)		(-0.01)	(6.60)	(-17.37)	(-6.09)	(22.85)	
SR	-0.0003	0.6406	0.0161	0.0005	0.0017	0.0067	-0.0162	-0.0098	0.0153	0.5046
	(-1.04)	(0.73)	(0.04)		(1.19)	(4.51)	(-24.25)	(-6.75)	(30.79)	
RM	0.0000	-0.5979	1.3171	0.0013	0.0025	0.0082	-0.0205	-0.0126	0.0187	0.5309
	(0.02)	(-0.51)	(1.17)		(0.94)	(3.01)	(-21.39)	(-4.62)	(27.26)	
OI	-0.0006	-0.6516	1.6253	0.0015	-0.0004	0.0078	-0.0143	-0.0069	0.0133	0.5221
	(-1.74)	(-0.44)	(1.56)		(-0.31)	(5.86)	(-21.34)	(-5.30)	(26.08)	
C	0.0002	-1.7168	0.1445	0.0017	0.0000	0.0045	-0.0090	-0.0056	0.0099	0.4435
	(1.22)	(-1.76)	(0.20)		(-0.01)	(2.81)	(-23.32)	(-3.45)	(24.77)	
CS	-0.0001	0.1514	0.2905	0.0001	-0.0012	0.0089	-0.0153	-0.0063	0.0139	0.5045
	(-0.27)	(0.07)	(0.12)		(-0.71)	(4.99)	(-16.38)	(-3.57)	(18.33)	
A	0.0003	-0.4427	-0.3102	0.0009	0.0009	0.0069	-0.0157	-0.0092	0.0155	0.4684
	(1.17)	(-0.68)	(-0.36)		(0.58)	(4.21)	(-26.25)	(-5.39)	(19.85)	
M	0.0004	0.0179	-0.1526	0.0001	0.0021	0.0082	-0.0197	-0.0123	0.0193	0.5244
	(1.33)	(0.03)	(-0.19)		(1.33)	(5.13)	(-30.58)	(-7.50)	(24.62)	
Y	0.0003	-0.3125	-0.7159	0.0026	0.0009	0.0083	-0.0185	-0.0104	0.0178	0.5028
	(0.83)	(-0.38)	(-1.29)		(0.53)	(4.87)	(-26.43)	(-5.98)	(21.67)	
P	0.0003	-0.7271	-0.5763	0.0034	0.0026	0.0081	-0.0211	-0.0138	0.0201	0.5304
	(0.75)	(-0.96)	(-1.01)		(1.28)	(3.85)	(-28.99)	(-6.49)	(23.49)	
JD	-0.0002	-1.4340	1.7953	0.0012	0.0020	0.0074	-0.0187	-0.0109	0.0162	0.4953
	(-0.30)	(-0.68)	(1.04)		(1.40)	(4.78)	(-24.37)	(-7.02)	(21.97)	

Notes: The regression (1) fits the next period individual asset daily return $\widetilde{r}_{i,d_{t+1}}$ with the ex-ante positive realized semivariance $RS^+_{i,t}$ and the ex-ante negative realized semivariance $RS^+_{i,t}$:

$$\widetilde{r}_{i,d_{t+1}} = \alpha_1 + \beta^+ RS^+_{i,t} + \beta^- RS^-_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}}.$$

The regression (2) fits the next period individual asset daily return $\widetilde{r}_{i,d_{t+1}}$ with dummy variables of different momentum indicators:

$$\widetilde{r}_{i,d_{t+1}} = \alpha_2 + \beta_U I_U + \beta_{U,F}\left(I_U \cdot \widetilde{I}_F\right) + \beta_D I_D + \beta_{D,R}\left(I_D \cdot \widetilde{I}_R\right) + \widetilde{\epsilon}_{i,d_{t+1}},$$

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 coefficient estimates and adjusted R-square are reported. West & Newey (1987) standard errors are employed, and the adjusted statistical significance is documented in terms of t-statistics in parentheses. The sectors MET, ENG, IND and AGI stand for the market sectors of metals, energy products, industrial materials, and agriculture products, respectively.

Moreover, we summarize the model coefficients of (7) under different episodes of time series momentum in Figure 2. Specifically, as illustrated in the graph, the red bars of the $\left|\hat{\gamma}^+_{U,F}\right|$ and $\left|\hat{\gamma}^-_{U,F}\right|$ are greater than the blue bars of $\left|\hat{\gamma}^+_U + \hat{\gamma}^+_{U,F}\right|$ and $\left|\hat{\gamma}^-_U + \hat{\gamma}^-_{U,F}\right|$ for all contracts. This indicates that the effect of RS^+ and RS^- in the subsequent falling days of the upward momentum episode (uptrending market) turns out to be stronger than during periods of ordinary upward momentum. Consistently, this pattern is also confirmed for RS^+ and RS^- in the subsequent rising days of the downward momentum episode (downward trending market) when compared with the ordinary downward momentum. To illustrate our regression results in detail, we take the case of the copper contract (CU) as an example (see Figure 2 and Panel A of Table 4). The estimated $\left|\hat{\gamma}^+_{U,F}\right|$ of 10.33 for $RS^+_{i,t}$ and $\left|\hat{\gamma}^-_{U,F}\right|$ of 16.30 for $RS^-_{i,t}$, are larger than the estimated $\left|\hat{\gamma}^+_U + \hat{\gamma}^+_{U,F}\right| = 5.38$ and $\left|\hat{\gamma}^-_U + \hat{\gamma}^-_{U,F}\right| = 7.31$, respectively. Meanwhile, the estimated coefficients of the interaction term $I_D \cdot \widetilde{I}_R$ ($\left|\hat{\gamma}^+_{D,R}\right| = 14.09$, $\left|\hat{\gamma}^-_{D,R}\right| = 8.30$) show similar results to I_D ($\left|\hat{\gamma}^+_D + \hat{\gamma}^+_{D,R}\right| = 8.96$, $\left|\hat{\gamma}^-_D + \hat{\gamma}^-_{D,R}\right| = 3.25$).

These results imply that a more significant increment in RS^+ or RS^- will potentially contribute to more severe losses during the reversal episodes of time series momentum, i.e., future slumps during periods of upward momentum and future rebounds during periods of downward momentum. Volatility clustering is another reason why we monitor the "bad" side risk for the time series momentum portfolio when the ex-ante risk estimators $RS^+_{i,t}$ and/or $RS^-_{i,t}$ proceed to the tailed groups of their empirical distribution, this being the right 20% percentiles (the top group of segmenting the population into five groups). Such moments of risk estimators RS^+ and RS^- imply a high probability of time series momentum losses.

Figure 2: Least square estimates for the coefficients of the momentum timing regression in terms of each commodity future contract from the start date of the data sample to December 2018. The momentum timing regression fits the next period individual asset daily return $\widetilde{r}_{i,d_{t+1}}$ with the ex-ante positive realized semivariance $\mathrm{RS}^{+}_{i,t}$ and the ex-ante negative realized semivariance $\mathrm{RS}^{+}_{i,t}$ conditional on different momentum indicators:

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} = \gamma_0 &+ [(\gamma^{+}_{U} I_U + \gamma^{+}_{U,F} I_U \cdot \widetilde{I}_F) + (\gamma^{+}_{D} I_D + \gamma^{+}_{D,R} I_D \cdot \widetilde{I}_R)]\mathrm{RS}^{+}_{i,t} \\ &+ [(\gamma^{-}_{U} I_U + \gamma^{-}_{U,F} I_U \cdot \widetilde{I}_F) + (\gamma^{-}_{D} I_D + \gamma^{-}_{D,R} I_D \cdot \widetilde{I}_R)]\mathrm{RS}^{-}_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}},\end{aligned}$$

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 subsequent falling days in the upward momentum $I_U \cdot \widetilde{I}_F$ and the subsequent 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.

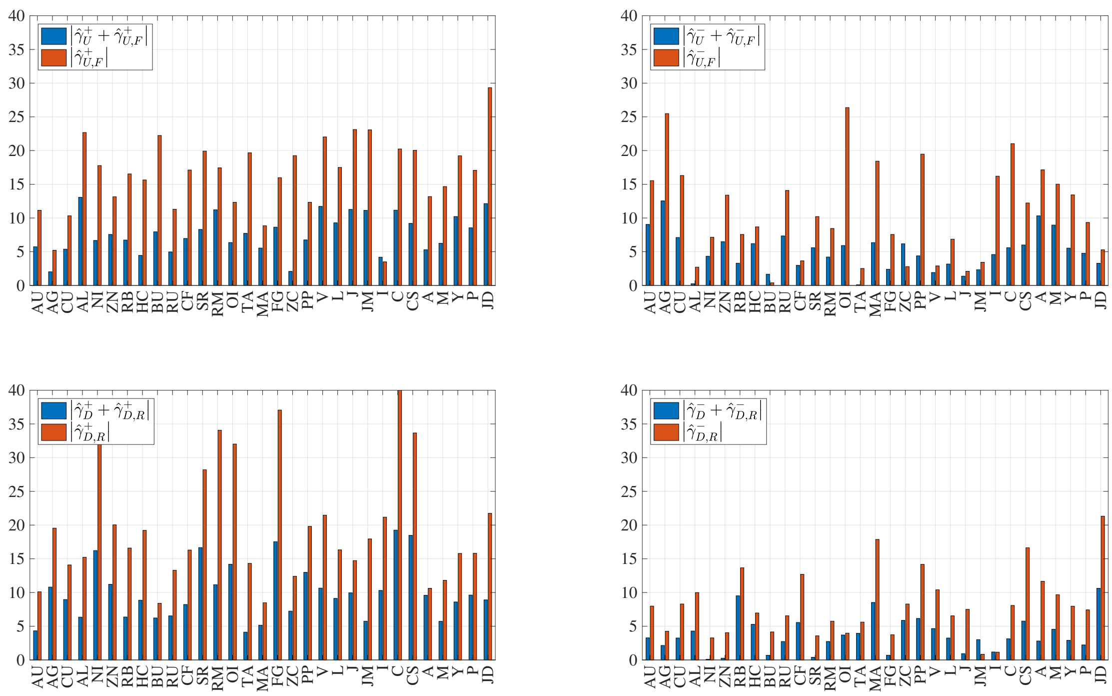


Table 4: Momentum timing regression results from January 2007 to December 2018

Heteroskedasticity and Autocorrelation Consistent Estimator										
Variable	Intercept	$I_U \cdot \mathrm{RS}^+_{i,t}$	$I_U \cdot \widetilde{I}_F \cdot \mathrm{RS}^+_{i,t}$	$I_D \cdot \mathrm{RS}^+_{i,t}$	$I_D \cdot \widetilde{I}_R \cdot \mathrm{RS}^+_{i,t}$	$I_U \cdot \mathrm{RS}^-_{i,t}$	$I_U \cdot \widetilde{I}_F \cdot \mathrm{RS}^-_{i,t}$	$I_D \cdot \mathrm{RS}^-_{i,t}$	$I_D \cdot \widetilde{I}_R \cdot \mathrm{RS}^-_{i,t}$	R^2_{adj}
Coefficient	$\hat{\gamma}_0$	$\hat{\gamma}^+_U$	$\hat{\gamma}^+_{U,F}$	$\hat{\gamma}^+_D$	$\hat{\gamma}^+_{D,R}$	$\hat{\gamma}^-_U$	$\hat{\gamma}^-_{U,F}$	$\hat{\gamma}^-_D$	$\hat{\gamma}^-_{D,R}$	
Panel A: MET sector										
AU	0.0003	5.4056	-11.1490	-5.7878	10.1075	6.4920	-15.5424	-4.7114	7.9864	0.2898
	(1.33)	(5.13)	(-5.53)	(-1.70)	(1.70)	(3.29)	(-4.00)	(-3.58)	(3.24)	
AG	-0.0006	3.1878	-5.2138	-8.7421	19.5513	12.9430	-25.4831	-2.1154	4.2590	0.2793
	(-1.64)	(1.38)	(-1.65)	(-4.13)	(4.15)	(4.54)	(-6.57)	(-3.09)	(2.76)	
CU	-0.0004	4.9489	-10.3292	-5.1285	14.0878	9.1992	-16.3049	-5.0444	8.2993	0.4466
	(-1.50)	(4.82)	(-6.46)	(-4.10)	(7.09)	(6.63)	(-7.52)	(-6.96)	(7.46)	
AL	0.0000	9.6056	-22.6754	-8.8829	15.2334	2.4624	-2.7148	-5.7032	9.9928	0.3984
	(-0.15)	(4.23)	(-5.61)	(-2.84)	(3.66)	(1.35)	(-0.95)	(-4.37)	(9.17)	
NI	-0.0007	11.1052	-17.7788	-20.1969	36.4163	2.8140	-7.1512	3.1643	-3.2697	0.4347
	(-0.88)	(3.67)	(-3.36)	(-4.76)	(7.93)	(1.16)	(-1.39)	(1.20)	(-0.80)	
ZN	0.0002	5.5900	-13.1504	-8.8169	20.0366	6.8997	-13.3954	-3.7850	4.0472	0.4303
	(0.76)	(3.79)	(-6.96)	(-5.44)	(7.84)	(4.02)	(-5.86)	(-2.74)	(1.76)	
Panel B: ENG sector										
RB	-0.0008	9.8008	-16.5363	-10.2310	16.5980	4.2627	-7.5621	-4.1543	13.6717	0.4328
	(-2.36)	(3.24)	(-4.09)	(-4.11)	(3.99)	(1.41)	(-2.07)	(-1.89)	(3.38)	
HC	-0.0007	11.1866	-15.6434	-10.3508	19.2163	2.4798	-8.6825	-1.6727	6.9628	0.4657
	(-1.19)	(2.90)	(-3.08)	(-4.39)	(3.95)	(0.72)	(-1.89)	(-1.10)	(1.61)	
J	-0.0005	11.8462	-23.1186	-4.7776	14.7338	-0.7227	2.1025	-6.5668	7.5007	0.4653
	(-1.12)	(4.56)	(-5.40)	(-1.93)	(3.72)	(-0.31)	(0.50)	(-3.05)	(2.24)	
JM	-0.0006	11.9382	-23.0731	-12.2046	17.9503	-1.1021	3.4356	2.1747	0.8394	0.5041
	(-1.14)	(4.93)	(-5.84)	(-3.26)	(4.05)	(-0.61)	(0.84)	(0.73)	(0.22)	
I	-0.0013	-0.6947	-3.4963	-10.8717	21.1796	11.6183	-16.2055	0.0247	1.1572	0.5141
	(-1.59)	(-0.20)	(-0.73)	(-6.70)	(8.29)	(3.48)	(-3.58)	(0.02)	(0.56)	
Panel C: IND sector										
BU	-0.0013	14.2810	-22.2394	-2.1771	8.4033	-2.0561	0.3850	-3.4565	4.1549	0.3574
	(-2.31)	(3.74)	(-3.98)	(-0.99)	(2.34)	(-0.50)	(0.06)	(-1.32)	(0.93)	
RU	-0.0006	6.3338	-11.3032	-6.7677	13.3056	6.7457	-14.0874	-3.8217	6.5529	0.4453
	(-1.13)	(5.03)	(-5.72)	(-3.66)	(5.87)	(5.16)	(-6.19)	(-5.37)	(4.05)	
TA	-0.0006	11.9440	-19.6687	-10.1940	14.3207	2.4096	-2.5145	-1.6600	5.6113	0.3650
	(-1.85)	(6.59)	(-6.66)	(-4.60)	(4.37)	(1.30)	(-0.70)	(-0.74)	(2.26)	
MA	-0.0006	3.3061	-8.8531	-3.3291	8.4846	12.0776	-18.4309	-9.3447	17.8708	0.4882
	(-0.78)	(1.48)	(-2.30)	(-1.03)	(2.01)	(5.10)	(-4.31)	(-2.53)	(4.77)	
FG	-0.0007	7.3356	-15.9817	-19.5203	37.0582	5.1566	-7.5597	4.4409	-3.7400	0.4282
	(-1.40)	(3.23)	(-4.21)	(-3.80)	(4.82)	(1.81)	(-1.34)	(1.03)	(-0.54)	
ZC	-0.0013	17.1625	-19.2474	-5.1753	12.4171	-3.3876	-2.7911	-2.4287	8.2973	0.3675
	(-1.96)	(5.01)	(-2.62)	(-2.08)	(2.02)	(-0.89)	(-0.54)	(-0.64)	(1.05)	
PP	-0.0010	5.5840	-12.3387	-6.8146	19.8063	15.0910	-19.4793	-8.0193	14.1737	0.4645
	(-1.83)	(1.46)	(-2.05)	(-1.91)	(3.54)	(3.73)	(-3.17)	(-2.47)	(2.95)	
V	0.0000	10.2983	-22.0233	-10.8155	21.4728	0.9797	-2.8971	-5.7496	10.4080	0.4269
	(-0.04)	(5.64)	(-7.96)	(-4.18)	(4.59)	(0.50)	(-1.08)	(-2.99)	(3.10)	
L	-0.0002	8.2133	-17.5013	-7.1958	16.3222	3.6872	-6.8633	-3.2938	6.5458	0.4622
	(-0.59)	(5.90)	(-8.06)	(-7.46)	(7.20)	(2.67)	(-2.60)	(-3.33)	(3.74)	

continued on the next page

(Continued) Momentum timing regression results from January 2007 to December 2018

Heteroskedasticity and Autocorrelation Consistent Estimator										
Variable	Intercept	$I_U \cdot \mathrm{RS}^+_{i,t}$	$I_U \cdot I_F \cdot \mathrm{RS}^+_{i,t}$	$I_D \cdot \mathrm{RS}^+_{i,t}$	$I_D \cdot \widetilde{I}_R \cdot \mathrm{RS}^+_{i,t}$	$I_U \cdot \mathrm{RS}^-_{i,t}$	$I_U \cdot I_F \cdot \mathrm{RS}^-_{i,t}$	$I_D \cdot \mathrm{RS}^-_{i,t}$	$I_D \cdot \widetilde{I}_R \cdot \mathrm{RS}^-_{i,t}$	R^2_{adj}
Coefficient	$\hat{\gamma}_0$	$\hat{\gamma}^+_U$	$\hat{\gamma}^+_{U,F}$	$\hat{\gamma}^+_D$	$\hat{\gamma}^+_{D,R}$	$\hat{\gamma}^-_U$	$\hat{\gamma}^-_{U,F}$	$\hat{\gamma}^-_D$	$\hat{\gamma}^-_{D,R}$	
Panel D: AGI sector										
CF	-0.0002	10.1511	-17.1159	-8.0771	16.2995	0.6714	-3.6470	-7.1423	12.6977	0.3940
	(-0.74)	(5.67)	(-5.03)	(-4.10)	(4.63)	(0.56)	(-1.39)	(-3.14)	(3.64)	
SR	-0.0004	11.6201	-19.9240	-11.5443	28.2082	4.6160	-10.2116	-3.1824	3.5761	0.3840
	(-1.67)	(4.29)	(-4.63)	(-4.70)	(6.10)	(1.64)	(-2.44)	(-1.33)	(1.00)	
RM	0.0016	6.2222	-17.4406	-22.9164	34.0781	4.2350	-8.4469	-3.0105	5.7493	0.4419
	(3.32)	(3.75)	(-4.73)	(-7.34)	(7.89)	(1.93)	(-1.60)	(-1.38)	(1.87)	
OI	-0.0009	5.9666	-12.3301	-17.8237	32.0220	20.4580	-26.3767	-0.2753	3.9745	0.3650
	(-2.02)	(1.51)	(-1.98)	(-4.21)	(4.51)	(3.70)	(-3.74)	(-0.07)	(0.69)	
C	-0.0002	9.0696	-20.2376	-21.4440	40.7009	15.4279	-21.0269	-4.9390	8.0799	0.3630
	(-0.99)	(1.60)	(-2.24)	(-6.09)	(7.25)	(2.03)	(-1.91)	(-3.82)	(3.58)	
CS	-0.0001	10.8363	-20.0391	-15.1835	33.6607	6.2276	-12.2294	-10.8804	16.6440	0.4409
	(-0.37)	(2.34)	(-2.99)	(-2.79)	(3.52)	(1.14)	(-1.40)	(-2.43)	(2.07)	
A	-0.0001	7.8777	-13.1790	-1.0299	10.6241	6.8222	-17.1441	-8.8573	11.6643	0.3855
	(-0.32)	(4.83)	(-4.85)	(-0.45)	(2.89)	(4.35)	(-7.54)	(-7.56)	(5.46)	
M	0.0003	8.4069	-14.6621	-6.0803	11.8123	6.0703	-15.0248	-5.1195	9.6782	0.4004
	(1.03)	(6.54)	(-7.00)	(-2.48)	(2.91)	(4.35)	(-5.07)	(-4.35)	(4.31)	
Y	-0.0001	9.0121	-19.2313	-7.1916	15.7939	7.8908	-13.4288	-5.0536	7.9728	0.4547
	(-0.40)	(6.74)	(-9.87)	(-4.55)	(5.64)	(4.91)	(-5.49)	(-5.56)	(5.59)	
P	-0.0002	8.5221	-17.0720	-6.2062	15.8268	4.5614	-9.3409	-5.1980	7.4245	0.4518
	(-0.80)	(4.97)	(-7.13)	(-3.10)	(4.10)	(1.80)	(-2.56)	(-4.82)	(3.90)	
JD	-0.0003	17.1934	-29.3317	-12.8346	21.7451	1.9948	-5.2828	-10.6997	21.3241	0.4108
	(-0.62)	(4.88)	(-5.34)	(-3.30)	(3.63)	(0.57)	(-0.89)	(-3.41)	(4.18)	

Notes: The momentum timing regression fits the next period individual asset daily return $\widetilde{r}_{i,d_{t+1}}$ with the ex-ante positive realized semivariance $\mathrm{RS}^+_{i,t}$ and the ex-ante negative realized semivariance $\mathrm{RS}^-_{i,t}$ conditional on different momentum indicators:

$$\begin{aligned}\widetilde{r}_{i,d_{t+1}} &= \gamma_0 + [(\gamma^+_U I_U + \gamma^+_{U,F} I_U \cdot \widetilde{I}_F) + (\gamma^+_D I_D + \gamma^+_{D,R} I_D \cdot \widetilde{I}_R)]\mathrm{RS}^+_{i,t} \\ &+ [(\gamma^-_U I_U + \gamma^-_{U,F} I_U \cdot \widetilde{I}_F) + (\gamma^-_D I_D + \gamma^-_{D,R} I_D \cdot \widetilde{I}_R)]\mathrm{RS}^-_{i,t} + \widetilde{\epsilon}_{i,d_{t+1}},\end{aligned}$$

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 coefficient estimates and adjusted R-square are reported. West & Newey (1987) standard errors are employed, and the adjusted statistical significance is documented in terms of t-statistics in parentheses. The sectors MET, ENG, IND and AGI stand for the market sectors of metals, energy products, industrial materials, and agriculture products, respectively.

4. Tuned time series momentum

Although the return formula in (4) shows a well-defined, weight-generating function built upon the idea of volatility scaling and risk parity, the long/short signals derived from the signs of past cumulative returns of single risky assets are less effective, particularly during the reversals of momentum and in sideways markets. In Section 3, we show a significant lead-lag effect between commodity futures returns and the realized semivariance estimators, even during the reversal episodes of time series momentum. In this section, we explore how we can use the intraday information implied in the positive and negative realized semivariance when timing the life cycle of time series momentum.

We design a set of rules that adjust the trading signals of the original time series momentum in different regions of the joint distribution of RS^+ and RS^-. The empirical results on the Chinese commodity futures markets demonstrate that the tuning signals of the original time series momentum can be used to mitigate strategy losses.

4.1. Portfolio construction

Our rule-based tuning approach has been developed following the analysis of different scenarios in which time series momentum suffers losses. Figure 3 shows four regions on the surface of the joint distribution of the positive and negative realized semivariance. These four regions are divided by their quantile-related reference points, which are recursively generated from the joint (80%, 80%) percentiles of the historical distribution of $(RS^+_{i,t}, RS^-_{i,t})$, with a 250 trading days fixed-length rolling window.[18] Figure 3 demonstrates the reference points in the coordinate plane, and also lists the associated strategies that are considered during the holding period for each of these four regions. These four regions enable us to filter the moments when the upside risk measurement (RS^+) and/or the downside risk measurement (RS^-) distribute into their right tails.

Then, the portfolio return formula of our tuned time series momentum (TTSM) is given by

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

where the long/short decision of the tuned portfolio is the outcome of a nonlinear function $\mathcal{B}(\cdot)$. This decision function $\mathcal{B}(\cdot)$ is built upon the past returns, the positive realized semivariance, and the negative realized semivariance of the underlying individual commodity futures

$$\text{sign}^{ttsm}_{i,d_t} = \mathcal{B}\left(\text{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right), \text{RS}^+_{i,t}(\Delta), \text{RS}^-_{i,t}(\Delta)\right).$$

We explain, in further detail, the outcome gained by the nonlinear decision function $\mathcal{B}(\cdot)$ in Table 5.

[18] The choice of 250 days is arbitrary but matches a 12-month-long experimental window, which is considered to cover 250 observations and to derive a stable empirical distribution along time. We note that this window could be modified as long as the (80%, 80%) percentile value is stable.

Figure 3: Choices of the tuned time series momentum in different regions on the surface of the joint distribution of the positive realized semivariance (RS^+) and the negative realized semivariance (RS^-). The surface of the joint distribution is divided into four regions by the reference point that generated from the joint (80%, 80%) percentiles of their historical distribution.

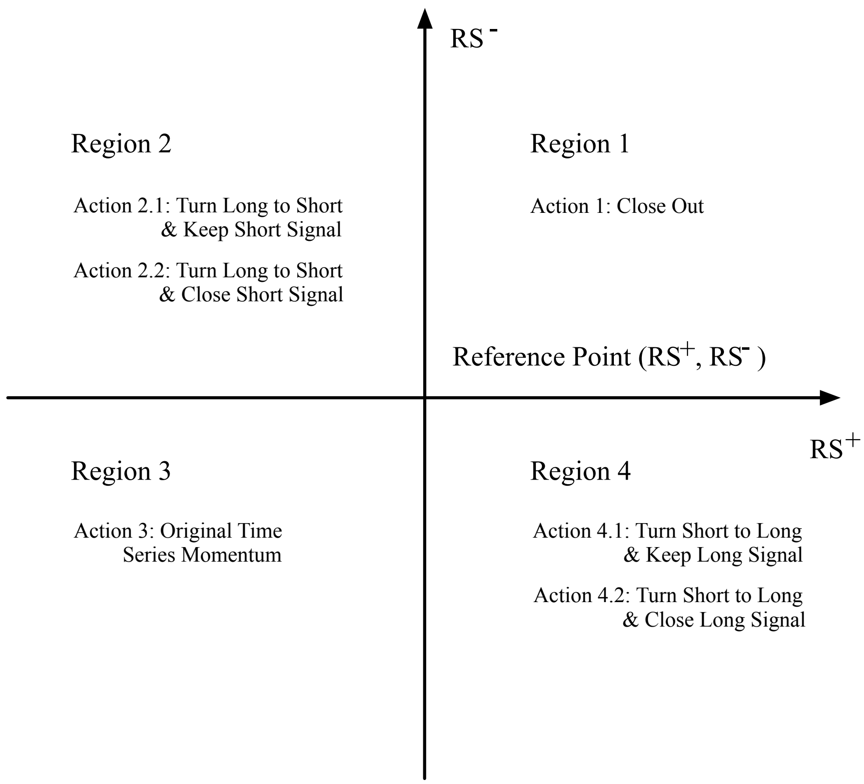


Table 5 reports the different actions and holding period portfolio returns of the tuning choices under each of the four regions presented in Figure 3, and we refer to them as TTSM-S1 and TTSM-S2. As documented in Section 2, the realized semivariance can provide more accurate risk estimates in the reversal episodes of momentum. More specifically, the risk measurements of positive and negative realized semivariance are relatively high when there is a severe fluctuation in the sideways market, which can still lead to losses for both long and short signals. Meanwhile, both are relatively low when there is a less volatile upward momentum, which can lead to positive results for the long signal. Consistently, one can find a similar pattern in the less volatile downward momentum. In this case, we choose to close out all long and short positions in Region 1, and retain the original time series momentum signals in Region 3.[19]

Table 5: Methodologies and results of the tuned time series momentum strategy construction using the nonlinear decision function $\mathcal{B}(\cdot)$

Strategy	Region 1		Region 2		Region 3		Region 4	
	Action	Return	Action	Return	Action	Return	Action	Return
TTSM-S1	1	0	2.1	$-r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	3	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	4.1	$r^{tsm}_{l,d_t} + r^{tsm}_{s,d_t}$
TTSM-S2	1	0	2.2	$-r^{tsm}_{l,d_t}$	3	$r^{tsm}_{l,d_t} - r^{tsm}_{s,d_t}$	4.2	r^{tsm}_{s,d_t}

Notes: 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:

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

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

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

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}. The decision function $\mathcal{B}(\cdot)$ of the tuned time series momentum (TTSM) is built upon the past returns, the positive realized semivariance, and the negative realized semivariance of underlying individual asset

$$\text{sign}^{ttsm}_{i,d_t} = \mathcal{B}\left(\text{sign}\left(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\right), \text{RS}^{+}_{i,t}(\Delta), \text{RS}^{-}_{i,t}(\Delta)\right),$$

and the corresponding portfolio return formula is given by

$$r^{ttsm}_{p,d_{t+1}} = \frac{1}{N_t}\sum_{i=1}^{N_t}\text{sign}^{ttsm}_{i,d_t}\frac{\sigma_{target}}{\sigma_{i,d_t}} r_{i,d_{t+1}}.$$

Action 1: close out; Action 2.1: turn long to short and keep short signal; Action 2.2: turn long to short and close short signal; Action 3: original time series momentum; Action 4.1: turn short to long and keep long signal; Action 4.2: turn short to long and close long signal.

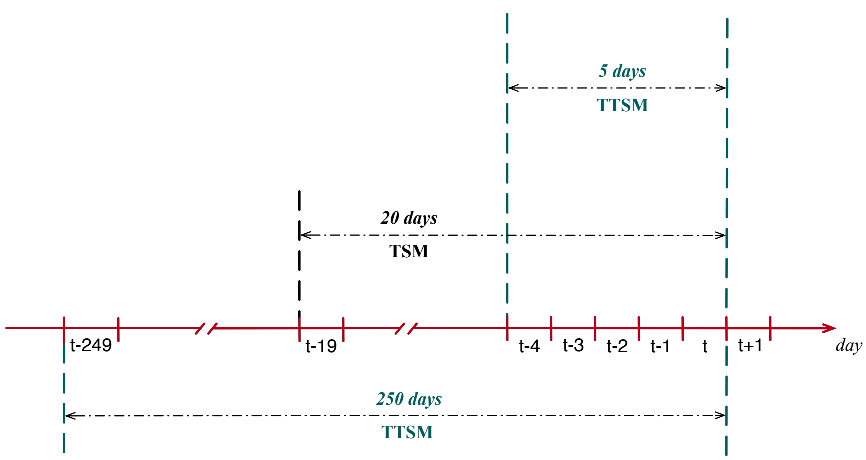
The tuning choices under Region 2 and Region 4 are complicated due to the fact that the corresponding asymmetric structures of positive and negative realized semivariance have wholly

[19] The term "close out" means that we treated those days as zero returns.

different meanings for the long signal in periods of upward momentum and the short signal during periods of downward momentum. Considering the predictable pattern of the "bad" side risk to the reversals of momentum, we design to reverse the signals of the original time series momentum when the "bad" side risk is relatively high in the construction of the TTSM-S1 strategy. Namely, turning the long signal into a short signal in Region 2, and turning the short signal into a long signal in Region 4.

The existing time series momentum market anomaly has been regarded as the market reaction process from an initial under-reaction to a delayed over-reaction toward the incoming new information (Hurst et al., 2013). Owing to the imperfect market and irrational trading, the delayed market overreaction is accompanied by the herding behavior of market participants. We then interpret it as the period in which an asset price increases (decreases) rapidly along with the upward (downward) momentum. Considering the TTSM-S2 strategy to be an enhanced version of the TTSM-S1, we further explore the predictable pattern of "good" side risk to market overreaction. Namely, closing out the short position in Region 2, and closing out the long position in Region 4, to avoid market uncertainties following the irrational trading behavior.

Figure 4: The rolling windows used in generating the trading signals of TSM and TTSM strategies.



We later examine the out-of-sample strategy performance of the tuned time series momentum (TTSM) empirically based on the Chinese commodity futures markets. The out-of-sample portfolio is rebalanced daily with a rolling window procedure, which is the same size as the lookback window. The results allow us to evaluate how the intraday information implied in the realized semivariance can predict the life cycle of time series momentum. To clarify various windows in our analysis, we streamline the rolling-window set-up for construction procedure for the TTSM in Figure 4. For a given day d_t, the constructing procedure of TTSM trading signal contains the following four steps:

Step (i). We obtain the original time series momentum signal for each individual commodity futures using cumulative returns over the past 20 days (i.e., the lookback window from d_{t-19} to d_t). If the cumulative return is positive, it indicates an upward momentum and a long position. Otherwise, it indicates a downward momentum and a short position.

Step (ii). We calculate the positive realized semivariance $\mathrm{RS}^+_{i,t}$ and negative realized semivariance $\mathrm{RS}^-_{i,t}$ using intraday 5-min returns over the past five days (i.e., from d_{t-4} to d_t). We include the intraday returns in day d_t in the calculation to ensure all available information is used.

Step (iii). As explained in Step (ii) we calculate $\mathrm{RS}^+_{i,t}$ and $\mathrm{RS}^-_{i,t}$ on every trading day d_t giving us time series observations for both estimators. We derive the (80%, 80%) percentiles, denoted as the reference point (x^+, x^-), of the joint distribution of positive realized semivariance (RS^+) and negative realized semivariance (RS^-) using historical sample observations from d_{t-249} to d_t.[20]

Step (iv). We compare $\mathrm{RS}^+_{i,t}$ and $\mathrm{RS}^-_{i,t}$ obtained in Step (ii) with the reference point (x^+, x^-) obtained in Step (iii) to identify where current estimators sit in relation to the historical distribution. Following the rules illustrated in Figure 3, we then generate TTSM trading signals for the next trading day d_{t+1} by adjusting the original long or short positions obtained in Step (i).

[20]Denote the joint empirical CDF (cumulative distribution function) of RS^+ and RS^- as $F_{\mathrm{RS}^+,\mathrm{RS}^-}(\mathrm{rs}^+, \mathrm{rs}^-)$, the reference point of (80%, 80%) percentiles means the marginal CDFs satisfy $F_{\mathrm{RS}^+,\mathrm{RS}^-}(x^+, \infty) = F_{\mathrm{RS}^+}(x^+) = P(\mathrm{RS}^+ \leq x^+) = 80\%$ and $F_{\mathrm{RS}^+,\mathrm{RS}^-}(\infty, x^-) = F_{\mathrm{RS}^-}(x^-) = P(\mathrm{RS}^- \leq x^-) = 80\%$.

4.2. Strategy performance

As an example, the performance of the TTSM approach is examined on the basis of an original time series momentum (TSM) strategy with a 20-trading-days (nearly one month in the calendar) lookback window. Our following robustness check also produces consistent results when using different lookback windows. Recall that, owing to the night-trading policy implemented in 2013, the out-of-sample performance should be examined over different subsamples. As a result, performance evaluation measures, including the annual return, annualized Sharpe ratio, maximum drawdown, t-statistics of one-sided t-test, and others, are tabulated according to different subsamples.

In Table 6, we report the empirical results corresponding to a 20 trading days lookback window in Panel A for the first subsample from January 2008 to December 2012, in Panel B for the second subsample from January 2013 to December 2018, and in Panel C for the whole sample period. The TTSM strategies perform better than the original TSM strategy over the first subsample, as well as the second subsample, with a higher Sharpe ratio, a higher Sortino ratio, a higher Calmar ratio, and a lower maximum drawdown. Using the bootstrap approach proposed by Ledoit & Wolf (2008), we test the null hypothesis of no difference in the Sharpe ratios of the TTSM strategies compared to the original TSM strategy. We have used $B = 1,000$ bootstrap resamples and a block size of $b = 5$ to generate the resulting bootstrap p-values.

In the first subsample from 2008 to 2012, the TTSM-S2 enhances the original TSM strategy with a statistically significant increase of 21% (1.55 to 1.87) in the Sharpe ratio and a drop of 43% (26.02% to 14.77%) in the maximum drawdown. Consistently, it shows a significant improvement by 45% in the Sharpe ratio of 1.77, compared to the original TSM strategy of 1.22 during the second subsample from 2013 to 2018. The maximum drawdown decreases from 14.25% to 8.92% by a proportion of 37% at the same time. This evidence proves that the TTSM approach effectively mitigates the TSM strategy losses by systematically reducing risk exposure during scenarios of time series momentum reversals. Furthermore, we argue that the proposed tuning decisions have reshaped the distribution of time series momentum portfolio returns with higher positive skewness and higher kurtosis. It has also improved the percentage of winning trades when using the time series momentum strategy.

Interestingly, TTSM-S2 documents a greater performance enhancement than TTSM-S1 over the first subsample, as well as over the second subsample. Therefore, in terms of measuring the positive and negative realized semivariance, the "bad" side risk estimator predicts future time series momentum reversals, and the "good" side risk estimator captures the moments of market overreaction in time series momentum. Recall that different tuning actions are designed for TTSM-S1 and TTSM-S2 under different regions (see Table 5). This provides an explicit and rational interpretation of the life cycle of time series momentum, details of which we discuss in the following section.

We also provide the performances of TSM and TTSM strategies with the added consideration of transaction cost. Due to the lack of comprehensive research unveiling the real transaction costs in Chinese futures markets (see also in Bianchi et al., 2021), it would be inaccurate to employ a fixed rate for evaluating the strategy performance using costs.[21] Nevertheless, we applied an aggressive transaction cost of one basis-point (i.e., 1%%) to all commodities to test the outperformance of the TTSM strategies with cost included. Taking the actual portfolio turnover into account, we presented the Sharpe ratio with cost of the TSM and TTSM strategies in Table 6. Both TTSM-S1 and TTSM-S2 strategies document consistent outperformances over the TSM strategy, showing higher Sharpe ratios even when the transaction cost is taken into consideration.

[21]The three commodity futures exchanges in China have changed the official rate of the commission fee multiple times in the past. One can find the historical notices of commission fee adjustment on the three exchanges' official websites: `http://www.shfe.com.cn/` (SHFE), `http://www.dce.com.cn/` (DCE), and `http://www.czce.com.cn/` (CZCE).

Table 6: Performance of the TSM and TTSM strategies

Evaluating Statistics	Annual Return (%)	Sharpe Ratio	Maximum D.D. (%)	Sortino Ratio	Calmar Ratio	Percentage of Win (%)	$\frac{\text{Ave. P.}}{\text{Ave. L.}}$	Skewness	Kurtosis	TO	BTC (%)	Sharpe Ratio with Cost
Panel A: In the first subsample (January 2008–December 2012)												
BAH	-4.65	-0.28	49.23	-0.37	-0.09	52.09	0.90	-0.46	4.49	0.05	-1.51	-0.28
		(0.07)										
TSM	37.28	1.55	26.02	2.40	1.43	52.91	1.20	0.46	6.38	0.58	1.15	1.49
		(1.00)										
TTSM-S1	36.80	1.78	16.70	2.78	2.20	54.14	1.20	0.54	6.83	0.67	0.80	1.70
		(0.06)										
TTSM-S2	32.53	1.87	14.77	2.83	2.20	54.63	1.22	0.56	8.55	0.71	0.82	1.77
		(0.05)										
Panel B: In the second subsample (January 2013–December 2018)												
BAH	-4.58	-0.39	44.80	-0.57	-0.10	50.55	0.93	-0.12	4.93	0.04	-0.04	-0.39
		(0.03)										
TSM	19.50	1.22	14.25	2.01	1.37	52.81	1.13	0.65	8.76	0.67	0.21	1.12
		(1.00)										
TTSM-S1	18.95	1.52	9.29	2.58	2.04	52.40	1.21	0.62	5.87	0.80	0.13	1.36
		(0.03)										
TTSM-S2	19.11	1.77	8.92	3.07	2.14	53.91	1.19	0.62	5.33	0.84	0.14	1.58
		(0.02)										
Panel C: In the whole sample (January 2008–December 2018)												
BAH	-4.61	-0.32	58.70	-0.44	-0.08	51.25	0.92	-0.38	5.19	0.05	-2.66	-0.33
		(0.06)										
TSM	27.59	1.37	26.02	2.14	1.06	52.86	1.17	0.58	7.96	0.63	0.64	1.30
		(1.00)										
TTSM-S1	27.08	1.62	16.70	2.54	1.62	53.19	1.21	0.66	8.32	0.74	0.44	1.51
		(0.04)										
TTSM-S2	25.22	1.78	14.77	2.76	1.71	54.24	1.21	0.66	9.79	0.78	0.45	1.64
		(0.04)										

Notes: BAH stands for the buy-and-hold strategy. TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. The values in parentheses denote the p-values of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the reconstructed strategies. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$. An aggressive transaction cost of one basis-point (i.e., 1%%) is employed to calculate the Sharpe Ratio with Cost. Abbreviations: Maximum D.D., maximum drawdown; Ave. P. /Ave. L., the ratio of the average profit divided by the average loss; TO, the actual portfolio turnover, BTC, the break-even transaction cost.

Moreover, we compute the portfolio turnover and the break-even transaction cost to show more details. Following Bianchi et al. (2021), we calculate the actual portfolio turnover (TO)

$$\mathrm{TO} = \frac{1}{T-J}\sum_{t=J+1}^{T}\sum_{i=1}^{N_t}\left(\left|\omega_{i,d_t} - \omega^{+}_{i,d_{t-1}}\right|\right), \tag{8}$$

where ω_{i,d_t} is the portfolio weight of commodity i in day d_t, $\omega^{+}_{i,d_{t-1}} = \omega_{i,d_{t-1}} \times e^{r^{tsm}_{i,d_{t-1}}}$ is the actual portfolio weight of commodity i immediately prior to the rebalancing at the end of day d_{t-1}, and $r^{tsm}_{i,d_{t+1}} = \mathrm{sign}\Big(\sum_{j=0}^{J-1} r_{i,d_{t-j}}\Big)\frac{\sigma_{target}}{\sigma_{i,d_t}} r_{i,d_{t+1}}$ is the TSM return of commodity i in day d_{t+1}. The break-even transaction cost (BTC) is defined by $\tilde{r}_{p,d_t}$ satisfying

$$\tilde{r}_{p,d_t} = r_{p,d_t} - \mathrm{BTC}\sum_{i=1}^{N_t}\left|\omega_{i,d_t} - \omega^{+}_{i,d_{t-1}}\right| = 0, \tag{9}$$

where r_{p,d_t} is the portfolio return in day d_t. This provides the transaction cost required to eliminate the premia of the TSM and TTSM strategies. Table 6 reports the portfolio turnover and the break-even transaction cost of TSM, TTSM-S1, and TTSM-S2 in the first and the second subsamples. It appears that both TTSM-S1 and TTSM-S2 exhibit a comparable portfolio turnover (0.67 and 0.71 in Panel A, 0.80 and 0.84 in Panel B) which can be noted to be significantly higher than that of TSM (0.58 in Panel A and 0.67 in Panel B). In terms of the break-even transaction cost, an average of 1.15%, 0.80%, and 0.82% were required for TSM, TTSM-S1, and TTSM-S2 in the first subsample, respectively. In the second subsample, they were 0.21%, 0.13%, and 0.14%, which is lower than in the first subsample due to lower portfolio premia. Overall, the merits of the TTSM strategies compared to the TSM strategy can not be overturned by considering the transaction cost.

In Table 7, we present further subsample performances of the TTSM strategies. In particular, we compare the Sharpe ratios of the TTSM strategies with the TSM strategy for each year in the first subsample from 2008 to 2012 and in the second subsample from 2013 to 2018. We also tabulate the p-values in the parentheses to test the null hypothesis of no difference in the Sharpe ratios of the TTSM strategies and the TSM strategy in each year. From the statistics shown, we find consistent and significant results of higher Sharpe ratios for both TTSM-S1 and TTSM-S2 strategies in all eleven years from 2008 to 2018. In addition, the TTSM-S2 strategy reports higher Sharpe ratios than the TTSM-S1 strategy in ten out of eleven years, except for 2008.

Table 7: Annual Sharpe ratio of the TSM and TTSM strategies

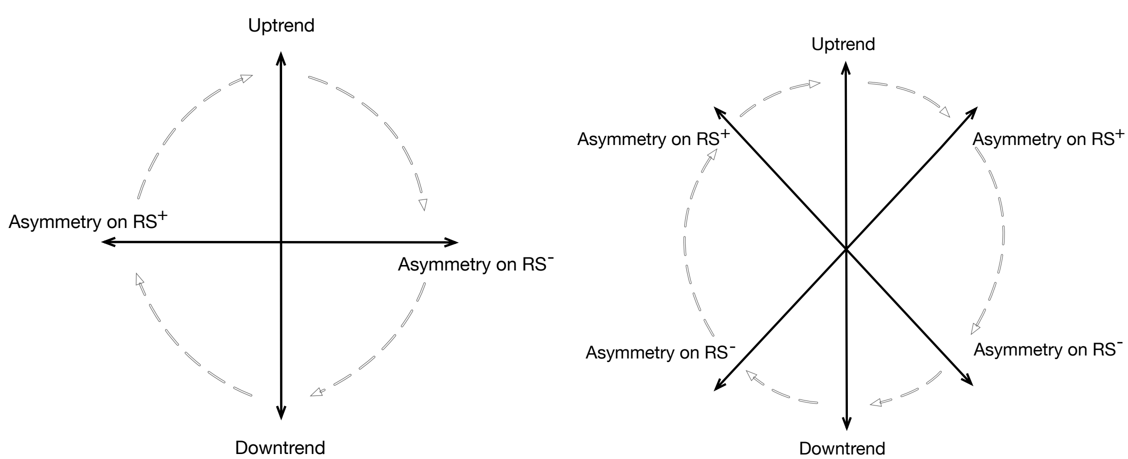
Panel A: In the first subsample (January 2008–December 2012)						
Strategy	2008	2009	2010	2011	2012	
BAH	-2.19	2.29	0.59	-1.49	-0.23	
	(0.09)	(0.03)	(0.06)	(0.06)	(0.06)	
TSM	2.84	2.03	1.38	-0.16	1.67	
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
TTSM-S1	4.14	2.04	1.64	-0.26	2.01	
	(0.04)	(0.03)	(0.07)	(0.03)	(0.03)	
TTSM-S2	4.09	2.27	1.85	0.04	2.06	
	(0.04)	(0.02)	(0.05)	(0.03)	(0.04)	
Panel B: In the second subsample (January 2013–December 2018)						
Strategy	2013	2014	2015	2016	2017	2018
BAH	-1.83	-2.24	-1.65	2.07	0.17	-0.80
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
TSM	0.97	2.35	2.00	1.25	0.31	0.12
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
TTSM-S1	1.42	3.18	2.10	1.36	0.84	0.15
	(0.02)	(0.03)	(0.05)	(0.02)	(0.10)	(0.03)
TTSM-S2	1.63	3.53	2.89	1.41	1.09	0.20
	(0.04)	(0.04)	(0.03)	(0.02)	(0.12)	(0.04)

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

4.3. An explanation of time series momentum life cycle hypothesis

An intriguing explanation for the improved performance of the TTSM strategies, compared to the original TSM strategy, is depicted in Figure 5. This figure presents a simple conceptual diagram that helps to integrate the empirical evidence presented in this paper. We refer to this diagram as the time series momentum life cycle (TSMLC) hypothesis, in a similar way to the momentum life cycle (MLC) hypothesis, first proposed by Lee & Swaminathan (2000). However, we here associate it with the endogenous variables of risk estimators from asset returns here, rather than an exogenous variable, such as trading volume.

Figure 5: The time series momentum life cycle (TSMLC) hypothesis. Panel (a) describes the underlying time series momentum life cycle corresponding to the tuned time series momentum strategy TTSM-S1; the dynamic cyclical pattern shows asymmetric lean on RS^- when transforming from an upward momentum to a downward momentum, and asymmetric lean on RS^+ when transforming from a downward momentum to an upward momentum. Panel (b) describes the underlying time series momentum life cycle corresponding to the tuned time series momentum strategy TTSM-S2; the dynamic cyclical pattern shows an alternation pattern between asymmetric lean on RS^+ and RS^- when transforming from an upward momentum to a downward momentum, and vise versa.



(a) TTSM-S1 (b) TTSM-S2

As shown in Panel (a) of Figure 5, we depict the logic of the tuned trading signals in the TTSM-S1 strategy as a relatively simple dynamic structure, which combines the life cycle of time series momentum with the asymmetrically distributed pattern of RS^+ and RS^-. After the joint distribution exhibits the asymmetric lean on RS^- during slumps in the upward momentum, the time series momentum transfers from an episode of upward momentum to an episode of downward momentum. Meanwhile, the TTSM-S1 strategy adjusts the long trading signal to a short signal in a timely manner to mitigate TSM strategy losses, and vice versa for the process from a period of downward momentum to that of an upward momentum. Therefore, we describe time series momentum as a dynamic cyclical process shown in the Panel (a) of Figure 5, in terms of the TTSM-S1 strategy.

Moreover, as shown in Panel (b) of Figure 5, following the TTSM-S2 strategy, the dynamic cycle shows an alternating pattern between an asymmetric lean on RS^+ and RS^- before transforming from an upward momentum to a downward momentum, and vice versa. When we take the upward momentum as an example, time series momentum continues with a mild uptrending market at the beginning. Until the trend is excessively self-accelerated with positive feedback, the asymmetric structure leans to RS^+ because of rapid increases in the upward momentum. As we mentioned in the previous section, this asymmetric pattern captures the moments of market overreaction in the upward momentum. Following the overreaction, a subsequent asymmetric lean to RS^- is exhibited and predicts future slumps in the upward momentum. Consequently, the upward momentum becomes unsustainable and transfers to the downward momentum, and vice versa for the process changing from a downward momentum to an upward momentum.

4.4. Risk exposures

Next, we explore the sources of risk premia of the TSM, TTSM-S1 and TTSM-S2 strategies. We investigate connections between such premia and a set of risk factors documented by Bakshi et al. (2019) and Bianchi et al. (2021). Bakshi et al. (2019) proposed a three-factor model for understanding the cross section of commodity returns. The three risk factors are: i) AVG is the equally weighted portfolio return, ii) CARRY is constructed by buying and selling five commodities in the most backwardation and contango, and iii) MOM is a long–short portfolio that buys and sells past winner and loser commodities. Bianchi et al. (2021) documented excess risk premia of the Basis-Momentum (BMOM) strategy by regressing out the three factors. Based on these works, we run a set of contemporaneous regressions with the four risk factors: AVG, CARRY, MOM, and BMOM, and an additional AR(1) factor that accounts for the Adaptive Market Hypothesis advocated by Lo (2019). Lo (2019) argued that the financial market is adaptive when reacting to changes in the market environment, which implies autocorrelation in asset returns. Therefore, in this paper, we incorporate the first-order lagged return as the adaptive factor in assessing the risk exposures of the TSM and TTSM portfolios (Lo, 2004). Additionally, in order to accommodate the unique characteristics of Chinese commodity futures markets, we follow Fan & Zhang (2020) and Bianchi et al. (2021) to construct the CARRY, MOM, and BMOM signals based on the third-nearest futures contract, rather than the nearest one. For MOM and BMOM signals, we employ the same lookback window J as the TTSM signal.

Table 8 reports the risk exposures of the TSM, TTSM-S1, and TTSM-S2 strategies across the whole sample from January 2008 to December 2018. The TSM and TTSM portfolios are constructed with a lookback window of 20 trading days, which is consistent with our previous setting. From the adjusted R^2 tabulated, an increasing number of elements relating to the TSM, TTSM-S1, and TTSM-S2 premia can be explained as more risk factors are considered in the regression. In all panels, both TTSM-S1 and TTSM-S2 have a lower adjusted R^2 than TSM, which indicates that they were less exposed to these risk factors than TSM.

Moreover, the estimates in Panel D show that the TSM, TTSM-S1, and TTSM-S2 premia cannot be fully explained by the five–factor model in China. The estimated intercepts were economically and statistically significant. Owing to the robustness of the trend-following strategy in both bull and bear markets, all three strategies do not report a significant coefficient on AVG, which is to be expected. Interestingly, while they loaded negatively on the CARRY and BMOM factors, MOM showed up as a positive driving force. The TSM premia has nearly twice as much of the MOM factor. However, TTSM-S2 reduced its factor exposure to MOM significantly down to 0.95. In addition, all showed evidence of significant exposure to the adaptive factor AR(1). This proves that the TSM, TTSM-S1, and TTSM-S2 premia were in a negative feedback loop of the adaptive ecosystem.

Table 8: Risk exposures of the TSM and TTSM strategies

	Constant	AVG	CARRY	MOM	BMOM	AR(1)	R^2_{adj}
Panel A: Single risk factor							
TSM	0.0012	-0.0396					0.0004
	(4.77)	(-1.45)					
TTSM-S1	0.0012	-0.0245					0.0001
	(5.62)	(-1.08)					
TTSM-S2	0.0011	0.0229					0.0002
	(6.21)	(1.19)					
Panel B: Three risk factors							
TSM	0.0009	-0.0342	-0.1378	1.8146			0.2985
	(4.55)	(-1.46)	(-2.85)	(33.70)			
TTSM-S1	0.0010	-0.0191	-0.1118	1.2835			0.2150
	(5.45)	(-0.92)	(-2.63)	(27.05)			
TTSM-S2	0.0010	0.0249	-0.0635	0.9373			0.1593
	(5.85)	(1.37)	(-1.70)	(22.53)			
Panel C: Four risk factors							
TSM	0.0009	-0.0366	-0.1330	1.8369	-0.1930		0.3002
	(4.22)	(-1.56)	(-2.75)	(33.77)	(-2.73)		
TTSM-S1	0.0010	-0.0212	-0.1076	1.3028	-0.1675		0.2169
	(5.13)	(-1.03)	(-2.53)	(27.18)	(-2.69)		
TTSM-S2	0.0009	0.0231	-0.0599	0.9537	-0.1422		0.1611
	(5.53)	(1.27)	(-1.61)	(22.69)	(-2.61)		
Panel D: Five risk factors							
TSM	0.0010	-0.0357	-0.1365	1.8429	-0.1879	-0.0627	0.3039
	(4.58)	(-1.53)	(-2.84)	(33.96)	(-2.67)	(-3.89)	
TTSM-S1	0.0010	-0.0220	-0.1065	1.3044	-0.1642	-0.0405	0.2182
	(5.35)	(-1.07)	(-2.51)	(27.23)	(-2.64)	(-2.37)	
TTSM-S2	0.0010	0.0223	-0.0577	0.9544	-0.1384	-0.0428	0.1626
	(5.77)	(1.23)	(-1.55)	(22.73)	(-2.54)	(-2.41)	

Notes: TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. AVG is the equally weighted portfolio return. CARRY is constructed by buying and selling five commodities in the most backwardation and contango. MOM is a 2-1 portfolio that buys and sells past winner and loser commodities. BMOM is a 2-1 portfolio that takes long and short positions of commodities according the ex-ante basis-momentum signal. AR(1) is the first–order lagged return of the underlying strategy. Numbers in the parentheses are t-statistics.

5. Robustness check

To complement the outperformance of the TTSM strategies, we conducted robustness tests including volatility scaling, using different lookback windows, and an execution lag as detailed in this section.

5.1. Volatility scaling

As we explained in Section 3.1, there is a component of volatility scaling, $\sigma_{target}/\sigma_{i,d_t}$, in the time series momentum formula of (4) to maintain the constant risk parity across commodities within the portfolio. As a result, it is essential to check if the volatility–scaling component affects the TTSM superiority over TSM. In Table 9, we show the performance of the TSM and TTSM strategies without volatility scaling. In other words, the target portfolio is equally weighted based only on the trading signal of each commodity in this case.

We denote TSM-NVS, TTSM-S1-NVS, and TTSM-S2-NVS as the non–volatility–scaling versions of the TSM, TTSM-S1, and TTSM-S2 strategies, respectively. As shown in Table 9, TTSM-S1-NVS and TTSM-S2-NVS are still outperforming TSM-NVS in both the first and the second subsamples. The Sharpe ratios were 1.44 (TTSM-S1-NVS) and 1.52 (TTSM-S2-NVS) v.s. 1.15 (TSM-NVS) from January 2008 to December 2012, and were 0.98 (TTSM-S1-NVS) and 1.25 (TTSM-S2-NVS) v.s. 0.75 (TSM-NVS) from January 2013 to December 2018. Importantly, focusing on the last column of Table 9, TTSM-S1-NVS and TTSM-S2-NVS consistently report a higher Sharpe ratio than TSM-NVS, after taking into account transaction cost. Our results suggest that the superiority of TTSM over TSM is robust, even when the volatility–scaling approach is not taken into consideration.

5.2. Different lookback windows

The TTSM strategies with lookback window $J = 20$ trading days has been shown to outperform the TSM strategy in the previous subsection. The effectiveness of the TTSM approach should be proved non-coincidental using a variety of lookback windows if the TTSM strategy is to be considered a robust rule-based choice for time series momentum tuning. We further report the results for various lookback windows during the first subsample from January 2008 to December 2012 in Table 10, and during the second subsample from January 2013 to December 2018 in Table 11. The length of the lookback window expands from 20 trading days (one month in calendar days) to 250 trading days (one year in calendar days). Likewise, we include the p-values in the parentheses to exhibit the statistical significance in the difference between the Sharpe ratios.

Table 9: Performance of the TSM and TTSM strategies without volatility scaling

Evaluating Statistics	Annual Return (%)	Sharpe Ratio	Maximum D.D. (%)	Sortino Ratio	Calmar Ratio	Percentage of Win (%)	$\frac{\text{Ave. P.}}{\text{Ave. L.}}$	Skewness	Kurtosis	TO	BTC (%)	Sharpe Ratio with Cost
Panel A: In the first subsample (January 2008–December 2012)												
BAH	-4.65	-0.28 (0.07)	49.23	-0.37	-0.09	52.09	0.90	-0.46	4.49	0.05	-1.51	-0.28
TSM-NVS	15.75	1.15 (1.00)	16.09	1.69	0.98	53.49	1.11	0.38	6.49	0.23	1.97	1.11
TTSM-S1-NVS	15.56	1.44 (0.05)	9.06	2.17	1.72	53.98	1.15	0.34	6.10	0.27	2.28	1.38
TTSM-S2-NVS	12.74	1.52 (0.06)	7.17	2.22	1.78	54.14	1.18	0.31	7.47	0.29	1.84	1.43
Panel B: In the second subsample (January 2013–December 2018)												
BAH	-4.58	-0.39 (0.03)	44.80	-0.57	-0.10	50.55	0.93	-0.12	4.93	0.04	-3.62	-0.39
TSM-NVS	6.09	0.75 (1.00)	9.45	1.10	0.64	52.81	1.06	0.29	8.10	0.22	0.51	0.68
TTSM-S1-NVS	5.81	0.98 (0.03)	7.10	1.51	0.82	53.22	1.09	0.44	6.72	0.28	0.31	0.86
TTSM-S2-NVS	6.36	1.25 (0.03)	5.40	2.01	1.18	53.16	1.17	0.67	7.85	0.29	0.28	1.11
Panel C: In the whole sample (January 2008–December 2018)												
BAH	-4.61	-0.32 (0.06)	58.70	-0.44	-0.08	51.25	0.92	-0.38	5.19	0.05	-2.66	-0.33
TSM-NVS	10.49	0.95 (1.00)	16.09	1.37	0.65	53.12	1.09	0.44	8.38	0.23	1.17	0.90
TTSM-S1-NVS	10.25	1.20 (0.04)	9.06	1.77	1.13	53.57	1.13	0.47	8.11	0.28	1.20	1.12
TTSM-S2-NVS	9.27	1.36 (0.04)	7.17	2.01	1.29	53.60	1.18	0.47	9.28	0.29	0.99	1.25

Notes: BAH stands for the buy-and-hold strategy. TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. TSM-NVS, TTSM-S1-NVS, and TTSM-S2-NVS are the non–volatility–scaling version of TSM, TTSM-S1, and TTSM-S2. The values in parentheses denote the p-values of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the reconstructed strategies. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$. An aggressive transaction cost of one basis-point (i.e., 1%%) is employed to calculate the Sharpe Ratio with Cost. Abbreviations: Maximum D.D., maximum drawdown; Ave. P. /Ave. L., the ratio of the average profit divided by the average loss; TO, the actual portfolio turnover, BTC, the break-even transaction cost.

We find that the out-of-sample performance of the TTSM strategies, in which the lookback window increases from 30 to 250 trading days, shows statistically significant results which are consistent with the previous results of the lookback window of 20 trading days. These consistent and significant results are shown in terms of the annual return, Sharpe ratio, Sortino ratio, Calmar ratio, and the maximum drawdown. Moreover, the consistency of the performance enhancement holds in the first subsample from 2008 to 2012, as well as in the second subsample from 2013 to 2018. The TTSM approach reports an improvement in the Sharpe ratio by almost 30% on average across different lookback windows during the second subsample period (see Table 11).

5.3. Execution lag

In the literature, there are concerns around executing a daily rebalanced strategy in practice due to market friction. It is possible that the proposed predictable pattern of time series momentum reversal is driven by noises in daily commodity futures returns. Therefore, we implemented an execution lag by assuming that the predictability is still effective after one day. In this case, the trading signal is constructed using the information available at the end of day d_t, and the position is established at the end of day d_{t+1} and holds for one day in day d_{t+2}.

We tabulate the strategy performance with the execution delay in Table 12 for the first subsample from January 2008 to December 2012 and in Table 13 for the second subsample from January 2013 to December 2018. Our results demonstrate that the TTSM strategies were not subject to a one–day execution delay. TTSM-S1 and TTSM-S2 continued to significantly outperform the TSM strategy with a higher Sharpe ratio. This pattern holds, not only when the lookback window is 20 trading days, but also in relation to some longer lookback horizons.

Table 10: Performance of the TSM and TTSM strategies with various lookback windows over the first subsample from January 2008 to December 2012

		Lookback Window (days)						
		20	30	40	60	90	120	250
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)
	Maximum D.D. (%)	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
	Ave. P. /Ave. L.	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
TTSM-S1	Annual Return (%)	36.80	27.12	30.34	17.27	14.36	13.53	6.70
	Sharpe Ratio	1.78	1.38	1.57	0.98	0.84	0.79	0.41
		(0.04)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.04)
	Maximum D.D. (%)	16.70	18.56	16.93	22.78	28.69	19.96	31.63
	Sortino Ratio	2.78	2.06	2.40	1.53	1.32	1.21	0.61
	Calmar Ratio	2.20	1.46	1.79	0.76	0.50	0.68	0.21
	% of Win	54.14	54.14	55.37	53.57	52.75	52.34	52.71
	Ave. P. /Ave. L.	1.20	1.11	1.10	1.06	1.06	1.07	0.98
	Skewness	0.54	0.42	0.51	0.61	0.50	0.45	0.19
	Kurtosis	6.83	7.06	6.80	6.84	5.85	6.30	5.43
TTSM-S2	Annual Return (%)	32.53	22.87	25.56	12.91	9.11	8.03	2.77
	Sharpe Ratio	1.87	1.39	1.61	0.90	0.66	0.57	0.20
		(0.04)	(0.05)	(0.06)	(0.08)	(0.07)	(0.06)	(0.05)
	Maximum D.D. (%)	14.77	15.67	15.47	21.09	24.43	17.55	29.13
	Sortino Ratio	2.83	2.03	2.40	1.37	1.02	0.83	0.28
	Calmar Ratio	2.20	1.46	1.65	0.61	0.37	0.46	0.10
	% of Win	54.63	53.40	55.13	53.49	52.34	52.67	53.37
	Ave. P. /Ave. L.	1.22	1.17	1.13	1.05	1.05	1.02	0.93
	Skewness	0.56	0.45	0.48	0.47	0.43	0.28	0.02
	Kurtosis	8.55	9.16	7.90	7.34	5.99	6.73	5.40

Notes: TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. The values in parentheses denote the p-values of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the reconstructed strategies. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$. Abbreviations: Maximum D.D., maximum drawdown; Ave. P. /Ave. L., the ratio of the average profit divided by the average loss.

Table 11: Performance of the TSM and TTSM strategies with various lookback windows over the second subsample from January 2013 to December 2018

		Lookback Window (days)						
		20	30	40	60	90	120	250
TSM	Annual Return (%)	19.50	18.08	17.12	13.68	12.80	14.77	16.43
	Sharpe Ratio	1.22	1.14	1.06	0.85	0.81	0.91	1.01
		(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	Maximum D.D. (%)	14.25	18.73	27.24	16.83	18.70	18.29	28.92
	Sortino Ratio	2.01	1.84	1.74	1.33	1.22	1.36	1.49
	Calmar Ratio	1.37	0.97	0.63	0.81	0.68	0.81	0.57
	% of Win	52.81	51.51	51.10	51.99	50.55	53.22	52.95
	Ave. P. /Ave. L.	1.13	1.17	1.17	1.09	1.15	1.05	1.08
	Skewness	0.65	0.56	0.74	0.23	0.05	0.19	0.22
	Kurtosis	8.76	7.79	10.41	6.56	6.47	5.83	8.56
TTSM-S1	Annual Return (%)	18.95	15.26	13.77	11.60	10.31	11.98	14.05
	Sharpe Ratio	1.52	1.25	1.15	0.97	0.91	1.04	1.21
		(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.04)	(0.03)
	Maximum D.D. (%)	9.29	12.19	19.78	11.44	15.23	13.78	20.10
	Sortino Ratio	2.58	2.05	1.91	1.63	1.50	1.62	1.88
	Calmar Ratio	2.04	1.25	0.70	1.01	0.68	0.87	0.70
	% of Win	52.40	53.09	52.67	53.02	51.58	52.95	52.88
	Ave. P. /Ave. L.	1.21	1.13	1.12	1.07	1.13	1.09	1.13
	Skewness	0.62	0.69	0.73	0.82	0.59	0.49	0.47
	Kurtosis	5.87	7.64	7.94	8.23	6.38	7.33	7.40
TTSM-S2	Annual Return (%)	19.11	14.51	12.93	10.73	9.91	11.74	13.93
	Sharpe Ratio	1.77	1.38	1.25	1.05	1.02	1.17	1.37
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Maximum D.D. (%)	8.92	11.00	18.91	10.28	13.48	13.40	14.84
	Sortino Ratio	3.07	2.32	2.05	1.74	1.70	1.84	2.17
	Calmar Ratio	2.14	1.32	0.68	1.04	0.74	0.88	0.94
	% of Win	53.91	53.22	52.95	53.43	52.26	53.02	53.50
	Ave. P. /Ave. L.	1.19	1.15	1.13	1.07	1.12	1.12	1.14
	Skewness	0.62	0.69	0.66	0.80	0.67	0.63	0.57
	Kurtosis	5.33	6.72	7.48	8.37	6.86	8.35	8.11

Notes: TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. The values in parentheses denote the p-values of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the reconstructed strategies. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$. Abbreviations: Maximum D.D., maximum drawdown; Ave. P. /Ave. L., the ratio of the average profit divided by the average loss.

Table 12: Performance of the TSM and TTSM strategies with a one–day execution lag over the first subsample from January 2008 to December 2012

		Lookback Window (days)						
		20	30	40	60	90	120	250
TSM	Annual Return (%)	37.89	22.85	32.57	17.66	15.12	10.50	3.51
	Sharpe Ratio	1.57	0.97	1.36	0.79	0.70	0.49	0.17
		(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	Maximum D.D. (%)	30.05	25.62	19.01	28.21	26.78	30.75	41.95
	Sortino Ratio	2.36	1.43	2.02	1.15	1.04	0.71	0.24
	Calmar Ratio	1.26	0.89	1.71	0.63	0.56	0.34	0.08
	% of Win	54.80	53.16	53.98	52.83	52.09	52.50	52.61
	Ave. P. /Ave. L.	1.12	1.07	1.11	1.05	1.06	1.00	0.94
	Skewness	0.43	0.20	0.40	0.37	0.23	0.01	0.10
	Kurtosis	6.61	6.13	6.65	7.38	6.49	5.09	5.95
TTSM-S1	Annual Return (%)	35.59	22.11	31.24	15.86	13.16	10.05	2.28
	Sharpe Ratio	1.73	1.14	1.62	0.90	0.78	0.59	0.14
		(0.06)	(0.05)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
	Maximum D.D. (%)	20.49	18.41	15.29	23.19	29.57	23.85	38.66
	Sortino Ratio	2.67	1.72	2.47	1.39	1.19	0.88	0.20
	Calmar Ratio	1.74	1.20	2.04	0.68	0.44	0.42	0.06
	% of Win	54.39	53.16	54.55	53.49	54.06	53.08	52.63
	Ave. P. /Ave. L.	1.18	1.11	1.14	1.04	0.99	1.00	0.94
	Skewness	0.63	0.44	0.56	0.52	0.35	0.39	0.03
	Kurtosis	7.62	7.37	7.30	7.19	6.19	6.94	5.51
TTSM-S2	Annual Return (%)	29.80	16.86	26.07	10.72	8.77	5.67	-0.27
	Sharpe Ratio	1.74	1.06	1.66	0.76	0.64	0.41	-0.02
		(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)
	Maximum D.D. (%)	20.50	18.75	13.39	22.33	26.15	22.76	36.81
	Sortino Ratio	2.63	1.56	2.51	1.15	0.95	0.58	-0.03
	Calmar Ratio	1.45	0.90	1.95	0.48	0.34	0.25	-0.01
	% of Win	54.63	53.24	54.96	52.99	54.80	54.14	51.73
	Ave. P. /Ave. L.	1.20	1.10	1.15	1.05	0.95	0.94	0.95
	Skewness	0.73	0.49	0.63	0.45	0.29	0.28	-0.05
	Kurtosis	9.51	9.29	8.28	7.33	6.73	7.33	5.29

Notes: TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. The values in parentheses denote the p-values of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the reconstructed strategies. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$. Abbreviations: Maximum D.D., maximum drawdown; Ave. P. /Ave. L., the ratio of the average profit divided by the average loss.

Table 13: Performance of the TSM and TTSM strategies with a one–day execution lag over the second subsample from January 2013 to December 2018

		Lookback Window (days)						
		20	30	40	60	90	120	250
TSM	Annual Return (%)	16.04	17.20	17.70	16.18	13.19	14.19	15.71
	Sharpe Ratio	1.01	1.09	1.10	1.02	0.85	0.89	0.97
		(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	Maximum D.D. (%)	14.28	14.11	21.28	15.58	21.44	18.16	28.66
	Sortino Ratio	1.57	1.74	1.75	1.62	1.35	1.31	1.41
	Calmar Ratio	1.12	1.22	0.83	1.04	0.61	0.78	0.55
	% of Win	52.33	51.85	51.92	52.74	49.86	53.02	52.74
	Ave. P. /Ave. L.	1.11	1.14	1.14	1.08	1.18	1.05	1.08
	Skewness	0.24	0.48	0.65	0.27	0.30	0.07	0.20
	Kurtosis	7.71	8.46	11.41	5.32	4.85	5.50	8.53
TTSM-S1	Annual Return (%)	14.91	13.74	13.37	13.37	9.19	10.62	12.04
	Sharpe Ratio	1.19	1.11	1.11	1.11	0.80	0.91	1.01
		(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.05)
	Maximum D.D. (%)	11.42	14.88	17.99	10.64	14.91	14.03	19.04
	Sortino Ratio	1.93	1.84	1.87	1.80	1.30	1.41	1.54
	Calmar Ratio	1.31	0.92	0.74	1.26	0.62	0.76	0.63
	% of Win	52.26	51.78	51.17	52.67	51.03	52.47	52.95
	Ave. P. /Ave. L.	1.15	1.15	1.18	1.11	1.13	1.09	1.08
	Skewness	0.44	0.62	0.67	0.47	0.47	0.46	0.30
	Kurtosis	5.57	6.79	7.09	6.29	5.80	7.35	6.58
TTSM-S2	Annual Return (%)	14.63	13.02	12.16	12.88	7.58	9.95	11.64
	Sharpe Ratio	1.35	1.22	1.17	1.24	0.76	0.97	1.11
		(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
	Maximum D.D. (%)	10.85	11.57	16.93	8.70	13.40	13.51	21.18
	Sortino Ratio	2.19	2.04	1.95	1.97	1.21	1.48	1.68
	Calmar Ratio	1.35	1.13	0.72	1.48	0.57	0.74	0.55
	% of Win	54.05	51.44	52.19	52.95	50.89	52.74	52.47
	Ave. P. /Ave. L.	1.11	1.20	1.15	1.13	1.13	1.09	1.13
	Skewness	0.47	0.61	0.55	0.44	0.46	0.51	0.29
	Kurtosis	5.69	6.40	6.25	6.20	6.43	8.64	7.01

Notes: TSM stands for the original time series momentum strategy. TTSM-S1 and TTSM-S2 stand for two different tuning strategies on the original time series momentum according to the asymmetrically tail-distributed positive and negative realized semivariance. The values in parentheses denote the p-values of testing the null hypothesis that there is no difference in the Sharpe ratios between the original time series momentum strategy and the reconstructed strategies. Following Ledoit & Wolf (2008), we choose bootstrap samples of $B = 1,000$ and block size $b = 5$. Abbreviations: Maximum D.D., maximum drawdown; Ave. P. /Ave. L., the ratio of the average profit divided by the average loss.

6. Conclusion

Time series momentum, also known as a trend-following strategy, has had a tremendous influence on individuals in financial academia and practitioners. However, its poor performance in recent years is also being discussed by an increasing number of researchers. The time-series return predictability suggested by the first moment of asset returns (i.e., the historical sample mean) is challenging to replicate when using the data of new time periods. In this paper, we incorporated information from the second moment to enhance the return predictability.

By measuring the "good" and "bad" side risk of time series momentum, we have developed our study to examine the extent to which the positive and negative realized semivariance are able to predict future time series momentum losses. The employed weekly aggregation of positive and negative realized semivariance were derived from the 5-min high-frequency intraday returns of individual commodity futures contracts over the previous five trading days. We discovered that the asymmetric dynamics of the positive and negative realized semivariance estimators can generate predictable patterns for the moments of market overreaction, the reversal episodes of momentum, and in episodes of a sideways market in the time series momentum life cycle. Specifically, the attempts to monitor tail risks measured by the positive and negative realized semivariance, and tuning the decisions of momentum indicators, have been proved to be effective in relation to time series momentum.

By constructing a tuned time series momentum (TTSM) strategy and examining its out-of-sample performance on the Chinese commodity futures markets, we have empirically examined the feasibility and robustness of the rule-based nonlinear decision function in the actual application. It has been proved to be a superior approach with a statistically significant higher Sharpe ratio, a higher Sortino ratio, and a higher Calmar ratio. This outperformance of TTSM still holds when transaction cost is taken into account. Our results were consistent with non–volatility–scaling, various lookback windows, and a one–day execution lag. We mainly focused on the Chinese markets, rather than the international markets. This is due to our access to high-frequency data being limited to China. Researchers can further verify the feasibility of our TTSM strategies for commodity futures traded in other markets. Future research may also explore the possibility of incorporating the high-frequency data of external variables to provide further insights into the life cycle of time series momentum.

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