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Intraday time-series momentum: Evidence from China

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Abstract

This study conducts an investigation of intraday time-series momentum across four Chinese commodity futures contracts: copper, steel, soybean, and soybean meal. Our results indicate that the first half-hour return positively predicts the last half-hour return across all four futures. Furthermore, in metals markets, we find that first trading sessions with high volume or volatility are associated with the strongest intraday time-series momentum dynamics. Based on this, we propose an intraday momentum informed trading strategy that earns a return in excess of standard always long and buy-and-hold benchmarks.

KEYWORDS

intraday predictability, momentum, time-series

JEL CLASSIFICATION

G12; G13; G15

1 | INTRODUCTION

Momentum effect can be broadly defined as the empirically observed tendency for rising asset prices to continue rising and falling prices to continue falling (Jegadeesh & Titman, 2001). There are two main strands in the momentum literature, cross-sectional and time-series. Cross-sectional momentum uses a security's past outperformance relative to its peers to predict future outperformance (Jegadeesh & Titman, 1993). In contrast, time-series momentum uses a security's own past return to predict its future return (Moskowitz, Ooi, & Pedersen, 2012). Focusing on the more recently proposed time-series momentum dynamic, we contribute by analyzing the intraday momentum effect in the increasingly important and as yet unstudied Chinese commodity futures market.

The four largest metals and agricultural futures markets in the world are located in China. Motivated by its large size, we employ a unique intraday data set of Chinese commodities. Our work contributes to the literature by closely analyzing intraday time-series momentum properties of the four futures: Copper, Steel Rebar, Soybean, and Soybean Meal. We seek to answer three simple questions: (a) Is an intraday time-series momentum pattern present, whereby the return in the opening period predicts the return in the market closing period for Chinese commodities? (b) Can such a pattern be economically exploited through the implementation of a trading strategy? (c) What explanations are there for the presence of such patterns?

Time-series momentum focuses on endogenously achieving excess returns using an asset's own return series. It is broadly similar to testing the random walk hypothesis for a single asset or examining the persistence of an asset's returns. Time-series momentum has widespread applicability, as evidence has been documented for numerous asset classes around the world, including those subject to short sale constraints. Commodity trading advisors (CTAs) achieved strong performance using time-series momentum strategies, in particular, during the 2008 global financial crisis (Baltas & Kosowski, 2013), piquing the interest of market practitioners and academic scholars, alike. This provides strong motivation, from both an academic and market practitioner perspective, to study the intraday time-series momentum effect in commodity markets.

Most existing cross-sectional and time-series momentum studies are based on interday trading. However, driven by technological developments and enhanced data availability in recent years, intraday high-frequency momentum strategies, such as those that we consider, can now be examined. For instance, Kang (2005) uses two thousand NYSE stocks, documenting an intraday cross-sectional momentum strategy that generates winners and losers according to their hourly returns, and compares their performance over a given trading day. The results suggest that winners outperform losers for about one and a half hours, with a subsequent reversal observed for large stocks. Small stocks, in contrast, tend to continue their momentum effect throughout the day. Venter (2009) also follows the winner/loser ranking method to study intraday cross-sectional momentum on Johannesburg Stock Exchange stocks, arguing that a cross-sectional momentum effect can be uncovered within a day. Furthermore, Gao, Han, Zhengzi Li, and Zhou (2018) and Sun, Najand, and Shen (2016) utilize the time-series momentum approach of Moskowitz et al. (2012) to study the S&P 500, they document an intraday time-series momentum pattern that the first half-hour return is able to predict the last half-hour return. Similarly, Elaut, Kevin, and Michael (2018) find that the first half-hour return can be used to predict the last half-hour return in the RUB-USD FX market. Liu and Tse (2017) focus on S&P 500 ETFs as well as 12 international index futures contracts, finding that, despite the first half-hour return not exhibiting predictive power, that overnight returns positively predict the last half-hour return. As outlined, the majority of both intraday cross-sectional and time-series momentum studies are based on stocks or stock indices, with intraday momentum in commodity markets remaining an open research question.

We present evidence consistent with Gao et al. (2018), with the first half-hour return significantly predicting the last half-hour return across all four commodity futures markets. We provide two explanations for this intraday momentum. The first explanation is the liquidity provision of intraday traders. For instance, day traders provide liquidity by taking the opposing direction to the rest of the market, however, these day traders subsequently close their positions at the end of the day to avoid overnight risk. Since trades occur more rapidly at the beginning and end of a given trading day (Hora, 2006), many of the day traders provide liquidity in the morning and subsequently close out their positions at the end of the day, causing prices during the last trading session to move in the same direction as the first. The second explanation is the trading time preference of the strategically informed traders. The informed traders prefer to trade during high trading volume periods to camouflage their information and limit their price impact. Therefore, the informed traders primarily execute their transactions at the beginning and near the end of the day because of the U-shape intraday trading volume pattern (Hora, 2006).

We also find that for metals futures, the opening trading sessions with the highest volume or volatility have the greatest intraday time-series momentum predictability. We confirm that this dynamic also holds when specifying a 15-min time-frequency. However, we did not find the above phenomenon for agricultural futures, with one possible explanation being the high proportion of noise traders active in the market. Furthermore, we also find, that using intraday time-series momentum as a trading strategy earns greater abnormal profits relative to “always long” and “buy-and-hold” strategies.

The rest of the paper is organized as follows: Section 2 is devoted to the description of the data used in our study. In Section 3, we present the intraday time-series momentum methodology employed in the paper. We present our main findings in Section 4, Section 5 assess the robustness of our results, with Section 6 concluding.

2 | DATA DESCRIPTION

2.1 | Commodity markets in China

Using the 2014 Futures Industry Association (FIA) world ranking in Table A1 of Appendix A (Acworth, 2015), we observe that trading volume in Chinese markets occupies the top four positions worldwide, for both metals and agricultural contracts in 2014. This paper focuses on four Chinese commodity futures contracts: copper, steel rebar, soybean, and soybean meal.

Copper futures are the longest established metals market in China. The market was established in China in 1992, however, it was not until rectification in 2003, that it became a relatively mature market. Again based on the FIA 2014 report (Acworth, 2015), the trading volume of Chinese copper contracts means it is the largest copper futures market in the world and fourth in the rankings of the top metals futures and options contracts. As well as copper, China is also the largest steel producer and consumer in the world, based on the FIA report (Acworth, 2015). This is despite the market for steel rebar in China having only been established in 2009. The trading volume of Chinese steel futures contracts makes it the largest among the world's metals futures and options contracts, again according to the FIA report (Acworth, 2015). For these reasons studying the properties of Chinese copper and steel markets is of great importance.

We also focus on futures markets for agricultural products; China is the fourth largest soybean and soybean meal producing country in the world, as well as the largest soybean importer. Soybean meal was the first agricultural futures contract traded in China, with it being established in 2000, whereas soybean was established in 2002. According to the FIA report (Acworth, 2015), the trading volume of Chinese soybean meal futures contracts means it is the world's largest soybean meal futures market and is also ranked as second among the agricultural futures and options contracts traded. Trading of the No.1 soybean futures contract is the second-largest soybean market, and also the largest Non-GMO soybean market in the world. Therefore, understanding the price evolution of Chinese soybean and soybean meal futures are of great practical and academic importance. Details of the four different futures contract specifications are given in Table A2 of Appendix A.

2.2 | Data and sample selection

The original data for all four contracts are the two times a second snapshot tick records. The data set excludes the call auction before and after the market opening. The trading hours for all four contracts are the same: 9:00–11:30 and 13:30–15:00, Monday to Friday. There is also a short break in trading of 15 min from 10:15 to 10:30 each day. The sample period of the data set of copper totals 2,655 trading days, from July 1, 2002 to June 25, 2013; March 27, 2009 to June 27, 2013 for steel, totaling 1,029 days; July 01, 2002 to June 27, 2013 for soybeans, totaling 2,245 trading days; and June 02, 2008 to June 28, 2013 for soybean meal, totaling 1093 trading days.

Furthermore, there are 12 futures contracts traded on the metals futures market at any one time with each contract having a different maturity time, ranging from 1 to 12 months. For soybean futures, there are six contracts traded at any one time, these contracts mature in January, March, May, July, September, and November. For soybean meal futures, there are eight contract maturities, they are January, March, May, July, August, September, November, and December.

There are two common methods to construct a single time-series of price data from multiple contracts with different maturities. The first method is to use the nearest-to-maturity contract as the representative contract in constructing the price series. This method splices the price of nearest-to-maturity futures contracts conditional on liquidity (Booth, So, & Tse, 1999). This method is based on the rationale that the expiring contract has more information contained in its price. The second commonly used approach utilizes only recently issued or on-the-run contracts instead of the expiring contract only. Fricke and Menkhoff (2011) present a method that uses on-the-run contracts with the highest trading volume to combine multiple contracts into a single price series. Both methods are conditional on the trading activity or liquidity when combining prices of contracts of different maturities.

However, the trading of Chinese agricultural futures (soybean and soybean meal) is unusual because it is dominated by three contracts that mature in January, May, and September, even though contracts that mature in other months are available. The contracts with maturity in these 3 months account for about 99% of the trading volume. This is primarily due to the seasonality of agricultural products. In China, September is the last month before the autumn harvest, and January is the main time to sell agricultural products. Despite May being of no great significance to agricultural production, it is used to fill the remaining market demand in the gap between January and September. Similarly, steel rebar is dominated by contracts that mature in January, May, and October. The nearest-to-maturity method is only appropriate for copper futures contract since it has active trading across all maturities.

Therefore, we follow an approach similar to Fricke and Menkhoff (2011) by constructing a single time-series based on each contract's trading volume. To avoid rolling forward and backward on contracts with different maturities, we combine our price series on a month-by-month basis. Specifically, we use the price series from the maturity month with the highest trading volume when computing the return time-series for that month. Moreover, once a contract with a later maturity is used, the earlier maturity contract is not used again, even in the case where the earlier maturity has a higher trading volume in a subsequent month.[1]

[1]Combining price series with different maturities does not cause any major issues for our return calculations since all returns are calculated intraday. However, we need to make an adjustment for the overnight return calculation in Section 4.2 if the overnight return happens at the joining point. When the overnight return occurs at the joining point, we utilize the overnight return from the latter maturity series. For example, if the price series switches from January maturity to May maturity on December 1, then the overnight return from November 31 to December 1 is computed using the price of the May contract instead of combining prices from the January and May contracts. We apply the same method in Section 4.2 when we compute the first 30-min return including the overnight return.

2.3 | Summary statistics

The data set for all four contracts comprises two times a second snapshot tick record. To construct a continuous time-series of returns, we sample the price at a fixed time interval and calculate half-hour returns and cumulative returns:

$$\begin{aligned} r_{j,t} &= \log\left(\frac{p_{j,t}}{p_{j-1,t}}\right), \quad t = 1, \ldots, T, \\ cr_{j,t} &= \log\left(\frac{p_{j,t}}{p_{open,t}}\right), \quad t = 1, \ldots, T, \end{aligned} \tag{1}$$

where $r_{j,t}$ is the half-hour return for day t using interval j, $cr_{j,t}$ is the cumulative return for day t using interval j, $p_{open,t}$ represents the opening price for day t, and $p_{j,t}$ represents the futures price at the end of interval j for day t.[2]

In Figure 1, we report both the current day cumulative return and the return for the individual period for each of these four commodity futures. From this we observe the cumulative return for all four commodity futures going up during the opening time period and then down, with it finally reversing during the last trading period of the day. In parallel, the return exhibits a U-shape, whereby the half-hour return at the beginning and end of the trading day is higher than others. We also choose the first and last trading periods to calculate the summary statistics, as well as the second-to-last period. The descriptive statistics of the data used in our analysis are outlined in Table 1.

Looking at the statistics of the 30-min time interval returns, we find that compared with the first and last periods, the mean of each 30-min return is much lower than the first and last periods. Furthermore, the first 30-min return has the same sign as the last 30-min return for all futures contracts except for steel; corroborating the U-shape that is graphically exhibited in Figure 1. We also show the volume and realized volatility for each of the four commodity futures in Figures 2 and 3. It can be observed that both of these figures also exhibit a U-shape.

3 | INTRADAY TIME-SERIES MOMENTUM METHODOLOGY

The study of intraday time-series momentum can be decomposed into two aspects. The first is the existence of a momentum effect, that is, is the future return predictable? The second aspect is the formation of the effect, that is which factors impact the presence of momentum? To answer these questions, we first employ the predictive regressions of Gao et al. (2018) to examine the existence of intraday time-series momentum that the first half-hour return in the market predicts the last half-hour return, and subsequently test the impact of trading volume and realized volatility on momentum.

3.1 | The existence of intraday time-series momentum

We model the existence of intraday time-series momentum using the predictive regression of Gao et al. (2018):

$$r_{L,t} = \alpha + \beta_1 r_{1,t} + \epsilon_t, \quad t = 1, \ldots, T, \tag{2}$$

where $r_{L,t}$ is the return of the last trading session on day t, $r_{1,t}$ is the return during the opening market period on day t, and T is the total number of trading days in our sample.

[2]We compute the first half-hour return $r1,t$ starting with the opening price on a given day but excluding the overnight return. However, we also investigate the impact of overnight return on intraday momentum in Section 4.2.

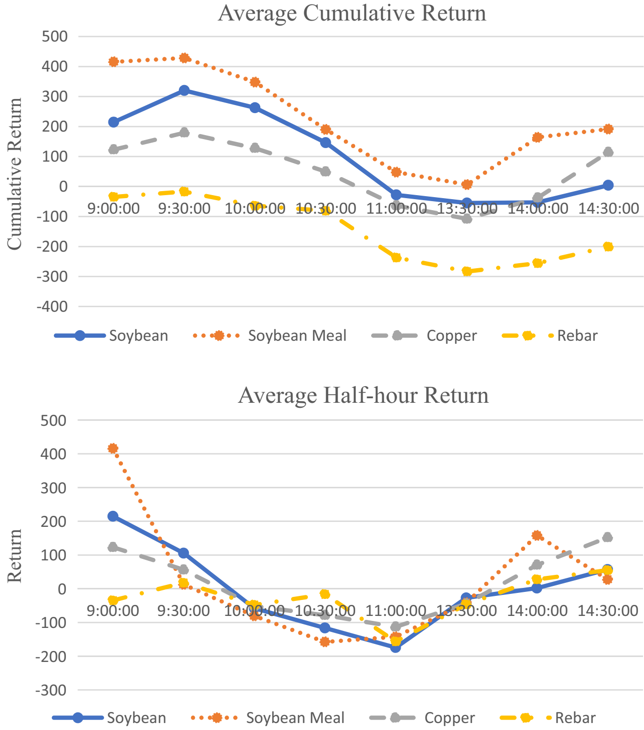

FIGURE 1 Average half-hour return and cumulative return. The average half-hour cumulative and the individual period return (all returns are $\times 10^{-6}$) for Soybean, Soybean Meal, Copper and Steel Rebar commodity futures are reported [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Summary statistics

$\times 10^{-6}$	*N*	Mean	*SD*	P5	P25	Median	P75	P95
Soybean								
All	17,392	0.53	2,800.73	−3,987.25	−1,090.81	0.00	1,062.70	4,110.16
First	2,174	214.72	4,545.22	−6,397.71	−2,125.96	0.00	2,395.21	7,579.62
Second-to-last	2,174	1.99	2,195.51	−2,940.10	−861.51	0.00	853.97	3,004.13
Last	2,174	57.16	2,485.61	−3,644.55	−1,131.44	0.00	1,187.41	4,064.30
Soybean meal								
All	8,861	23.93	3,272.61	−4,901.97	−1,269.04	0.00	1,374.10	5,066.97
First	1,108	415.80	5,642.68	−8,163.31	−2,458.30	330.20	3,565.85	9,475.15
Second-to-last	1,107	157.84	2,316.14	−3,216.01	−920.67	0.00	1,114.21	3,683.25
Last	1,107	27.55	3,093.67	−4,686.99	−1,412.93	0.00	1,643.93	5,037.79
Copper								
All	20,598	14.28	3,573.00	−5,293.02	−1,229.47	0.00	1,301.66	5,111.49
First	2,577	122.93	5,725.81	−8,503.20	−2,432.67	0.00	2,727.52	9,186.42
Second-to-last	2,571	70.45	2,766.58	−4,172.47	−999.50	0.00	1,218.03	4,056.80
Last	2,571	151.89	3,275.18	−4,776.66	−1,431.90	0.00	1,706.97	5,443.47
Steel rebar								
All	7,960	−25.07	3,184.89	−4,731.47	−1,271.94	0.00	1,261.03	4,720.53
First	995	−34.55	5,226.48	−7,852.23	−2,615.52	203.69	2,481.39	7,847.28
Second-to-last	995	27.75	2,292.63	−3,556.91	−1,018.33	0.00	972.05	3,449.13
Last	995	55.03	2,979.47	−4,541.33	−1,363.70	0.00	1,416.77	4,915.29

Note: The summary statistics of average return for four different commodity futures: Soybean, Soybean Meal, Copper and Steel Rebar are shown. The return is sampled at 30-min intervals. The summary statistics are calculated using full trading days (All) and three specific trading sessions (first, second-to-last, and last, respectively).

Abbreviations: N, number of observations; P, percentile values.

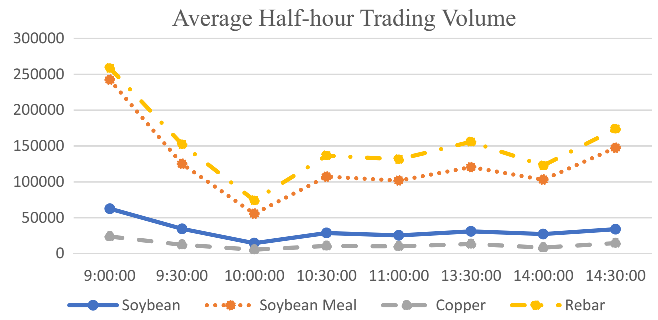

FIGURE 2 Average half-hour trading volume. The average half-hour trading volume for soybean, soybean meal, copper and steel rebar commodity futures are reported [Color figure can be viewed at wileyonlinelibrary.com]

Furthermore, if there is a strong price persistence, the return of the second-to-last trading session may affect the last trading session return. Therefore, we add the second-to-last trading session to the regression to control for any short-term persistence:

$$r_{L,t} = \alpha + \beta_1 r_{1,t} + \beta_2 r_{L-1,t} + \epsilon_t, \quad t = 1, \ldots, T, \tag{3}$$

where $r_{L-1,t}$ is the return of the second-to-last trading session on day t. If $r_{1,t}$ is significant it means that the first trading session impacts the last trading session. A positive β_1 parameter means that we have an intraday time-series momentum effect, with a negative β_1 signaling a reversal effect.

Another way to examine time-series predictability is based on the method of Moskowitz et al. (2012) which simply focuses on the sign of the past return.

$$r_{L,t} = \alpha + \beta_1 \text{sign}(r_{1,t}) + \epsilon_t, \quad t = 1, \ldots, T, \tag{4}$$

where $\text{sign}(r_{1,t})$ is the signal from the first-period return on day t, if the return is positive then we set it to +1, if not we set it to −1.

Again, we add the second-to-last trading session to the regression:

$$r_{L,t} = \alpha + \beta_1 \text{sign}(r_{1,t}) + \beta_2 \text{sign}(r_{L-1,t}) + \epsilon_t, \quad t = 1, \ldots, T. \tag{5}$$

In addition to the intraday time-series momentum pattern of Gao et al. (2018), we also examine if the return during the market opening period can predict the whole day return, after removing the first trading session:

$$r_{\text{rest},t} = \alpha + \beta_1 r_{1,t} + \epsilon_t, \quad t = 1, \ldots, T, \tag{6}$$

where $r_{\text{rest},t}$ is the total return except for the first trading session for day t.

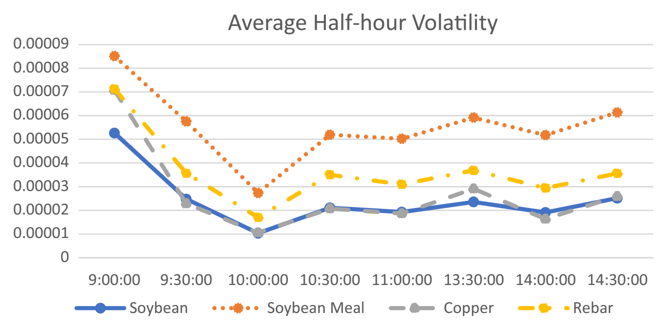

FIGURE 3 Average half-hour volatility. The average half-hour volatility for soybean, soybean meal, copper and rebar commodity futures are reported [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | The impact of volatility and volume

We not only study the existence of intraday time-series momentum but also analyze the impact of volatility and trading volume on its presence. To assess the impact of volatility, we use second-by-second returns to compute realized volatility. We sort all trading days and divide them into three different groups using the first trading session's volume and realized volatility. We then use the magnitude and t statistic of the slope from Equation (3) to examine which groups are the most significant. We use the R^2 in parallel to evaluate performance across groups. In general, the higher the R^2, the better the momentum model fits our data. Therefore, we employ the slope and R^2 to ascertain the group displaying the strongest momentum effect. If the high volatility or high trading volume group is more significant, we can infer that either volatility or volume drives intraday time-series momentum.

As there is a large unpredictable component inherent in the return of any trading session and we have only a maximum of two independent variables in our regression model, the R^2 statistics calculated will be relatively small. However, based on approaches taken in prior studies by Kandel and Stambaugh (1996), Campbell and Thompson (2008), and Gao et al. (2018), R^2 values near 0.5% can be considered to significantly predict returns.

4 | EMPIRICAL FINDINGS

4.1 | Can the first-period return predict the last?

Table 2 reports the predictability of the last half-hour returns (Panel A), using the returns of the first and the second-to-last trading sessions as explanatory variables. We observe that the first 30-min returns positively predict the last 30-min returns for all four contracts with a slope of 0.073 for soybean, 0.052 for soybean meal, 0.067 for copper, and 0.103 for steel.[3] All of these are significant at a 5% level. Furthermore, the R^2 for these four contracts are 1.80%, 0.90% 1.36%, and 3.32%, respectively. The size of these calculated R^2 values is much higher than in prior literature, with Rapach and Zhou (2013) and Gao et al. (2018) citing their lower R^2 levels as being promising. Gao et al. (2018) state that strong persistence during the day might lead to the second-to-last trading session affecting the last. However, using a 30-min return, only the second-to-last 30-min of soybean meal trading can predict the last 30-min return at a 5% significant level. This is not entirely consistent with the result uncovered by Gao et al. (2018), who find that both the first and the second-to-last half-hour return are independent and complementary in forecasting the last half-hour return. Therefore, we need to further investigate the predictability of this second-to-last half-hour return.

As the results of the four contracts differ, we establish that the return of the first trading period predicts the last, but we cannot conclusively state that the return of the second-to-last period predicts the last. Therefore, we now seek to ascertain if we can extract information from the return direction, by using the return sign of the first and second-to-last trading periods to predict the last return.

Panel B of Table 2 reports the results of a regression that uses the last trading session return as a dependent variable with the sign of the first and second-to-last returns constituting the independent variables. We find that for all four futures, the first-period return direction predicts the last period at a 1% significant level; with it positively impacting the last return. This is consistent with the result observed in Panel A. Furthermore, the results of the second-to-last return direction are now also consistent with Gao et al. (2018). Gao et al. (2018) find that both first and second-to-last returns positively impact the last return. Therefore, based on this analysis, we conclude that the first trading session and the direction of the second-to-last return are positive predictors of the last return using 30-min frequency data for four Chinese futures.

In unreported analysis, we also study if the last half-hour return can be explained using each trading sessions' return, the total day's return except the last, and the total day return except the first and last. We find that only the total day's return except the last can be used to predict the last trading session. When we build a multiple regression using both first and the total day return except the last, we find that only the first half-hour's return retains strong explanatory power. From this, we infer that none of the intervening trading sessions possess meaningful explanatory power. We now explore the effect of the overnight return in predicting the last 30-min return.

[3]The coefficients presented in the tables are multiplied by 1,000 for presentation purpose.

TABLE 2 Predictability of the last trading period return

Panel A: Last half-hour returns on the returns of first and second-to-last trading session

	Soybean			Soybean meal		
Predictor $\times 10^{-3}$	r_1	r_7	r_1 and r_7	r_1	r_7	r_1 and r_7
Intercept	0.041	0.057	0.042	0.006	0.009	−0.010
	(0.83)	(1.15)	(0.84)	(0.07)	(0.09)	(−0.12)
β_{r1}	73.274***		72.065***	51.997***		50.382**
	(5.06)		(5.02)	(2.60)		(2.53)
β_{r7}		49.895	40.734		120.053**	115.890**
		(1.16)	(0.99)		(2.48)	(2.39)
R^2	1.80%	0.19%	1.92%	0.90%	0.81%	1.65%

	Copper			Steel rebar		
Predictor $\times 10^{-3}$	r_1	r_7	r_1 and r_7	r_1	r_7	r_1 and r_7
Intercept	0.144**	0.148***	0.14**	0.059	0.052	0.056
	(2.51)	(2.59)	(2.44)	(0.67)	(0.58)	(0.63)
β_{r1}	66.552***		65.988***	103.862***		105.212***
	(4.26)		(4.23)	(4.48)		(4.54)
β_{r7}		59.264*	56.436		94.675	101.916
		(1.72)	(1.64)		(1.41)	(1.54)
R^2	1.36%	0.25%	1.58%	3.32%	0.53%	3.93%

Panel B: Last half-hour returns on the signs of first and second-to-last trading session

	Soybean			Soybean Meal		
Predictor $\times 10^{-3}$	sign(r_1)	sign(r_7)	sign(r_1, r_7)	sign(r_1)	sign(r_7)	sign(r_1, r_7)
Intercept	0.047	0.053	0.044	0.009	0.001	−0.02
	(0.95)	(1.08)	(0.89)	(0.09)	(0.01)	(−0.17)
$\beta_{\mathrm{sign}(r1)}$	0.303***		0.291***	0.266***		0.247***
	(5.80)		(5.57)	(2.89)		(2.67)
$\beta_{\mathrm{sign}(r7)}$		0.181***	0.157***		0.367***	0.353***
		(3.17)	(2.77)		(3.96)	(3.85)
R^2	1.42%	0.47%	1.78%	0.70%	1.26%	1.87%

	Copper			Steel rebar		
Predictor $\times 10^{-3}$	sign(r_1)	sign(r_7)	sign(r_1, r_7)	sign(r_1)	sign(r_7)	sign(r_1, r_7)
Intercept	0.143**	0.138***	0.130**	0.048	0.051	0.044
	(2.51)	(2.42)	(2.28)	(0.54)	(0.57)	(0.49)
$\beta_{\mathrm{sign}(r1)}$	0.280***		0.272***	0.384***		0.387***
	(4.08)		(3.97)	(4.19)		(4.25)
$\beta_{\mathrm{sign}(r7)}$		0.238***	0.228***		0.179*	0.186*
		(3.29)	(3.16)		(1.75)	(1.83)
R^2	0.69%	0.46%	1.11%	1.63%	0.33%	1.99%

Note: Panel A reports the results of regressing the return of the last half-hour on the first and second-to-last half-hour returns of the day, both separately and simultaneously. The predictability of the last half-hour returns using the sign of the first and second-to-last trading session is given in Panel B. Each panel includes four commodity futures: Soybean, Soybean Meal, Copper, and Steel Rebar. r_1 represents the return during the first trading session, r_7 is the return during the second-to-last trading session. The t statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively.

4.2 | The effects of overnight return

In the previous section, we use the return of the first 30-min trading interval to predict the return of the last 30-min interval. We measure the first 30-min return as the return from the market opening to the 30th min. We do not include the overnight return when computing this first 30-min return, as in the case of prior literature such as Gao et al. (2018) and Elaut et al. (2018). In this section, however, we examine the impact of including the overnight return in this first 30-min return.

In Table 3, we repeat the analysis using four different models for each commodity. First, we compute the first 30-min return (r_1) including the overnight return (r_0) that is ($r_0 + r_1$). Then we investigate the impact of overnight return (r_0) and the first 30-min return (r_1) separately. Finally, we study the prediction model that includes both overnight return and the first 30-min return simultaneously (r_0 and r_1). The result in Table 3 shows that the first 30-min return including the overnight return ($r_0 + r_1$) is able to predict the last 30-min return for soybean meal, copper, and steel rebar; but it is unable to predict the last 30-min return for soybean. Furthermore, the overnight return (r_0) has no explanatory power for the last 30-min return for soybean and copper. However, the overnight return (r_0) has explanatory power for the last 30-min return for soybean meal and steel rebar. The results are similar if both the overnight return and the first 30-min return (r_0 and r_1) are simultaneously included in the model.

In short, the result for soybean is rendered insignificant if we include the overnight return into the first 30-min return. The first 30-min return (without the overnight return) however, has explanatory power for the last 30-min return across all four commodities, while the overnight return has explanatory power only for soybean meal and steel rebar. In unreported correlation analysis, we also find that the overnight return is negatively correlated to the first 30-min return across all commodities, a finding that is similar to Liu and Tse (2017). Furthermore, we also find that the

TABLE 3 Predictability of the last trading period return using overnight return

	Soybean				**Soybean meal**			
Predictor $\times 10^{-3}$	**$(r_0 + r_1)$**	**r_0**	**r_1**	**r_0 and r_1**	**$(r_0 + r_1)$**	**r_0**	**r_1**	**r_0 and r_1**
Intercept	0.050 (1.00)	0.060 (1.20)	0.041 (0.83)	0.043 (0.86)	−0.001 (−0.01)	0.016 (0.17)	0.006 (0.07)	−0.006 (−0.07)
$\beta_{(r0+r1)}$	11.629 (1.31)				34.664*** (4.13)			
β_{r0}		−7.780 (−0.82)		−3.330 (−0.35)		28.895*** (2.96)		29.518*** (3.05)
β_{r1}			73.274*** (5.06)	72.573*** (4.92)			51.997*** (2.60)	53.205*** (2.70)
R^2	0.18%	0.07%	1.80%	1.81%	1.76%	0.97%	0.90%	1.91%
	Copper				**Steel rebar**			
Predictor $\times 10^{-3}$	**$(r_0 + r_1)$**	**r_0**	**r_1**	**r_0 and r_1**	**$(r_0 + r_1)$**	**r_0**	**r_1**	**r_0 and r_1**
Intercept	0.138** (2.38)	0.149*** (2.58)	0.144** (2.51)	0.138** (2.37)	0.076 (0.88)	0.066 (0.75)	0.059 (0.67)	0.073 (0.85)
$\beta_{(r0+r1)}$	16.271*** (2.90)				96.343*** (6.62)			
β_{r0}		4.513 (0.82)		8.192 (1.48)		58.023*** (3.42)		77.321*** (4.33)
β_{r1}			66.552*** (4.26)	68.752*** (4.34)			103.862*** (4.48)	117.898*** (5.39)
R^2	0.44%	0.03%	1.36%	1.46%	4.99%	1.15%	3.32%	5.30%

Note: The results of regressing the return of the last half-hour on the previous day's overnight and the first half-hour return of the day are reported. There are four commodity futures: Soybean, Soybean Meal, Copper and Steel Rebar. ($r_0 + r_1$) represents the return from the previous day's close until the end of the first half-hour trading session, r_0 is the return from the previous day's close until today's open (overnight return), and r_1 represents the return during the first half-hour trading session (excluding the overnight return). The t statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively.

overnight return is negatively correlated to the subsequent last 30-min intraday return for soybean, but the relationship is positive for the other commodities. Therefore, including the overnight return into the first 30-min return neutralizes the positive relationship between the first 30-min and the last 30-min return for soybean futures. In contrast, the correlation between the first and last 30-min returns are positive across all commodities. We now explore theoretical explanations for these empirical results.

4.3 | Explanation

Empirically, the first trading session return positively predicts the last return across all contracts, with the direction of the second-to-last trading session also positively predicting the last return using 30-min frequency Chinese futures market data. We now provide two different theoretical explanations for this observed dynamic.

An explanation for the first return predicting the last is based on day trading liquidity provision, similar to what is put forward by Elaut et al. (2018). Due to the cessation of overnight trading, a large amount of information is reflected in the market during the opening period. This motivates day traders to provide liquidity at this time by taking the opposite side of the trades. These liquidity day traders then close their position by the end of the day to avoid overnight risk, causing price fluctuations (Locke & Mann, 2005). Thus, if informed traders bid prices up (down) during the opening 30 min, the liquidity providers collectively must take the opposite side and go net short (long). Later on, when the liquidity providers cover these positions during the last 30 min of trading, prices rise (fall) as a result.

An alternative explanation for the first return predicting the last return is based on the behavior of informed traders. Kyle (1985), Admati and Pfleiderer (1988), Bloomfield, O'Hara, and Saar (2005), and Bogousslavsky (2016) hypothesize that informed traders prefer to trade during high trading volume periods to hide their information and limit their price impact. Since trading volume exhibits a U-shape intraday pattern (Hora, 2006), the informed traders execute the majority of their portfolio rebalancing transactions at the beginning and end of the day. If the informed traders trade strategically in these first and last trading sessions, then these two trading sessions will move in the same direction creating the phenomenon of intraday momentum.

Unfortunately, we do not have sufficient data to fully support one explanation over the other. Disentangling these two explanations would require us to identify and separate liquidity traders from informed traders, however, our data does not include information on trader identity. While CITIC Futures Co.'s research indicates that more than 95% of traders in the Chinese futures market are intraday, we cannot assume that all these intraday traders are liquidity traders. In fact, both liquidity provision and strategically informed trading explanations could be occurring simultaneously. that is the liquidity day traders and informed traders trade in the opposite direction in the first trading session but trade in the same direction during the last trading sessions. The above two explanations are consistent with those put forward by Gao et al. (2018).

4.4 | Volume and volatility

Gao et al. (2018) find that the greater either the volume or volatility, the greater the predictability for intraday time-series momentum. This is consistent with the theoretical model of Zhang (2006), whereby the greater the uncertainty, the more defined the trend observed. Therefore, to study if this phenomenon is also present in Chinese Futures markets, we sort all trading days into three groups; low, medium, and high, based on both the trading volume and volatility of the first half-hour.

Panel A of Table 4 classifies the predictability results of the last half-hour returns into three separate trading volume groups. We find that the high trading volume group exhibits a stronger effect than the other two groups for soybean, copper, and steel futures contracts. Meanwhile, predictability is an increasing function of trading volume using both metals futures contracts, copper, and steel. The above phenomenon is consistent with the results of both Gao et al. (2018) and Sun et al. (2016). The results produced using the sign of the first and second-to-last returns are shown in Panel B of Table 4. We find that the high trading volume group shows the strongest effect for all four products. The predictive ability of the first trading session is an increasing function of trading volume for the soybean and steel futures contracts. Meanwhile, the t statistic of the first half-hour sign in the high trading volume group is greater than the other two groups for all four commodity contracts.

TABLE 4 The impact of the trading volume

Panel A: Last half-hour returns on the returns of first and second-to-last trading session

	Soybean			**Soybean meal**		
×10^{-3} Trading volume	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	−0.080 (−1.29)	−0.030 (−0.33)	0.224** (2.01)	−0.160 (−1.13)	0.074 (0.48)	0.037 (0.22)
β_{r1}	83.975*** (3.23)	77.476*** (2.83)	68.210*** (3.69)	96.161* (1.72)	33.340 (1.14)	49.358 (1.56)
β_{r7}	79.483 (1.41)	−16.280 (−0.30)	69.611 (1.00)	55.399 (0.87)	207.821** (2.57)	75.863 (0.86)
R^2	2.24%	1.69%	2.16%	2.32%	3.09%	1.09%
	Copper			**Steel rebar**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	0.076 (0.68)	0.142 (1.55)	0.209** (2.03)	−0.090 (− 0.55)	0.136 (1.06)	0.109 (0.62)
β_{r1}	42.678 (1.43)	47.639** (2.03)	89.696*** (4.17)	71.856 (1.61)	105.581*** (3.34)	136.015*** (5.08)
β_{r7}	45.917 (0.67)	82.740 (1.22)	50.816 (1.11)	−36.850 (− 0.30)	125.144* (1.79)	202.776** (2.20)
R^2	0.62%	1.00%	3.25%	2.12%	3.73%	7.06%

Panel B: Last half-hour returns on the signs of first and second-to-last trading session

	Soybean			**Soybean meal**		
×10^{-3} Trading volume	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	−0.07 (−1.20)	−0.02 (−0.27)	0.223** (2.01)	−0.17 (−1.20)	0.075 (0.50)	0.037 (0.21)
$\beta_{\text{sign}(r1)}$	0.151** (2.36)	0.221*** (2.78)	0.495*** (4.42)	0.273* (1.79)	0.149 (0.97)	0.327* (1.86)
$\beta_{\text{sign}(r7)}$	0.110* (1.65)	0.125 (1.37)	0.237* (1.91)	0.282* (1.87)	0.531*** (3.99)	0.235 (1.33)
R^2	1.21%	1.47%	2.72%	2.15%	3.14%	1.29%
	Copper			**Steel rebar**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	0.067 (0.61)	0.139 (1.52)	0.182* (1.76)	−0.07 (−0.44)	0.117 (0.90)	0.078 (0.44)
$\beta_{\text{sign}(r1)}$	0.237* (1.93)	0.124 (1.32)	0.451*** (3.22)	0.266* (1.73)	0.280** (2.11)	0.623*** (3.68)
$\beta_{\text{sign}(r7)}$	0.258** (2.01)	0.247** (2.51)	0.176 (1.28)	0.054 (0.34)	0.323** (2.21)	0.14 (0.67)
R^2	0.90%	0.92%	1.84%	0.91%	2.61%	3.27%

Note: Panel A reports the results of regressing the return of the last half-hour on the first and second-to-last half-hour returns of the day under different levels of the trading volume. The predictability of the last half-hour returns using the sign of the first and second-to-last trading session day under different levels of trading volume is given in Panel B. The first half-hour cumulative trading volume is ranked into three groups: low, medium, and high. Each panel includes four commodity futures: Soybean, Soybean Meal, Copper, and Steel Rebar. The *t* statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively.

Similarly, Panel A of Table 5 classifies the predictability results for the last half-hour returns into three volatility groups. The R^2 figures show a situation whereby higher levels of volatility increase predictability for both copper, and steel futures contracts. Again, this result is consistent with Gao et al. (2018) and Sun et al. (2016). When we use the direction change we uncover the results given in Panel B of Table 5, with the

TABLE 5 The impact of trading volatility

Panel A: Last half-hour returns on the returns of first and second-to-last trading session

	Soybean			Soybean meal		
$\times 10^{-3}$ Trading volume	Low	Medium	High	Low	Medium	High
Intercept	0.017	−0.070	0.166	0.164	−0.050	−0.180
	(0.29)	(−0.95)	(1.44)	(1.44)	(−0.34)	(−0.89)
β_{r1}	95.841***	93.364***	65.207***	42.244	72.917**	43.190*
	(3.55)	(3.84)	(3.57)	(1.02)	(2.08)	(1.69)
β_{r7}	93.750	66.505	14.469	137.971	243.398***	65.179
	(1.58)	(1.19)	(0.22)	(1.31)	(2.68)	(1.10)
R^2	2.33%	2.41%	1.86%	1.34%	3.94%	1.15%
	Copper			**Steel rebar**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	−0.020	0.136	0.301**	−0.120	0.030	0.260
	(−0.21)	(1.49)	(2.38)	(−1.08)	(0.20)	(1.29)
β_{r1}	80.160**	50.104*	67.886***	48.417	89.031***	115.410***
	(2.34)	(1.86)	(3.70)	(1.15)	(2.91)	(3.64)
β_{r7}	111.670**	5.621	69.752	−1.310	135.440	113.850
	(2.01)	(0.10)	(1.31)	(−0.02)	(1.97)**	(1.03)
R^2	1.49%	0.45%	2.32%	0.45%	2.95%	5.47%

Panel B: Last half-hour returns on the signs of first and second-to-last trading session

$\times 10^{-3}$	Soybean			Soybean meal		
Trading Volume	Low	Medium	High	Low	Medium	High
Intercept	0.020	−0.070	0.175	0.161	−0.030	−0.17
	(0.35)	(−0.97)	(1.51)	(1.41)	(−0.18)	(−0.82)
$\beta_{\text{sign}(r1)}$	0.150**	0.288***	0.417***	0.060	0.261*	0.372*
	(2.48)	(3.60)	(3.62)	(0.49)	(1.78)	(1.77)
$\beta_{\text{sign}(r7)}$	0.161**	0.290***	0.028	0.494***	0.573***	0.022
	(2.34)	(3.36)	(0.22)	(3.43)	(4.26)	(0.12)
R^2	1.68%	3.55%	1.61%	3.95%	4.53%	0.93%
	Copper			**Steel rebar**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	−0.020	0.116	0.279**	−0.120	0.026	0.227
	(−0.17)	(1.24)	(2.21)	(−1.08)	(0.17)	(1.16)
$\beta_{\text{sign}(r1)}$	0.096	0.196**	0.486***	0.076	0.207	0.850***
	(1.07)	(1.98)	(3.24)	(0.68)	(1.43)	(4.35)
$\beta_{\text{sign}(r7)}$	0.164	0.194*	0.310*	0.109	0.203	0.250
	(1.64)	(1.81)	(1.82)	(1.01)	(1.42)	(1.06)
R^2	0.51%	0.94%	1.84%	0.48%	1.22%	4.75%

Note: Panel A reports the results of regressing the return of the last half-hour on the first and second-to-last half-hour returns of the day under different levels of volatility. The predictability of the last half-hour returns using the sign of the first and second-to-last trading session day under different levels of volatility is given in Panel B. The first half-hour cumulative trading volatility is ranked into three groups: low, medium and high. Each panel includes four commodity futures: Soybean, Soybean Meal, Copper and Steel Rebar. The *t* statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively.

predictability of the first trading session being an increasing function of volatility in soybean, copper and steel futures contracts.

From the above results, we infer that the opening trading sessions with the highest volume or volatility have the greatest intraday time-series momentum predictability for metals futures. As day traders' participation increases when trading volume is high, we assume that the higher trading volume or volatility in the first half-hour means that there are more active day traders, which in turn leads to greater predictability. The above phenomenon can be explained by the preference of informed traders to trade during high trading volume periods to hide their information and limit price impact. However, we do not find the above phenomenon among agricultural futures, in particular, the soybean meal contract, even when we focus on return sign. One possible explanation is the large proportion of noise traders active in the market. According to Odean (1998) and Barber and Odean (2000), the participation of liquidity traders increases when trading volume is high. Therefore, we posit that both informed and liquidity traders prefer to trade near the beginning and end of the day. Furthermore, trading in the Chinese futures market requires the use of margins. However, the deposit for a metals futures contract stands at almost 10 times that of an agricultural product. Therefore, as the capital requirements are lower, noise traders prefer to trade agricultural futures, making the proportion of informed traders relatively low. For this reason, we hypothesize that volume and volatility have insignificant impacts on agricultural futures time-series momentum strategies.

4.5 | Can the first return predict the rest-of-day?

This brings us to a further question; can the first return be used to predict the full day return excluding the first period (i.e., can it predict the rest of the day). If the rest-of-day return can be positively predicted, and the slope is larger than the slope between the first and last session, it means that we can use the first half-hour as a signal to take a position at the end of the first half-hour, earning greater abnormal profits than waiting to take a position at the beginning of the last half-hour.

Table 6 reports the results of regressing the rest-of-day return on the first trading session. We find that the first 30-min return can predict the rest-of-day return for all contracts. The slopes estimated for the first 30-min return predicting the rest-of-day return are higher than those estimated when predicting the last session return (presented in Table 2). Although the slopes are greater across the contracts, we do not conclude that the intraday momentum between first and rest-of-day returns is stronger than the momentum between first and last session returns because the t statistics of the former are much smaller.

4.6 | Intraday time-series momentum trading strategies

As the first trading session's return positively predicts the last trading session in the Chinese market, we can use the first trading session as a signal and economically evaluate the performance of our method. If the return of the first trading session is positive, we then go long for the last trading period, if it is negative, we go short. Furthermore, to measure the performance of our method, we compare it against two commonly employed benchmark returns, "always long" and "buy-and-hold." "Always long" means taking a long position in the market at the beginning of the last half-hour and shorting it at the close of the market. "Buy-and-hold" means taking a long position in the market at the very beginning of the sample, and holding it to the end of the sample period. We also report the performance of using the first return as a signal for the rest-of-day, if the return of the first trading session is

TABLE 6 Using the first return to predict the rest-of-day return

Predictor $\times 10^{-3}$	Soybean	Soybean meal	Copper	Steel rebar
Intercept	−0.230*	−0.260	−0.020	−0.160
	(−1.85)	(−1.21)	(−0.14)	(−0.69)
β_{r1}	110.413**	91.149*	152.786***	146.249***
	(2.48)	(1.81)	(3.03)	(3.21)
R^2	0.0058	0.0048	0.0105	0.0098

Note: The results of regressing the day return excluding the first trading session (i.e., the rest-of-day return) on the first half-hour return are reported. The t statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively.

TABLE 7 Market timing performance

Timing signal		Soybean (%)	Soybean meal (%)	Copper (%)	Steel rebar (%)
Last	Mean return	7.62	6.12	6.80	10.30
	Success rate	51.15	51.81	49.67	52.46
Rest	Mean return	10.64	9.38	13.53	14.14
	Success rate	51.70	53.25	51.22	50.75
Always Long	Mean return	1.45	0.73	3.83	1.40
	Success rate	45.31	48.19	46.68	46.83
Buy and Hold	Mean return	6.78	−4.02	7.57	−0.29

Note: The return of timing a specific trading session using the return of the first half-hour is shown here. We use the sign of the first trading session to decide the trade direction. We take a long position if the return of the first trading session is positive, and a short position otherwise. Then we compute the return and success rate of the trading strategy if we trade for the last 30-min session (Last), or for the rest-of-day after the first trading session (Rest). "Always long" only takes a long position at the beginning of the last trading session and shorts it at market close. "Buy-and-Hold" simply goes long at the beginning of the sample period and holds the position until the end of the sample period.

positive, we then go long in the second trading period and hold the position until the end of the day, if it is negative, we subsequently go short.

Table 7 shows the results of the market timing strategy. From the table, we find that relative to the "always long" benchmark, our strategy which uses the first period as a signal to trade the last period achieves a greater annualized return across all four contracts. Meanwhile, compared to the "buy-and-hold" benchmark we also achieve greater profits. Even more promising are the results from our alternative strategy that uses the first period as a signal to trade the rest-of-day and outperforms both benchmarks.

Overall, these findings indicate that the intraday time-series momentum trading strategies that use the first half-hour return as a signal to trade both the last and the rest-of-day periods earn abnormal profits beyond those achieved by common benchmarks.

The returns comparison presented in Table 7 is based on gross returns that do not take transaction costs into account. It should be noted that trading costs vary according to the strategy followed. For instance, the trading costs for

TABLE 8 Predictability of the last trading period return using first 15-minute return

	Soybean			Soybean meal		
Predictor $\times 10^{-3}$	r_1	r_{14}	r_1 and r_{14}	r_1	r_{14}	r_1 and r_{14}
Intercept	0.057	0.069*	0.058	0.102	0.128*	0.115*
	(1.41)	(1.69)	(1.43)	(1.48)	(1.92)	(1.72)
β_{r1}	51.331***		50.129***	46.857**		43.031**
	(4.31)		(4.16)	(2.54)		(2.27)
β_{r14}		72.086	65.495		154.01***	145.842***
		(1.30)	(1.15)		(3.03)	(2.88)
R^2	1.18%	0.32%	1.44%	1.05%	1.56%	2.44%
	Copper			**Steel rebar**		
Predictor $\times 10^{-3}$	r_1	r_7	r_1 and r_7	r_1	r_7	r_1 and r_7
Intercept	0.112**	0.111**	0.108**	0.067	0.066	0.068
	(2.52)	(2.50)	(2.43)	(1.04)	(0.99)	(1.05)
β_{r1}	56.002***		55.698***	81.195***		79.871***
	(3.90)		(3.85)	(3.61)		(3.52)
β_{r14}		83.496**	82.048**		84.878	76.674
		(2.33)	(2.32)		(1.51)	(1.40)
R^2	1.49%	0.47%	1.95%	2.83%	0.52%	3.26%

Note: The results of regressing the return of the last 15 min on the first and second-to-last half 15-min returns of the day, both separately and simultaneously. There are four commodity futures: Soybean, Soybean Meal, Copper, and Steel Rebar. The t statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively. r_1 represents the return during the first trading session and r_{14} is the return during the second-to-last trading session.

TABLE 9 The impact of the trading volume

Panel A: Last half-hour returns on the returns of first and second-to-last trading session

	Soybean			**Soybean meal**		
$\times 10^{-3}$ Trading volume	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	−0.030 (−0.74)	0.020 (0.30)	0.179** (2.02)	0.061 (0.71)	0.144 (1.22)	0.152 (1.15)
β_{r1}	77.286*** (3.30)	40.086* (1.66)	48.788*** (3.31)	88.817** (2.28)	47.035 (1.48)	20.003 (0.78)
β_{r14}	−33.790 (−0.51)	41.320 (0.77)	100.389 (1.11)	209.065** (2.28)	80.623 (1.00)	176.796** (2.24)
R^2	1.75%	0.62%	2.07%	6.17%	1.68%	2.18%
	Copper			**Steel rebar**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	0.139 (1.57)	0.077 (1.21)	0.125 (1.50)	−0.140 (−1.32)	0.390*** (3.77)	−0.020 (−0.19)
β_{r1}	31.715 (1.15)	22.744 (1.10)	83.802*** (4.10)	55.928 (1.29)	102.606*** (3.14)	102.220*** (4.19)
β_{r14}	85.905 (1.57)	106.631 (1.41)	64.008 (1.17)	−13.320 (−0.13)	143.664 (1.41)	107.020 (1.31)
R^2	0.91%	1.00%	4.45%	1.82%	4.31%	5.66%

Panel B: Last half-hour returns on the signs of first and second-to-last trading session

	Soybean			**Soybean meal**		
$\times 10^{-3}$ Volatility	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	0.032 (0.66)	−0.003 (−0.05)	0.150* (1.65)	0.056 (0.68)	0.212** (2.01)	0.028 (0.21)
β_{r1}	29.884 (1.12)	100.665*** (4.41)	38.965*** (2.70)	151.623*** (3.34)	50.984 (1.51)	26.474 (1.13)
β_{r14}	103.735 (1.55)	21.441 (0.38)	76.499 (0.82)	166.676 (1.56)	66.839 (1.01)	180.154** (2.04)
R^2	0.88%	2.90%	1.29%	5.26%	1.07%	3.14%
	Copper			**Steel rebar**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Intercept	0.072 (1.06)	0.047 (0.69)	0.186* (1.90)	0.045 (0.52)	0.051 (0.47)	0.102 (0.76)
β_{r1}	24.970 (0.73)	71.853*** (3.13)	55.022*** (3.13)	30.944 (0.51)	50.21* (1.75)	90.417*** (3.05)
β_{r14}	−22.830 (−0.33)	−4.830 (−0.08)	163.691*** (3.19)	−105.03 (−1.00)	75.061 (0.82)	112.408 (1.55)
R^2	0.12%	1.26%	3.73%	0.64%	1.12%	6.07%

Note: Panel A reports the results of regressing the return of the last 15-min return on the first and second-to-last 15-min return of the day under different levels of the trading volume. The predictability of the last 15-min return on the first and second-to-last 15-min return of the day under different levels of volatility is given in Panel B. The first 15-min volatility and cumulative trading volume is ranked into three groups: low, medium, and high. Each panel includes four commodity futures: Soybean, Soybean Meal, Copper, and Steel Rebar. The *t* statistics are given in parenthesis, with ***, **, and * representing significance levels at 1%, 5%, and 10%, respectively.

our two proposed strategies and the "always long" benchmark are relatively high given that they require daily rebalancing. This is in contrast to the "buy-and-hold" benchmark which has much lower trading costs as it only requires trades to be made at the beginning and the end of the sample period, as well as when the futures contracts are rolled over.

5 | ROBUSTNESS CHECKS

The use of half-hour returns is in line with earlier studies on intraday time-series momentum in financial markets (Gao et al., 2018; Gao, Xing, Youwei, & Xiong, 2019, Komarov, 2017; Sun et al., 2016). However, can intraday time-series momentum also be observed at other time frequencies? We adopt a 15-min time-frequency to empirically test this. As all Chinese futures markets have a short break of 15 min from 10:15 to 10:30 each trading day we exclude this 15-min period from our analysis.

Table 8 reports the predictability of the last 15-min returns using the first and second-to-last 15-min returns. The results found are similar to our original 30-min frequency study, with the first trading session return being able to predict the last.

Table 9 shows the impact of trading volume and volatility on intraday time-series momentum using a 15-min return period. In Panel A, we observe that except for soybean meal, the predictability of the last 15-min return using the first 15-min return is greater in the high volume group than in others. When we study the impact of volatility in Panel B, only copper and steel perform well in the high volatility group.

Therefore, combined with our original 30-min frequency analysis, we can say that the first metals trading sessions with the highest volume or volatility possess the strongest intraday time-series momentum. This finding aligns with our hypothesis about the impact of margins on agricultural futures intraday price evolution.

6 | CONCLUSION

As the world's largest copper, steel, soybean meal markets and the world's second-largest soybean market, Chinese commodity futures are of great importance. Meanwhile, both market practitioners and academic scholars have studied the time-series momentum properties of various markets, demonstrating its use in constructing profitable trading strategies. This paper lies at the intersection of both topics by focusing on intraday time-series momentum in the important Chinese futures market.

We find that the first trading session return can accurately predict the last return across Chinese commodity futures. We hypothesize that such intraday time-series momentum is primarily formed through liquidity provision trading and informed trading, coupled with the high trading volume observed during the first and last trading sessions of the day. Furthermore, we find that the most actively traded and most volatile first trading sessions have the greatest intraday time-series momentum predictive ability in metals futures markets. Finally, the performance of our intraday time-series momentum strategy is shown to be superior to popular always long and buy-and-hold benchmarks.

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DATA AVAILABILITY STATEMENT

This paper was originally submitted before the adoption of the Expects Data policy by the Journal of Futures Markets and is exempt from the Data Citation and Data Availability Statement requirements of the policy.

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APPENDIX A

TABLE A1 Global futures and options volume contract rankings

Rank				Volume		
2014	2013	Contract	Contract size	2014	2013	Change (%)
Top 10 agricultural futures and options contracts						
1	2	Rapeseed Meal Futures, ZCE	10 ton	303,515,966	160,100,378	89.60
2	1	Soy Meal Futures, DCE	10 ton	204,988,746	265,357,592	−22.70
3	6	White Sugar Futures, ZCE	10 ton	97,726,662	69,794,046	40.00
4	5	Rubber Futures, SHFE	10 ton	88,631,586	72,438,058	22.40
5	4	Palm Oil Futures, DCE	10 ton	79,996,388	82,495,230	−3.00
6	7	Corn Futures, CBOT	5,000 bushels	69,437,304	64,322,600	8.00
7	3	Soy Oil Futures, DCE	10 ton	64,082,631	96,334,673	−33.50
8	8	Soybean Futures, CBOT	5,000 bushels	49,169,361	46,721,081	5.20
9	20+	Egg Futures, DCE	5 ton	35,188,187	1,951,323	1703.30
10	20+	Cotton No.1 Futures, ZCE	5 ton	31,782,665	7,452,748	326.50
13	19	No.1 Soybean Futures, DCE	10 ton	27,197,413	10,993,500	147.4
Top 10 metals futures and options contracts						
1	1	Steel Rebar Futures, SHFE	10 ton	408,078,103	293,728,929	38.90
2	2	Silver Futures, SHFE	15 kg	193,487,650	173,222,611	11.70
3	20+	Iron Ore Futures, DCE	100 ton	96,359,128	2,189,215	4301.50
4	3	Copper Futures, SHFE	5 ton	70,510,306	64,295,856	9.70
5	4	High Grade Primary Aluminium Futures, LME	25 ton	65,435,357	63,767,903	2.60
6	6	Comex Gold Futures, Nymex	100 troy ounces	40,518,804	47,294,551	−14.30
7	20+	Zinc Futures, SHFE	5 ton	40,429,347	12,083,166	234.60
8	7	Copper Grade A futures, LME	25 ton	38,807,667	40,486,017	−4.10
9	9	Special High Grade Zinc Futures, LME	25 ton	30,321,911	30,270,370	0.20
10	5	SPDR Gold Shares ETF Option	N/A	29,470,882	49003859	−39.90

Note: These two tables report the world ranking of Agricultural Futures and Options Contracts and the world ranking of Metals Futures and Options Contracts.
Source: Acworth (2014, 2015).

TABLE A2 Chinese futures contract specifications

	Soybean meal	Soybean	Copper	Steel rebar
Product symbol	M	A	CU	RB
Venue	Dalian Commodity Exchange	Dalian Commodity Exchange	Shanghai Futures Exchange	Shanghai Futures Exchange
Hours	Monday to Friday 9:00 a.m.–11:30 a.m. and 1:30 p.m.–3:00 p.m.	Monday to Friday 9:00 a.m.–11:30 a.m. and 1:30 p.m.–3:00 p.m.	Monday to Friday 9:00 a.m.–11:30 a.m. and 1:30 p.m.–3:00 p.m.	Monday to Friday 9:00 a.m.–11:30 a.m. and 1:30 p.m.–3:00 p.m.
Contract size	10 ton per board lot	10 ton per board lot	5 ton per board lot	10 ton per board lot
Price quotation	CN Yuan per ton	CN Yuan per ton	CN Yuan per ton	CN Yuan per ton
Minimum fluctuation	CN Yuan 1 per ton	CN Yuan 1 per ton	CN Yuan 10 per ton	CN Yuan 1 per ton
The maximum daily price fluctuation limit	No more than ±4% of the previous day's settlement price	No more than ±4% of the previous day's settlement price	No more than ±3% of the previous day's settlement price	No more than ±3% of the previous day's settlement price
Minimum trading deposit	5% of the contract value	5% of the contract value	5% of the contract value	5% of the contract value
Termination of trading	Trading terminates on the 10th day of the delivery month	Trading terminates on the 10th day of the delivery month	Trading terminates on the 15th day of the delivery month	Trading terminates on the 15th day of the delivery month
Listed contracts	Jan, Mar, May, Jul, Aug, Sep, Nov, Dec	Jan, Mar, May, Jul, Sep, Nov	Jan to Dec	Jan to Dec
Settlement type	Physical	Physical	Physical	Physical
Delivery period	3 business days after the last trading day	3 business days after the last trading day	5 business days after the last trading day	5 business days after the last trading day
Extension cost	No more than 3 Yuan per lot	No more than 4 Yuan per lot	Exchange charge 0.02% of the turnover	Exchange charge 0.02% of the turnover