Received: 7 January 2019 | Accepted: 17 August 2019
DOI: 10.1002/fut.22053

RESEARCH ARTICLE

FUTURES MARKETS WILEY

Time-series momentum in China's commodity futures market

Hyuna Ham[1] | **Hoon Cho**[2] | **Hyeongjun Kim**[3] | **Doojin Ryu**[4]

[1]December & Company Inc, Seoul, Korea

[2]Graduate School of Finance, Korea Advanced Institute of Science and Technology, Seoul, Korea

[3]Department of Business Administration, Yeungnam University, Gyeongsan, Korea

[4]Department of Economics, Sungkyunkwan University, Seoul, Korea

Correspondence
Doojin Ryu, Department of Economics, Sungkyunkwan University, 25-2 Sungkyunkwan-ro, Jongno-gu, Seoul 03063, Korea
Email: sharpjin@skku.edu

Abstract

This study examines the time-series momentum in China's commodity futures market. We find that a time-series momentum strategy outperforms classical passive long and cross-sectional momentum strategies in terms of the Sharpe ratio, risk-adjusted excess returns, and cumulative returns. The time-series momentum strategy with a 1-month look-back period and a 1-month holding period exhibits the best performance. We observe clear time-series momentum patterns and find that the time-series momentum strategy is effective in the Chinese commodity futures market. However, the momentum lasts for less time in China than in the United States because China's futures market seems to have a greater number of speculative investors.

KEYWORDS

China, commodity futures, market anomaly, time-series momentum, trading strategy

JEL CLASSIFICATION

G12; G13; G15

1 | INTRODUCTION

Asset price momentum, a financial market anomaly, is actively researched in the fields of behavioral finance and asset pricing (Andrei & Cujean, 2017). Momentum strategies, which are based on the momentum anomaly, can be classified as either cross-sectional or time-series momentum strategies. In the last decade, numerous studies have examined the momentum anomaly in global financial markets to demonstrate the effectiveness of these momentum-based strategies. These previous studies predominantly focus on the cross-sectional momentum in stock markets (Barroso & Santa-Clara, 2015; Docherty & Hurst, 2018). Cross-sectional momentum strategies assume that the equity portfolios with the highest earnings on recent trading days, that is, the so-called "winner portfolios," will outperform the portfolios with the worst returns, that is, the so-called "loser portfolios." For example, Jegadeesh and Titman (1993) show that cross-sectional momentum strategies yield significant excess returns in equity markets.

The following studies examine momentum in derivatives markets worldwide to demonstrate the effectiveness and implications of momentum strategies, but they also mainly focus on cross-sectional momentum strategies. Asness, Moskowitz, and Pedersen (2013), Bakshi, Gao, and Rossi (2019), Blitz and de Groot (2014), Fuertes, Miffre, and Rallis (2010), Miffre and Rallis (2007), and Shen, Szakmary, and Sharma (2007) all study the cross-sectional momentum in commodity futures markets, although they use different definitions of winner and loser portfolios. Miffre (2016) reports that the average Sharpe ratio of a cross-sectional momentum strategy is 0.5, which is greater than the corresponding value of −0.24 for a long-only equally weighted portfolio. Kang and Kwon (2017) argue that cross-sectional momentum prevails in the global commodity futures markets. They find that the observed cross-sectional momentum patterns are not explained by traditional risk factors, macroeconomic indicators, or sector-specific momentum.

In contrast to the active research on cross-sectional momentum strategies, time-series momentum is a relatively new research topic and receives little academic attention relative to cross-sectional momentum despite its economic implications. Several recent studies on time-series momentum suggest that time-series momentum strategies can outperform cross-sectional momentum strategies in developed countries (Cheema, Nartea, & Man, 2017; Clare, Seaton, Smith, & Thomas, 2014). Unlike cross-sectional momentum strategies, time-series momentum strategies focus on the past returns of individual commodity futures. Such strategies take a long position if a commodity has had positive past returns and a short position if it has had negative past returns. Furthermore, time-series momentum, unlike cross-sectional momentum, is based on absolute returns rather than relative returns. Time-series momentum is an anomaly related to the autocorrelation of asset returns and the continuation of asset return trends that contradicts the random-walk hypothesis. Recent empirical studies on the time-series momentum in futures markets find that time-series momentum strategies significantly outperform cross-sectional momentum strategies. Moskowitz, Ooi, and Pedersen (2012) show that time-series momentum can be a significant risk factor in explaining equity indices, currencies, commodities, and bond futures returns in developed countries, such as the United States, the United Kingdom, Australia, New Zealand, Japan, France, Germany, Italy, the Netherlands, Spain, and other European countries. Their study is based on 58 wide-range instruments measured from January 1965 to December 2009. They show that a time-series momentum strategy outperforms both a classical passive long strategy and a cross-sectional momentum strategy using a regression analysis that controls for benchmarks, such as the Morgan Stanley Capital International (MSCI) World Equity Index, Barclay's Aggregate Bond Index, the S&P Goldman Sachs Commodity Index, long-short factors, and time-series momentum returns. The long-short factors used are the small-minus-big (SMB), high-minus-low (HML), and up-minus-down (UMD) factors. According to the Kenneth French's data library,[1] the SMB factor is defined as "the average return on three small portfolios minus the average return on three big portfolios," the HML factor is "the average return on two value portfolios minus the average return on two growth portfolios," and the UMD factor is "the average return on two high prior return portfolios minus the average return on two low prior return portfolios."

Moskowitz et al. (2012) also demonstrate the dynamic relationship between time-series and cross-sectional momentum and the predictive ability of positions, price changes, and the roll yield. Hurst, Ooi, and Pedersen (2013) show that time-series momentum strategies can increase the profits of futures portfolios. Hurst, Ooi, and Pedersen (2017) apply a time-series momentum strategy to global markets using a longer sample period and confirm that this strategy has been effective over the past 137 years. Koijen, Moskowitz, Pedersen, and Vrugt (2018) analyze carry trades using the time-series momentum returns as a risk factor. Gao, Han, Li, and Zhou (2018) introduce the intraday time-series momentum in the stock market and demonstrate statistically significant predictive ability using data on exchange-traded funds. In contrast, Goyal and Jegadeesh (2018) argue that cross-sectional momentum strategies outperform time-series momentum strategies after adjusting for risk.

Despite the recent focus on time-series momentum and the related trading strategies in the literature, existing studies of the time-series momentum in commodity futures markets have mainly focused on developed markets, such as the US market. To fill this gap, this study investigates the properties of time-series momentum and the empirical performance of time-series momentum strategies from an international perspective, focusing on China's commodity futures market. We examine the significance and effectiveness of time-series momentum strategies by comparing them with passive long and cross-sectional momentum strategies. China is a significant participant in world commodity markets owing to its rapid recent economic development (Roache, 2012).[2] Figure 1 shows the number of traded derivatives contracts by country as of 2017 and indicates that China's derivatives trading volume is the second largest in the world.[3] China's market will continue to grow, and, in turn, the international commodity market will become more dependent on the Chinese market, indicating a shift from the past dominance of the US market. Thus, we investigate the Chinese commodity futures market and, specifically, its time-series momentum, an anomaly observed in various asset markets. This study contributes to the existing literature on futures markets owing to the growing influence of China's futures market on international futures markets.

To allow comparisons with the US futures market, we construct a time-series momentum strategy following Jegadeesh and Titman's (1993) methodology. We analyze the predictive ability of time-series data for Chinese

[1]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html.

[2]Su and Liu (2016) note that human capital and foreign direct investment are major contributors to China's economic growth.

[3]The data are taken from Statista: "Largest derivatives exchanges worldwide in 2017, by the number of contracts traded (in millions)" (https://www.statista.com/statistics/272832/largest-international-futures-exchanges-by-number-of-contracts-traded/).

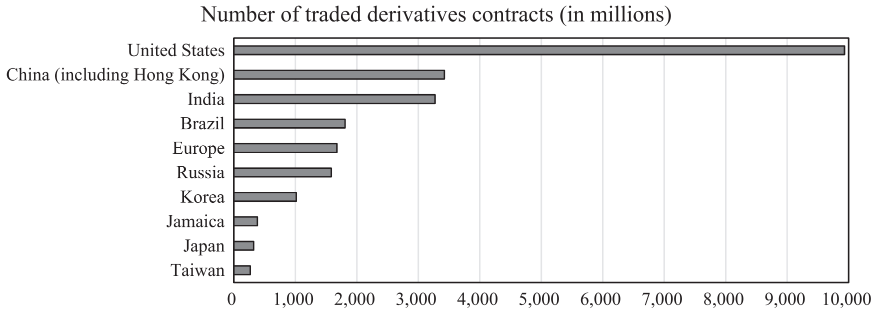

FIGURE 1 Number of traded derivatives contracts by country. It shows the number of traded derivative contracts by country as of 2017. Data on the trading volumes of the top 10 exchanges worldwide are taken from Statista, "Largest derivatives exchanges worldwide in 2017, by the number of contracts traded (in millions)" (https://www.statista.com/statistics/272832/largest-international-futures-exchanges-by-number-of-contracts-traded/). The data are classified by country

commodity futures and the effectiveness and validity of the time-series momentum strategy by regressing returns on risk factors for different look-back and holding periods. We also compare the empirical performances of trading strategies based on time-series momentum, cross-sectional momentum, and the classical passive long construction. Our empirical results suggest that the time-series momentum strategy outperforms the cross-sectional momentum and classical passive long strategies in the Chinese commodity futures market. We also find that the time-series momentum strategy has the best performance with a 1-month look-back period and a 1-month holding period, which means that the most recent month has the strongest and most significant return continuation in China's commodity futures market; this result is similar to those obtained by Kang and Kwon (2017) and Shen et al. (2007) in their studies of cross-sectional momentum strategies for commodity futures in the United States and China, respectively. To check the robustness of our findings, we evaluate the time-series momentum strategy using the Sharpe ratio, the risk-adjusted excess returns, and the cumulative returns. Then, we compare the results for that strategy to those for the passive long and cross-sectional momentum strategies based on Asness et al. (2013) methodology. In general, the time-series momentum strategy outperforms the latter two strategies.

The remainder of this paper proceeds as follows. Section 2 describes our sample data, and Section 3 explains the analytical and empirical methodologies. Section 4 presents the empirical results on the time-series momentum strategy. Lastly, Section 5 concludes.

2 | DATA

The data period starts on September 14, 2006, the earliest date on which at least 10 of the nearest-to-delivery commodity futures contracts (the most liquid contracts) were actively traded in the Chinese market. We analyze the 10 commodities that were traded during this period for which we can obtain the longest time series of historical data. We collected the daily closing prices (in USD) of generic first futures between September 14, 2006 and October 31, 2018 from Bloomberg (2019) (see Table 1). To prevent extreme price changes when there is a new contract, the prices from Bloomberg are processed by multiplying all the historical prices by the ratio of the front-month price to the expiration-month price.

Bloomberg provides data for 44 generic first futures, which are the nearest futures to the delivery contract, for Chinese commodities. Trading in copper cathode generic first futures began in 1999; that in soybean meal generic first futures began in 2000; that in no. 1 soybeans and natural rubber generic first futures began in 2002; that in aluminum, corn, and fuel oil generic first futures began in 2004; and that in Zhengzhou cotton, soybean oil, and white sugar generic first futures began in 2006. Because the Zhengzhou cotton trading data are available after September 14, 2006, the data period runs from September 14, 2006 to October 31, 2018. Table 1 provides summary statistics (annualized means and annualized volatilities) for the daily excess returns on the futures contracts used in this analysis. The average annualized mean and volatility of the Chinese commodity futures analyzed in this study are –3.05% and 22.70%, respectively.

Table 2 shows the correlations among the Chinese commodity futures used in this analysis for the sample period. The average correlation between these futures is 0.35. At 0.54, natural rubber and copper cathode futures

TABLE 1 List of commodity futures and summary statistics

Commodity futures (Bloomberg ticker)	Annualized mean (%)	Annualized volatility (%)
Aluminum (AA)	–3.20	15.31
Copper cathode (CU)	–4.84	24.18
Corn (AC)	0.60	15.56
Fuel oil (FO)	–5.73	33.70
Natural rubber (RT)	–7.80	32.44
No. 1 soybeans (AK)	1.77	16.25
Soybean meal (AE)	2.65	24.24
Soybean oil (SH)	–9.21	23.22
White sugar (CB)	–0.87	20.67
Zhengzhou cotton (VV)	–3.86	21.39

Note: It lists the commodity futures analyzed in this study and the annualized means and volatilities of their daily excess returns. We collect the daily closing prices of generic first futures (in USD) from September 14, 2006 to October 31, 2018 from Bloomberg.

have the highest correlation, whereas at 0.02, fuel oil and corn futures have the lowest correlation. The low correlations between commodity futures are controversial, and Erb and Harvey (2006) indicate that commodity futures have low correlations in the US market. Low correlations are similarly evident in China's commodity futures market, as shown in Table 2.

Moskowitz et al. (2012) utilize the MSCI World Equity Index and global long-short factors to evaluate the returns to different strategies. Because the MSCI World Equity Index excludes China's equity markets, we utilize the CSI 300 Index, which reflects capitalization-weighted Chinese stocks. Additionally, evidence suggests that the domestic versions of the Fama-French factors capture more variation in returns (Griffin, 2002), and, thus, we consider the Fama and French (1993) long-short factors for the Asia-Pacific region excluding Japan with Carhart's (1997) size, value, and cross-sectional momentum premiums rather than using global factors.[4]

TABLE 2 Correlations between Chinese commodity futures

	Aluminum	Corn	Soybean meal	No. 1 soybeans	White sugar	Copper cathode	Fuel oil	Natural rubber	Soybean oil	Zhengzhou cotton
Aluminum	1.00									
Corn	0.28	1.00								
Soybean meal	0.19	0.16	1.00							
No. 1 soybeans	0.06	0.2	0.3	1.00						
White sugar	0.2	0.03	0.04	0.13	1.00					
Copper cathode	0.52	0.06	0.29	0.08	0.27	1.00				
Fuel oil	0.08	0.02	0.15	0.22	0.22	0.27	1.00			
Natural rubber	0.35	0.08	0.27	0.14	0.33	0.54	0.2	1.00		
Soybean oil	0.18	0.08	0.25	0.34	0.19	0.31	0.21	0.21	1.00	
Zhengzhou cotton	0.19	0.06	0.14	0.15	0.34	0.17	0.13	0.34	0.24	1.00

Note: It reports the correlations between the 1-month returns of Chinese commodity futures from October 2006 to October 2018.

[4]The MSCI World Equity Index represents large and midcap equities in 23 developed markets. In this context, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States are considered developed markets (https://www.msci.com/documents/10199/178e6643-6ae6–47b9–82be-e1fc565ededb).

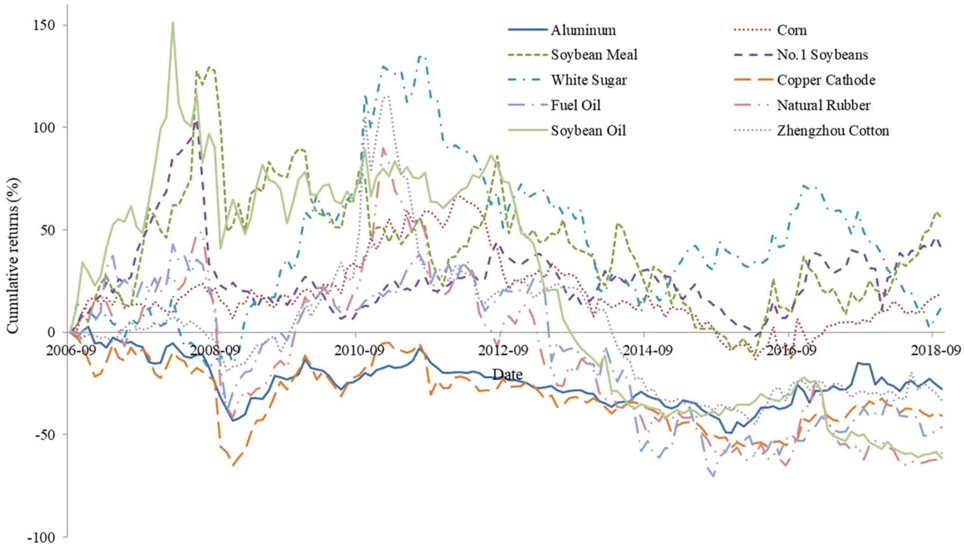

FIGURE 2 Monthly cumulative returns of Chinese commodity futures. We take the daily closing prices of generic first futures (in USD) from September 14, 2006 to October 31, 2018 from Bloomberg. We define the cumulative returns from the first to the last day of the month as the monthly returns [Color figure can be viewed at wileyonlinelibrary.com]

3 | METHODOLOGY

Following Moskowitz et al. (2012), we calculate the monthly returns for each commodity as the cumulative returns from the first day of the month to the last day of the month. Figure 2 illustrates the monthly cumulative returns for the Chinese commodity futures considered in this study.

Because the commodity futures have different volatilities, the returns are scaled by their volatilities. We calculate the ex ante annualized variance σ_t^s for each commodity s using exponential weights, as follows:

$$\sigma_t^s = 261\sum_{i=0}^{\infty}(1-\lambda)\lambda^i\left(r_{t-1-i}^s - \bar{r_t^s}\right)^2, \tag{1}$$

where 261 is a scale factor used to annualize the variance; λ, the exponential smoothing factor, satisfies $\sum_{i=0}^{\infty}(1-\lambda)\lambda^i = 1$; the "center of mass," calculated as $\sum_{i=0}^{\infty}(1-\lambda)\lambda^i i = \lambda/(1-\lambda)$, is 60 days; and $\bar{r_t}$ is the exponentially weighted average return with the same smoothing factor, λ.

The excess return r_t^s of commodity s in month t is regressed on its excess return lagged by h months to examine the predictive ability of futures returns over different time horizons. The excess returns are normalized by dividing them by their ex ante volatilities, σ_{t-1}^s, which are computed using Equation (1). Figure 3a shows the t-statistics for the following pooled panel regression:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h\frac{r_{t-h}^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s. \tag{2}$$

In addition, the excess return r_t^s is regressed on the sign of the excess return lagged by h months to examine the time-series momentum in a different way:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h\text{sign}\left(r_{t-h}^s\right) + \varepsilon_t^s. \tag{3}$$

In the specification in Equation (3), $\text{sign}(r_{t-h}^s)$ equals +1 if r_{t-h}^s is positive or −1 if it is negative. Figure 3b shows the t-statistics for the pooled panel regression given by Equation (3).

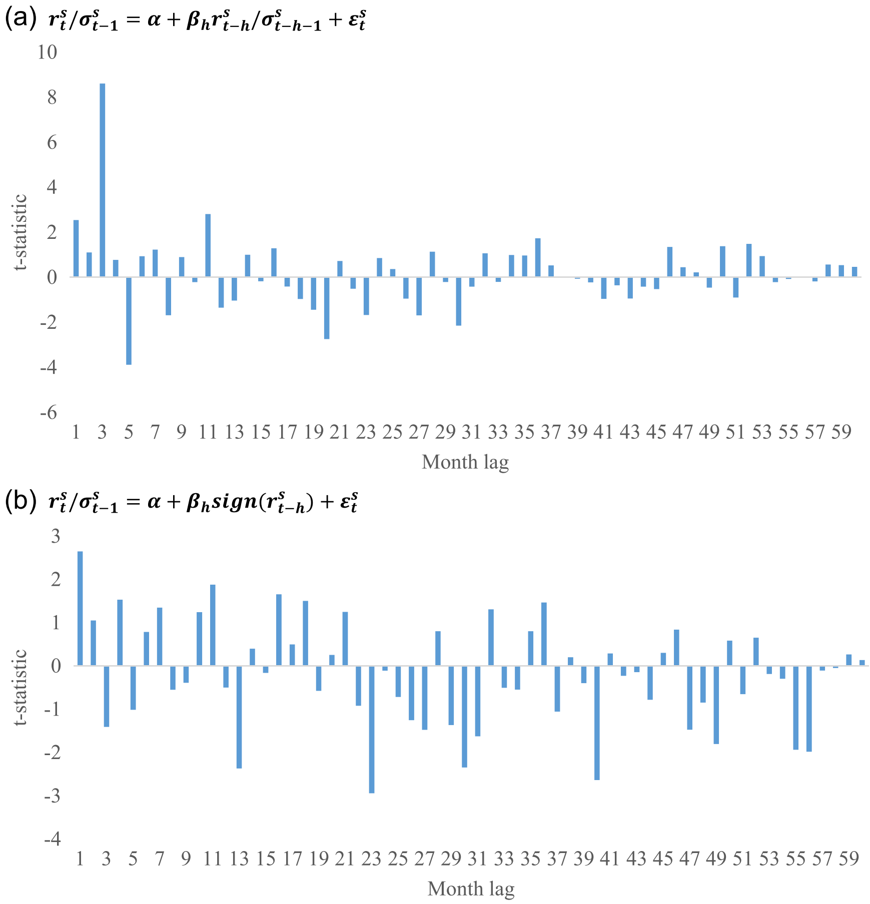

FIGURE 3 Predictive ability of the Chinese commodity futures time series. The monthly excess returns of each futures contract scaled by their ex ante volatilities are regressed on the scaled lagged excess returns and the signs of the lagged excess returns. (a) shows the results of the regression with the lagged excess returns as independent variables, and (b) shows the results with the signs of the lagged excess returns as independent variables. Both regressions use lags from 1 to 60 months, and the sample data period runs from September 2006 to October 2018 [Color figure can be viewed at wileyonlinelibrary.com]

Both regressions use lags from 1 to 60 months, and the sample period runs from September 2006 to October 2018. Figure 3 therefore indicates the predictive ability of historical Chinese commodity futures. We regress the monthly excess returns of each futures contract, scaled by their ex ante volatilities, on their scaled lagged excess returns and the signs of their lagged excess returns. Figure 3a illustrates the regression results when the lagged excess returns themselves are used as independent variables, and Figure 3b illustrates the regression results when the signs of the lagged excess returns are used as independent variables. Positive *t*-statistics indicate return continuations. Figure 3a,b show significant positive *t*-statistics for the first month. This result suggests that the most recent month has the strongest and most significant return continuation, indicating a shorter return continuation period than that observed by Moskowitz et al. (2012) for the US futures market.

4 | EMPIRICAL RESULTS

4.1 | Time-series momentum

The monthly returns to apply a time-series momentum strategy for each commodity s are calculated following Jegadeesh and Titman's (1993) methodology. For each commodity s and month t, if the cumulative return for the past k months, that is, the cumulative return from month $t-k$ to month $t-1$ (the look-back period), is positive or negative, then the strategy takes a long or short position with a value of $1/\sigma_{t-1}^{s}$ and holds it for h months (the holding period). Thus, for any month t after the first $h-1$ months, the number of portfolios held is h. Under this time-series momentum strategy, the return of commodity s at time t is the average return over all portfolios at time t, where the return at time $t, r_t^{TSMOM\,(k,h)}$, is defined as the average return across all commodities. The strategy's look-back and holding periods are either 1, 3, 6, 9, 12, 24, 36, or 48 months long. To evaluate the performance of the strategy, we run the following regression for each k and h:

$$r_t^{TSMOM\,(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 COMDTY_t + \beta_s SMB_t + \beta_h HML_t + \beta_m UMD_t + \varepsilon_t, \tag{4}$$

where *MKT* is the excess return on the CSI 300 Index; *BOND* is the excess return on Barclay's China Aggregate Bond Index; *COMDTY* is the excess return on the Australia and New Zealand (ANZ) Bank China Commodity Index; and *SMB*, *HML*, and *UMD* are the long-short factors for the Asia-Pacific region excluding Japan with Carhart's (1997) size, value, and cross-sectional momentum premiums.

Panel A of Table 3 shows the average monthly returns for the time-series momentum strategy with different look-back and holding periods. Panel B of Table 3 lists the *t*-statistics of the αs from the regression in Equation (4) for different look-back and holding periods. Compared with the United States' commodity futures market, China's commodity futures market has fewer significant excess returns when the time-series momentum strategy is used.

As shown, the strategy with 1-month look-back and holding periods has the highest *t*-statistic for China's commodity futures market, 2.59, whereas the strategy with a look-back period of 12 months and a holding period of 1 month has the highest *t*-statistic in the US market. This result is illustrated by the high predictive ability of the time-series with a 1-month lag, which indicates a significant return continuation over 1 month. This result may be associated with trading by speculative investors. Because China's futures market is highly volatile and has attracted many speculative investors (Fan, Mo, & Zhang, 2018; Fung, Liu, & Tse, 2010; Wu & Zhang, 2019),[5] time-series momentum can only be maintained in this market for a relatively shorter time, as many speculative investors compete for limited investment opportunities from the strategy. As Moskowitz et al. (2012) point out, speculators who benefit from a time-series momentum strategy do so at the expense of hedgers. When more speculators participate in a market, a time-series momentum strategy generates fewer profits. The results for the strategy with 1-month look-back and holding periods do correspond to those of Shen et al. (2007), who show that, in the US market, a 1-month cross-sectional momentum strategy earned the most significant profits, on average, for 28 commodities from 1959 to 2003. Kang, Rouwenhorst, and Tang (2019) also find that the momentum strategy underperforms for commodities that are primarily bought by speculators. Furthermore, the results mirror those of Kang and Kwon (2017), who examine a cross-sectional momentum strategy. They show that, in China's commodity futures market, the strategy with 1-month look-back and holding periods has the highest return and the highest Sharpe ratio. This result suggests that strategies with 1-month look-back and holding periods perform the best in the Chinese futures market, whereas strategies with relatively longer look-back and holding periods perform better in the United States.

We construct the time-series momentum (TSMOM) factor following Moskowitz et al. (2012) and the conventions used by other studies of cross-sectional momentum. This factor uses 1-month look-back and holding periods (i.e., $k = 1$ and $h = 1$). The TSMOM return for commodity futures contract s at time t is given as follows:

$$r_{t,t+1}^{TSMOM,s} = \text{sign}\left(r_{t-1,t}^{s}\right)\frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}, \tag{5}$$

where $r_{t,t+1}^{TSMOM,s}$ is the return in month t.

The overall return $r_{t,t+1}^{TSMOM}$ across all commodity futures S_t is defined as follows:

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t}\sum_{s=1}^{S_t}\text{sign}\left(r_{t-1,t}^{s}\right)\frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}, \tag{6}$$

where S_t is the total number of commodity futures contracts and we use 40% to more efficiently and accurately compare these portfolios to those in the literature.

4.2 | Time-series and cross-sectional momentums

The cross-sectional momentum strategy considers all commodity futures at one point in time and compares the past returns across the commodity futures. In contrast, the time-series momentum strategy focuses on the past returns of a single commodity future. In this study, we construct a cross-sectional momentum strategy following

[5]The dominance of speculative trading seems to be a common phenomenon observed in Asia's emerging futures markets. Many recent studies report the dominance of speculative trading in the Asian futures markets, including the Korean and Taiwanese futures markets (Atilgan, Demirtas, & Simsek, 2016; Chou, Wang, & Wang, 2015; Han, Hwang, & Ryu, 2015; Lee, Lee, & Ryu, 2019; Ryu, 2011, 2013, 2015; Webb, Ryu, Ryu, & Han, 2016), which are closely related to the Chinese futures markets in terms of geography, trading activities, and investor compositions.

TABLE 3 Performance of the time-series momentum strategy with different look-back and holding periods

		Holding period (months)							
		1	**3**	**6**	**9**	**12**	**24**	**36**	**48**
Panel A. Average monthly returns to the time-series momentum strategy with different look-back and holding periods									
Look-back period (months)	1	0.24**	0.07	0.05	0.06	0.06	0.02	0.02	0.04
		(2.52)	(1.17)	(1.32)	(1.54)	(1.61)	(0.77)	(0.80)	(1.34)
	3	0.09	0.06	0.05	0.07*	0.06	0.01	0.02	0.02
		(1.06)	(1.08)	(1.34)	(2.01)	(1.86)	(0.24)	(0.57)	(0.72)
	6	0.13	0.14**	0.10**	0.07	0.04	0.02	0.03	0.03
		(1.46)	(2.26)	(2.33)	(1.91)	(1.13)	(0.65)	(0.86)	(0.90)
	9	0.08	0.08	0.09	0.06	0.06	0.05	0.03	0.04
		(0.80)	(1.23)	(1.72)	(1.22)	(1.20)	(1.27)	(1.01)	(1.16)
	12	0.15	0.11	0.06	0.06	0.05	0.04	0.03	0.02
		(1.49)	(1.61)	(1.16)	(1.08)	(1.09)	(1.09)	(0.84)	(0.49)
	24	0.04	0.04	0.04	0.02	0.03	−0.04	−0.05	−0.08
		(0.36)	(0.47)	(0.59)	(0.36)	(0.52)	(−0.93)	(−1.48)	(−2.14)
	36	−0.01	0.00	−0.01	−0.02	−0.05	−0.09	−0.09	−0.08
		(−0.05)	(0.02)	(−0.08)	(−0.35)	(−0.81)	(−2.13)	(−2.72)	(−2.33)
	48	−0.21	0.17	−0.12	−0.10	−0.09	−0.07	−0.09	−0.04
		(−1.64)	(−1.97)	(−1.82)	(−1.86)	(−1.91)	(−2.23)	(−2.87)	(−1.46)
Panel B. αs from regressing the returns of the time-series momentum strategy on risk factors with different look-back and holding periods									
Look-back period (months)	1	0.29***	0.07	0.04	0.04	0.03	−0.01	−0.02	−0.01
		(2.59)	(0.98)	(0.80)	(1.07)	(0.62)	(−0.32)	(−0.50)	(−0.28)
	3	0.16	0.11	0.05	0.07	0.04	0.00	0.02	0.01
		(1.47)	(1.53)	(1.17)	(1.85)	(1.14)	(0.09)	(0.47)	(0.16)
	6	0.15	0.18**	0.12**	0.07	0.03	0.02	0.03	0.02
		(1.44)	(2.57)	(2.27)	(1.61)	(0.67)	(0.50)	(0.76)	(0.50)
	9	0.07	0.11	0.08	0.04	0.03	0.04	0.04	0.03
		(0.54)	(1.36)	(1.39)	(0.82)	(0.53)	(0.92)	(0.89)	(0.61)
	12	0.13	0.09	0.05	0.03	0.00	0.02	0.02	0.00
		(1.11)	(1.22)	(0.85)	(0.52)	(0.03)	(0.52)	(0.55)	(0.08)
	24	0.02	0.01	0.02	0.00	−0.01	−0.03	−0.03	−0.06
		(0.15)	(0.11)	(0.30)	(0.01)	(−0.21)	(−0.62)	(−0.58)	(−1.16)
	36	0.02	−0.01	0.01	0.00	−0.05	−0.05	−0.05	−0.04
		(0.13)	(−0.08)	(0.11)	(0.01)	(−0.79)	(−0.95)	(−1.15)	(−0.84)
	48	−0.19	−0.17	−0.10	−0.09	−0.11	−0.05	−0.07	−0.04
		(−1.40)	(−1.84)	(−1.36)	(−1.55)	(−2.06)	(−1.26)	(−1.74)	(−1.05)

Note: It presents the average monthly returns of the time-series momentum strategy and the αs from regressing the returns of the time-series momentum strategy on risk factors with different look-back and holding periods. Panel A shows the average monthly returns of the time-series momentum strategy with different look-back and holding periods, and Panel B shows the αs. The αs are the intercepts for $r_t^{TSMOM\,(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 COMDTY_t + \beta_s SMB_t + \beta_h HML_t + \beta_m UMD_t + \varepsilon_t$, where *MKT* is the excess return on the CSI 300 Index; *BOND* is the excess return on Barclay's China Aggregate Bond Index; *COMDTY* is the excess return on the ANZ Bank China Commodity Index; and *SMB*, *HML*, and *UMD* are long-short factors for the Asia-Pacific region excluding Japan with Carhart's (1997) size, value, and cross-sectional momentum premiums. The CSI 300 Index, Barclay's China Aggregate Bond Index, and the ANZ Bank China Commodity Index are obtained from Bloomberg, and the long-short factors are taken from Kenneth French's data library. The sample data spans the period from September 2006 to October 2018 (French, 2019a, 2019b). *t*-Statistics are reported in parentheses.

***, **, *Significant at the 1%, 5%, and 10% levels, respectively.

Asness et al. (2013) methodology, which compares and ranks the returns of the instruments over the past 12 months. The position of each commodity future at a given point in time is held in proportion to its rank relative to the median rank (Moskowitz et al., 2012).

The cross-sectional momentum return for commodity futures contract s at time t is given as follows:

$$r_{t,t+1}^{XSMOM,s} = \frac{\text{rank}(r_{t-12,t}^{s})}{2.5}\frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}, \tag{7}$$

TABLE 4 Comparison of the time-series momentum strategy with a cross-sectional momentum strategy

	XSMOM	Intercept	R^2	F	AIC
Coefficient	0.466***	0.003***	0.154	23.78	−767.7
(t-statistic)	(4.876)	(2.942)			

Note: It presents the results of regressing the returns of the time-series momentum strategy (TSMOM) on the returns of the cross-sectional momentum strategy (XSMOM). In the regression analysis, the dependent (independent) variable is TSMOM (XSMOM). TSMOM uses a 1-month look-back period and a 1-month holding period (i.e., $k = 1$ and $h = 1$), and XSMOM uses a 12-month look-back period and a 1-month holding period (i.e., $k = 12$ and $h = 1$). The sample period is from October 2007 to October 2018. t-Statistics are shown in parentheses. R^2 denotes the R-squared value of the regression. F denotes the F-statistic, and AIC is Akaike's information criterion.

***Significant at the 1% level.

where $\text{rank}(r^s_{t-12,t})$ is the difference between the rank of the past returns of the focal commodity futures contract and the median rank. For comparison, the position of the cross-sectional momentum strategy return of a commodity $r^{XSMOM,s}_{t,t+1}$ is set to $40\%/\sigma^s_t$, which is the same as that used for the time-series momentum for each commodity future. A scale factor of 2.5 is used so that $\text{rank}(r^s_{t-12,t})/2.5$ equals 0 on average and the maximum and minimum values equal 1 and −1, respectively, because the time-series momentum factor has a coefficient of 1 or −1 for $(40\%/\sigma^s_t)r^s_{t,t+1}$. Assume, for example, that aluminum and copper cathode futures have scaled excess returns of −0.59 and 1.39 and ranks of 5 and 1, respectively, on January 1, 2008. The values of $\text{rank}(r^s_{t-12,t})$ for aluminum and copper cathode futures should be −0.5 and −4.5, respectively, and the median rank is 5.5 when the number of futures contracts is 10. As in the case of the time-series momentum strategy, the overall returns for the cross-sectional momentum strategy are calculated using the following equation:

$$r^{XSMOM}_{t,t+1} = \frac{1}{S_t}\sum_{s=1}^{S_t}\frac{\text{rank}(r^s_{t-12,t})}{2.5}\frac{40\%}{\sigma^s_t}r^s_{t,t+1}, \tag{8}$$

where S_t is the total number of commodity futures contracts.

We carry out a regression analysis to determine the relationship between the time-series momentum strategy and the cross-sectional momentum strategy. The returns of the time-series momentum strategy are regressed on the returns of the cross-sectional momentum strategy for the sample period of October 2007 through October 2018.[6] Table 4 gives the results and shows that the t-statistic of the coefficient of the returns of the time-series momentum strategy is 4.876, suggesting that these returns are significantly related to those of the cross-sectional momentum strategy.

The results in Table 4 suggest that the time-series momentum strategy outperforms the cross-sectional momentum strategy. When we regress the returns of the time-series momentum strategy on the returns of the cross-sectional momentum strategy, we find that the intercept has a t-statistic of 2.942, which is significant.

4.3 | Performance evaluation of the time-series momentum strategy

Figure 4 reports the annualized Sharpe ratio for the time-series momentum (Figure 4a), passive long (Figure 4b), and cross-sectional momentum trading strategies (Figure 4c) by commodity futures contract for the sample period from October 2007 to October 2018. In general, the time-series momentum strategy has a greater Sharpe ratio than the passive long and cross-sectional momentum strategies have.

As risk factors, we use the excess returns of the ANZ Bank China Commodity Index and the SMB, HML, and UMD factors for the Asia-Pacific region excluding Japan, and we regress the returns of the time-series momentum strategy on these risk factors.[7] The results of regressing the monthly returns of the time-series momentum, passive long, and cross-sectional momentum strategies on the traditional risk factors are shown in Panels A, B, and C of Table 5, respectively.

[6]Because the cross-sectional momentum strategy requires a 12-month look-back period, the data on returns start in October 2007.

[7]We explain the details in Section 1.

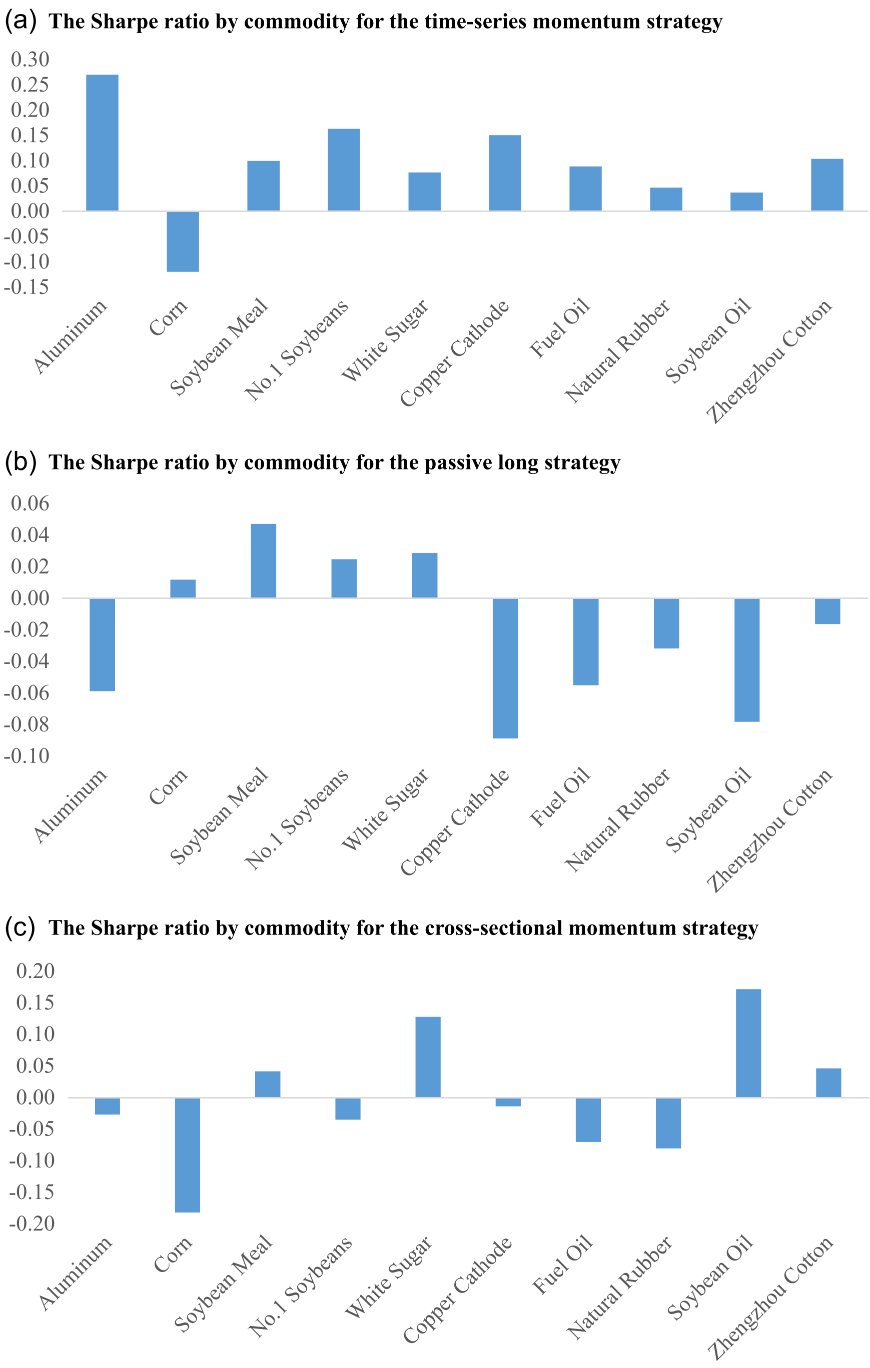

FIGURE 4 The annualized Sharpe ratio, by commodity, in the Chinese commodity futures market. It reports the annualized Sharpe ratio for the time-series momentum strategy (a), the passive long strategy (b), and the cross-sectional momentum strategy (c) by the commodity futures contract. The time-series momentum strategy uses 1-month look-back and holding periods (i.e., $k = 1$ and $h = 1$), and the cross-sectional momentum strategy uses a 12-month look-back period and a 1-month holding period (i.e., $k = 12$ and $h = 1$). The passive long strategy is a long-only strategy with risk-scaled positions constructed using the same method as that used for the time-series and cross-sectional momentum strategies. The sample period runs from October 2007 to October 2018 [Color figure can be viewed at wileyonlinelibrary.com]

As Table 5 shows, only the time-series momentum strategy has significant excess returns after controlling for the risk factors. The intercept of the regression for the time-series momentum strategy has a t-statistic of 2.257, whereas those for the passive long and cross-sectional momentum strategies have t-statistics of −1.207 and −1.139, respectively. These results indicate that the time-series momentum strategy performs better than the passive long and cross-sectional momentum strategies do in terms of risk-adjusted excess returns. The time-series momentum strategy has an α of .002, which implies a monthly return of 0.2%, whereas the αs for the other two strategies are not significant. The annualized α of the time-series momentum strategy is 2.4%, which is meaningful when we consider that the fund's annual transaction cost is about 1.44% (Edelen, Evans, & Kadlec, 2013).

We can also evaluate the performances of these strategies by examining cumulative returns. Figure 5 shows the cumulative returns of the time-series momentum, passive long, and cross-sectional momentum strategies from October 2007 to October 2018. The figure shows that the cumulative returns of the time-series momentum strategy are higher than those

TABLE 5 Regression analyses for the time-series momentum, passive long, and cross-sectional strategies on traditional risk factors

	COMDTY	SMB	HML	UMD	Intercept	R^2	F	AIC
Panel A. Regression analysis for the time-series momentum strategy								
Coefficient	−0.016	0.016	0.032	−0.018	0.002***	0.012	0.213	−480.5
(t-statistic)	(−0.613)	(0.381)	(0.648)	(−0.562)	(2.257)			
Panel B. Regression analysis for the passive long strategy								
Coefficient	0.160***	−0.029	0.016	0.000	−0.002	0.321	7.927	−453.6
(t-statistic)	(5.213)	(−0.576)	(0.275)	(0.006)	(−1.207)			
Panel C. Regression analysis for the cross-sectional momentum strategy								
Coefficient	−0.030	−0.013	0.016	0.009	−0.001	0.021	0.559	−476.7
(t-statistic)	(−1.139)	(−0.308)	(0.309)	(0.270)	(−1.139)			

Note: It presents the results of regressing the monthly returns of the time-series momentum, passive long, and cross-sectional strategies on traditional risk factors. The returns of the time-series momentum strategy are regressed on *COMDTY*, *SMB*, *HML*, and *UMD*. *COMDTY* is the excess returns of the ANZ Bank China Commodity Index, which reflects China's commodity market; *SMB* and *HML* are the size and value factors, respectively, for the Asia-Pacific region excluding Japan, following Fama and French (1993); and *UMD* is Carhart's (1997) momentum factor. The ANZ Bank China Commodity Index is taken from Bloomberg, and the SMB, HML, and UMD factors are taken from Kenneth French's data library. Panels A, B, and C show the results of regressions for the time-series momentum, passive long, and cross-sectional momentum strategies, respectively. The sample period is from October 2007 to October 2018. t-Statistics are shown in parentheses. R^2 denotes the R-squared value of each regression analysis. F denotes the F-statistic, and AIC is Akaike's information criterion.

***Significant at the 1% level.

of the passive long and cross-sectional momentum strategies, suggesting that the time-series momentum strategy outperforms the other two strategies. The passive long strategy has negative cumulative returns over time, whereas the momentum strategies perform better. The time-series momentum strategy not only yields the highest cumulative returns but also exhibits the best performance even after controlling for the risk factors.

Table 6 shows the correlations between the returns of each Chinese futures contract with the time-series momentum, passive long, and cross-sectional momentum strategies. The overall correlations between the returns of each commodity futures contract are 0.05, 0.23, and −0.01 for the time-series momentum, passive long, and cross-sectional momentum strategies, respectively. This result suggests that the time-series momentum strategy can reduce the correlations between Chinese commodity futures better than the passive long strategy can, but it is not as effective as the cross-sectional momentum strategy is.

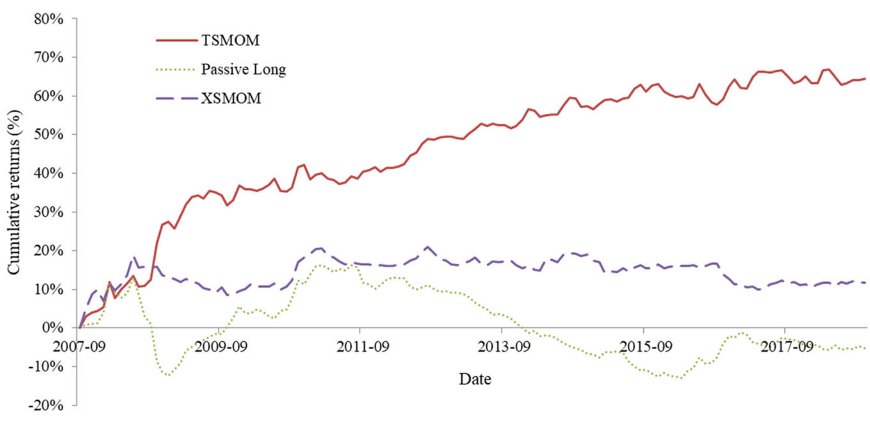

FIGURE 5 Cumulative returns of the time-series momentum, passive long, and cross-sectional momentum strategies. TSMOM and XSMOM denote the time-series momentum and cross-sectional momentum strategies, respectively. TSMOM uses 1-month look-back and holding periods (i.e., $k = 1$ and $h = 1$), and XSMOM uses a 12-month look-back period and a 1-month holding period (i.e., $k = 12$ and $h = 1$). The passive long strategy is a long-only strategy with risk-scaled positions constructed using the same method as that used for TSMOM and XSMOM. The sample period runs from October 2007 to October 2018 [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 6 Correlations between the returns of the time-series momentum, passive long, and cross-sectional momentum strategies

	Aluminum	Corn	Soybean meal	No. 1 soybeans	White sugar	Copper cathode	Fuel oil	Natural rubber	Soybean oil	Zhengzhou cotton
Panel A. Correlations between the returns for the time-series momentum strategy										
Aluminum	1.00									
Corn	0.13	1.00								
Soybean meal	0.15	−0.29	1.00							
No. 1 soybeans	0.25	−0.07	0.33	1.00						
White sugar	0.05	0.04	−0.12	0.03	1.00					
Copper cathode	−0.15	0.23	−0.78	−0.26	0.15	1.00				
Fuel oil	−0.19	−0.33	0.75	0.28	−0.06	−0.61	1.00			
Natural rubber	−0.15	−0.23	0.56	0.02	0.11	−0.38	0.71	1.00		
Soybean oil	−0.18	−0.21	0.25	0.23	0.14	−0.05	0.51	0.42	1.00	
Zhengzhou cotton	0.19	−0.11	0.31	0.21	0.20	−0.16	0.25	0.21	0.06	1.00
Panel B. Correlations between the returns for the passive long strategy										
Aluminum	1.00									
Corn	0.26	1.00								
Soybean meal	0.07	0.10	1.00							
No. 1 soybeans	0.09	0.11	0.30	1.00						
White sugar	0.19	0.01	0.03	0.23	1.00					
Copper cathode	0.46	0.17	0.28	0.12	0.26	1.00				
Fuel oil	0.21	0.09	0.19	0.29	0.26	0.43	1.00			
Natural rubber	0.30	0.10	0.27	0.20	0.32	0.47	0.27	1.00		
Soybean oil	0.11	0.01	0.31	0.53	0.25	0.32	0.35	0.27	1.00	
Zhengzhou cotton	0.28	0.10	0.11	0.20	0.29	0.30	0.25	0.40	0.30	1.00
Panel C. Correlations between the returns for the cross-sectional momentum strategy										
Aluminum	1.00									
Corn	−0.19	1.00								
Soybean meal	0.06	0.09	1.00							
No.1 soybeans	0.01	0.00	0.25	1.00						
White sugar	−0.01	−0.02	−0.08	−0.29	1.00					
Copper cathode	0.44	−0.31	−0.25	−0.02	−0.02	1.00				
Fuel oil	−0.06	0.00	−0.06	0.14	−0.15	0.09	1.00			
Natural rubber	−0.23	0.07	0.09	0.12	0.05	−0.08	0.10	1.00		
Soybean oil	−0.03	0.08	0.18	0.33	−0.36	−0.19	0.14	−0.03	1.00	
Zhengzhou cotton	−0.06	0.03	−0.02	−0.16	0.17	−0.09	−0.03	0.11	−0.12	1.00

Note: It presents the correlations between the monthly returns of the time-series momentum, passive long, and cross-sectional momentum strategies. The time-series momentum and cross-sectional momentum strategies use 1-month look-back and holding periods (i.e., $k = 1$ and $h = 1$). The passive long strategy is a long-only strategy with risk-scaled positions constructed using the same method as that used for the time-series momentum and cross-sectional momentum strategies. The sample period runs from October 2007 to October 2018.

5 | CONCLUSION

We examine the time-series momentum in China's commodity futures market. The results show that a strategy with 1-month look-back and holding periods performs the best, and thus our results are similar to those for the cross-sectional momentum strategy obtained by Kang and Kwon (2017) and Shen et al. (2007) for commodity futures in the United States and China, respectively. These results support the initial underreaction and delayed overreaction theories, as discussed by Moskowitz et al. (2012). However, the return on momentum lasts for less time in China than in the United States because the former market has a greater number of speculative investors. This result also seems to support the implication that speculators profit from time-series momentum strategies at the expense of hedgers.

This study illustrates that the time-series momentum strategy with 1-month look-back and holding periods performs the best in the Chinese commodity futures market. In this market, the time-series momentum strategy outperforms the passive long and cross-sectional momentum strategies constructed following the process suggested by Asness et al. (2013). Regressing the returns of the time-series momentum strategy on the returns of the cross-sectional momentum strategy verifies the finding that the former strategy outperforms the latter. Furthermore, we compare the Sharpe ratio, risk-adjusted performance, cumulative returns, and correlation structure of the time-series momentum strategy to those of the passive long and cross-sectional momentum strategies. In general, for the Chinese commodity futures market, the Sharpe ratio is greater for the time-series momentum strategy than for the other strategies. The time-series momentum strategy generally outperforms the passive long and cross-sectional momentum strategies. To analyze risk-adjusted performance, we use the ANZ Bank China Commodity Index excess returns and the SMB, HML, and UMD factors for the Asia-Pacific region excluding Japan as risk factors, and we find that, among the three strategies, only the time-series momentum strategy has significantly positive excess returns. The time-series momentum strategy also has a greater cumulative return than the other two strategies have. In addition, by comparing the correlation structures, we can confirm that the time-series momentum strategy is more effective at reducing the correlations between Chinese commodity futures than the passive long strategy is.

This study is limited by the small size of the Chinese commodity futures data set. Although a few Chinese commodity futures have been traded for over 25 years, the Chinese futures market has fewer commodities and shorter trading periods than the US market has. Trading in this market has been active recently; thus, the period and number of commodity futures are still insufficient for this type of analysis. Moreover, research on the momentum in futures markets is still generally lacking. In particular, the study of the time-series momentum in futures markets is relatively novel, and thus, few such studies have been conducted.

Momentum is an anomaly that prevails in financial markets around the world. Further studies analyzing momentum, applying various momentum strategies to commodity futures markets, and developing better strategies are necessary. Moreover, further research is needed to investigate the rationale for the better performance of the time-series momentum strategy relative to that of the cross-sectional momentum strategy and to identify the kinds of commodity futures that exhibit better or worse performances, especially for the time-series momentum strategy.

ORCID

Hyeongjun Kim http://orcid.org/0000-0003-0386-005X
Doojin Ryu http://orcid.org/0000-0002-0059-4887

REFERENCES

Andrei, D., & Cujean, J. (2017). Information percolation, momentum and reversal. Journal of Financial Economics, 123(3), 617–645.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. The Journal of Finance, 68(3), 929–985.

Atilgan, Y., Demirtas, K. O., & Simsek, K. D. (2016). Derivative markets in emerging economies: A survey. International Review of Economics and Finance, 42, 88–102.

Bakshi, G., Gao, X., & Rossi, A. G. (2019). Understanding the sources of risk underlying the cross section of commodity returns. Management Science, 65(2), 619–641.

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. Journal of Financial Economics, 116(1), 111–120.

Blitz, D., & Groot, W. (2014). Strategic allocation to commodity factor premiums. The Journal of Alternative Investments, 17(2), 103–115.

Carhart, M. M. (1997). On persistence in mutual fund performance. The Journal of Finance, 52(1), 57–82.

Cheema, M. A., Nartea, G. V., & Man, Y. (2017). Cross-sectional and time series momentum returns and market states. International Review of Finance, 18(4), 705–715.

Chou, R. K., Wang, G. H. K., & Wang, Y.-Y. (2015). The effects of margin changes on the composition of traders and market liquidity: Evidence from the Taiwan futures exchange. Journal of Futures Markets, 35(10), 894–915.

Clare, A., Seaton, J., Smith, P. N., & Thomas, S. (2014). Trend following, risk parity and momentum in commodity futures. International Review of Financial Analysis, 31, 1–12.
Docherty, P., & Hurst, G. (2018). Investor myopia and the momentum premium across international equity markets. Journal of Financial and Quantitative Analysis, 53(6), 2465–2490.
Edelen, R., Evans, R., & Kadlec, G. (2013). Shedding light on "invisible" costs: Trading costs and mutual fund performance. Financial Analysts Journal, 69(1), 33–44.
Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. Financial Analysts Journal, 62(2), 69–97.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.
Fan, J. H., Mo, D., & Zhang, T. (2018). *Commodity futures speculation in China* (Working Paper). https://acfr.aut.ac.nz/__data/assets/pdf_file/0006/185307/172978-D-Mo-FMZ_China-Speculation_21May_2018.pdf
Fuertes, A.-M., Miffre, J., & Rallis, G. (2010). Tactical allocation in commodity futures markets: Combining momentum and term structure signals. Journal of Banking and Finance, 34(10), 2530–2548.
Fung, H. G., "Wilson" Liu, Q., & Tse, Y. (2010). The information flow and market efficiency between the US and Chinese aluminum and copper futures markets. Journal of Futures Markets, 30(12), 1192–1209.
Gao, L., Han, Y., Zhengzi Li, S., & Zhou, G. (2018). Market intraday momentum. Journal of Financial Economics, 129(2), 394–414.
Goyal, A., & Jegadeesh, N. (2018). Cross-sectional and time-series tests of return predictability: What is the difference? Review of Financial Studies, 31(5), 1784–1824.
Griffin, J. M. (2002). Are the Fama and French factors global or country specific? Review of Financial Studies, 15(3), 783–803. https://doi.org/10.1093/rfs/15.3.783
Han, C., Hwang, S., & Ryu, D. (2015). Market overreaction and investment strategies. Applied Economics, 47(54), 5868–5885.
Hurst, B., Ooi, Y. H., & Pedersen, L. H. (2013). Demystifying managed futures. Journal of Investment Management, 11(3), 42–58.
Hurst, B., Ooi, Y. H., & Pedersen, L. H. (2017). A century of evidence on trend-following investing. The Journal of Portfolio Management, 44(1), 15–29.
Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance, 48(1), 65–91.
Kang, J., & Kwon, K. Y. (2017). Momentum in international commodity futures markets. Journal of Futures Markets, 37(8), 803–835.
Kang, W., Rouwenhorst, K. G., & Tang, K. (2019). *A tale of two premiums: The role of hedgers and speculators in commodity futures markets* Journal of Finance, Forthcoming. Available at SSRN: https://ssrn.com/abstract=2449315. or http://dx.doi.org/10.2139/ssrn.2449315
Koijen, R. S. J., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2018). Carry. Journal of Financial Economics, 127(2), 197–225.
Lee, J., Lee, G., & Ryu, D. (2019). The difference in the intraday return-volume relationships of spot and futures: A quantile regression approach. Economics, 13, 1–37.
Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. Journal of Banking and Finance, 31(6), 1863–1886.
Miffre, J. (2016). Long-short commodity investing: A review of the literature. Journal of Commodity Markets, 1(1), 3–13.
Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. Journal of Financial Economics, 104(2), 228–250.
Roache, S. K. (2012). *China's impact on world commodity markets* (No. 12-115). International Monetary Fund. https://www.imf.org/~/media/Websites/IMF/imported-full-text-pdf/external/pubs/ft/wp/2012/_wp12115.ashx
Ryu, D. (2011). Intraday price formation and bid-ask spread components: A new approach using a cross-market model. Journal of Futures Markets, 31(12), 1142–1169.
Ryu, D. (2013). Price impact asymmetry of futures trades: Trade direction and trade size. Emerging Markets Review, 14, 110–130.
Ryu, D. (2015). The information content of trades: An analysis of KOSPI 200 index derivatives. Journal of Futures Markets, 35(3), 201–221.
Shen, Q., Szakmary, A. C., & Sharma, S. C. (2007). An examination of momentum strategies in commodity futures markets. Journal of Futures Markets, 27(3), 227–256.
Su, Y., & Liu, Z. (2016). The impact of foreign direct investment and human capital on economic growth: Evidence from Chinese cities. China Economic Review, 37, 97–109.
Webb, R. I., Ryu, D., Ryu, D., & Han, J. (2016). The price impact of futures trades and their intraday seasonality. Emerging Markets Review, 26, 80–98.
Wu, Y., & Zhang, T. (2019). Effects of change in commission fees on China futures market. Finance Research Letters, 31, 54–65.

DATA CITATION

Bloomberg; 2019; Commodities; Available: Bloomberg.
French, K. R.; 2019a; Fama/French Asia Pacific ex Japan 3 Factors [Daily]; Available: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
French, K. R.; 2019b; Fama/French Asia Pacific ex Japan Momentum Factor (Mom) [Daily]; Available: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

How to cite this article: Ham H, Cho H, Kim H, Ryu D. Time-series momentum in China's commodity futures market. *J Futures Markets*. 2019;39:1515–1528. https://doi.org/10.1002/fut.22053