Exploring the predictability of intraday returns in China's stock market

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Abstract. With the rapid development of high-frequency trading, intraday trading has become more and more popular due to its important role in understanding the efficiency of the intraday market and capturing more trading opportunities. This article explores whether there is momentum effect and reversal effect in China’s stock market by studying the correlation and predictability between half-hour returns. The results show that there is an intraday momentum effect between the first half-hour and full-day returns. After the investment strategy, it is found that this effect has economic significance, but after considering the transaction costs, the momentum effect cannot make investors obtain excess returns. These costs are the reason for the long-term predictability of intraday returns.

Keywords: Intraday returns predictability, Trading costs, Momentum effect, Reversal effect

1. Introduction

With the rapid development of high-frequency trading, intraday trading is gaining popularity due to its important role in understanding intraday market efficiency and capturing more trading opportunities. However, intraday predictability received little attention prior to the seminal work of Gao[1], who extended Moskowitz[2]'s standard time-series momentum to intraday levels in US equities and found that the first half-hour returns are more than the second half-hour Returns have significant predictive power. Since then, this form of intraday return forecasting has been extended to several other markets, including Chu[3] who introduced this forecasting method to the Chinese stock market. Since the data sample date selected by Chu is from April 4, 2015 to December 31, 2015, the sample time is earlier, so this paper will continue this method and lock the sample time and object to the Chinese stock market after 2019.

Compared with the US stock market, the Chinese stock market has a special trading mechanism. Specifically, the U.S. stock market trades from 9:30 to 16:00 Eastern Time, while the Chinese stock market trades from 9:30 am to 11:30 am and 13:00 pm to 15:00 pm Beijing time. Different trading hours can lead to very different intraday momentum patterns between the U.S. and Chinese stock markets. The U.S. stock market has a 13.5-hour rate of return, however, the Chinese stock market has only an 8.5-hour rate of return per trading day, and more importantly, the Chinese stock market has a 90-minute lunch break where investors can learn New information or processing earlier information, thereby affecting intraday trends.

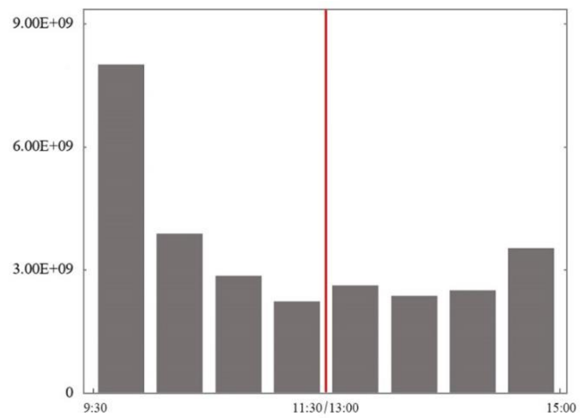

Figure 1. Half-hour average trading volume of Shanghai Composite Index

The trading volume is closely related to the attention of investors and the processing of information. Figure 1 shows the average half-hour trading volume of the Shanghai Composite Index. It can be seen from the figure that the average trading volume from the first hour to the last half hour presents a "W" shape, and the trading volume in the first hour is much higher than other times of the day After three hours, the transaction volume gradually decreased. After the lunch break, the transaction volume rebounded, and the last hour ushered in a small peak. This trading volume pattern reflects that the most active periods of the market are the beginning of the day, after the lunch break, and before the end, and these half-hours are also the time periods that this paper focuses on in the empirical process.

This paper studies the predictability of intraday returns in Chinese stock markets and makes some contributions to the existing literature. First, this paper explores whether there is a momentum effect and a reversal effect in the Chinese stock market by studying the correlation and predictability between half-hour returns, focusing on the first half hour, the fourth half hour, and the fifth Half-hour and eighth-half-hour predictability, combined with variables such as overnight returns, refine the model to further explore the predictability of each half-hour and full-day returns.

This paper selects the intraday data of the Shanghai Composite Index, the Shenzhen Stock Exchange Component Index, and the CSI 300 Index from January 2, 2019 to September 1, 2021 to study the predictability of intraday returns. First, we used univariate linear regression to explore the correlation between full-day and half-day returns, and then divided the opening time of the Chinese stock market into eight and a half hours to explore the correlation and predictability of half-hour returns. Finally, the univariate linear regression model was refined and new explanatory variables were added to explore the predictability of returns for each half-hour of the day.

After obtaining the results at the statistical level, this paper further studies whether this effect has an economic impact on investment: According to the empirical results, two active investment strategies and a set of control strategies are constructed, the annual rate of return of each strategy is calculated separately, and the economic significance is calculated. from the perspective of evaluating the obtained results.

2. Literature review

Momentum and reversal are two well-known return patterns. For example, the seminal work of Jegadeesh and Titman[4] found a well-known momentum strategy whereby buying past winners and selling past losers produces significantly positive returns over holding periods of 3 to 12 months; Daniel[5] proposed a theory based on investor overconfidence and the change in confidence due to biased self-attribution of investment outcomes, which implies that investors overreact to private information signals and underreact to public information signals, indicating that positive Return autocorrelation may be the result of persistent overreaction; Du[6] believed that momentum and reversal coexist in international stock indexes; Andrei and Cujean[7] proposed a joint theory of time-series momentum and reversal based on rational expectations model, in The necessary condition for generating momentum in this framework is that information flows at an increasingly faster rate; Gang[8] research investigates the profitability of momentum and reversal strategies for different investment horizons in Chinese stock markets, and the results show that momentum strategies are more effective for less than one-week investment. The investment period is profitable. For longer investment horizons, reversal strategies can be profitable; Zaremba[9] conducts a comprehensive test of long-term reversals of national stock indices, examining data from 1830-2019 for 71 countries, finds that past long-term returns are negative predictors of future performance, but very volatile over time. However, these studies have mainly focused on investigating cross-sectional momentum and reversal effects. In contrast to this cross-sectional momentum, Moskowitz[2] demonstrated the monthly time-series momentum of stock returns. Most studies have explored this effect based on low-frequency data (such as weekly or monthly), ignoring high-frequency data.

Gao[1] studied the intraday momentum effect of the US market for the first time, that is, the first half-hour return of the US stock market positively predicted the second half-hour return. Due to the digestion and reflection of new information, the trading volume in the first half-hour was very high. . Since then, a growing body of research has focused on exploring intraday momentum across a broad range of asset classes. Sun[10] and Renault[11] demonstrated that high-frequency investor sentiment can predict intraday stock returns, and Zhang[12], Chu[3], and Li[13] provided strong evidence for intraday time-series momentum in Chinese stock markets. Similarly, Jin[14] observed intraday momentum for four Chinese futures contracts, soybean, copper, steel, and soybean meal; however, Yang[15] showed that intraday strategies in the Chinese commodity futures market could not generate high excess returns due to transaction costs.

3. Empirical analysis

3.1 Data

This paper studies the predictability of intraday returns using the intraday data of the Shanghai Composite Index, the Shenzhen Stock Exchange Component Index, and the CSI 300 Index. The total sample is from January 2, 2019 to September 1, 2021, a total of 650 working days, of which the data in the sample is from January 2, 2019 to December 31, 2020, a total of 487 working days. All data come from Wind economic database and Reis database. The business hours of the China Stock Exchange are 9:30 am to 11:30 am and 1:00 pm to 3:00 pm Yield every half hour(r_1 - r_8)， Among them, this article focuses on the first half-hour yield and the last half-hour yield of each trading time period, namely r_1 , r_4 , r_5 , r_8 . In addition to this, this paper also considers the full-day yield (r_{whole}), half-day yield (r_{half1} , r_{half2}) and overnight yield (r_n).

3.2 Model Construction

According to Wen et al.'s method to explore the predictability of China's crude oil futures market through intraday trading data, this paper first constructs the following two models:

$$r_{i,t} = \alpha_1 + \beta_1 r_{j,t} + \varepsilon_t \tag{1}$$

$$r_{i,t} = \alpha_2 + \beta_2 r_{j,t-1} + \varepsilon_t \tag{2}$$

Where $r_{i,t}$ is the rate of return for the i-th half-hour on day t, $r_{j,t}$ is the rate of return for the j-th half-hour on day t. Referring to the methods of existing literature and the definitions of momentum effect and reversal effect, in this part of this paper, the first half-hour return and the last half-hour return of each day are mainly used as variables.

In order to test whether the predictors in predictive regression are still significant when recursive estimation is performed, the article uses out-of-sample regression and calculates out-of-sample R^2_{OS} , the formula is as follows:

$$R^2_{OS} = 1 - \frac{\sum_{t=m+1}^{T} (r_t - \hat{r}_t)^2}{\sum_{t=m+1}^{T} (r_t - \bar{r}_t)^2} \tag{3}$$

Where m is the number of days in the sample, that is, the working days between January 2, 2019 and December 31, 2020, a total of 487 days, and T is the total sample days, that is, January 2, 2019 to September 1, 2021.The working days between days, i.e. 650 days. r_t is the actual rate of return, $\hat{r}_t$ is the forecast rate of return, and $\bar{r}_t$ is the historical average rate of return.

3.3 Descriptive Statistics

In order to ensure the integrity of market data, this paper uses the intraday data of the Shanghai Composite Index, the Shenzhen Stock Exchange Component Index, and the CSI 300 Index, where r_{whole} represents the daily return (take the logarithmic return, the same below), r_{half1} and r_{half2} represent the first and second half-day returns, respectively, and r_1 - r_8 represent the first half-hour to Eighth and a half hour earnings. Table 1 shows the descriptive statistics of the sequences.

Table 1. Descriptive Statistics for Correlated Sequences

		mean	median	minimum	maximum	standard deviation	Skewness	Kurtosis
The Shanghai Composite Index	r_{whole}	0.000754	0.000700	0.057100	-0.077200	0.012255	-0.539362	9.074750
	r_{half1}	0.000917	0.000150	0.030509	-0.022388	0.006908	0.466772	4.880471
	r_{half2}	0.000084	0.000092	0.021342	-0.031999	0.006432	-0.602138	6.223978
	r_1	0.000336	0.000035	0.029030	-0.021429	0.004428	0.656239	8.147121
	r_2	0.000141	0.000030	0.012877	-0.013707	0.003176	-0.181160	4.878427
	r_3	0.000143	0.000055	0.010693	-0.014584	0.003011	-0.203564	4.762839
	r_4	0.000309	0.000330	0.013760	-0.013294	0.003273	-0.065647	5.189003
	r_5	-0.000096	-0.000107	0.024872	-0.015797	0.003265	0.556873	12.143970
	r_6	-0.000057	0.000015	0.008986	-0.012375	0.002561	-0.291548	5.335373
	r_7	0.000048	0.000160	0.011583	-0.011857	0.002973	0.173549	4.843358
	r_8	0.000205	0.000322	0.007722	-0.010598	0.002703	-0.668986	4.651984
Shenzhen Component Index	r_{whole}	0.001546	0.001300	0.055900	-0.084500	0.015702	-0.653454	6.587258
	r_{half1}	0.001331	0.001134	0.038008	-0.027701	0.009324	0.267598	4.039236
	r_{half2}	0.000024	0.000125	0.024380	-0.043595	0.008226	-0.745299	6.278618
	r_1	0.000765	0.000574	0.039721	-0.027084	0.006115	0.420162	7.353994
	r_2	0.000117	0.000268	0.019457	-0.019740	0.004444	-0.247772	4.711069
	r_3	0.000129	0.000064	0.014649	-0.017173	0.003957	-0.315037	4.417266
	r_4	0.000320	0.000422	0.019086	-0.017902	0.004295	-0.104997	5.227919
	r_5	-0.000170	-0.000090	0.030766	-0.023565	0.004405	0.084668	11.173600
	r_6	-0.000106	0.000068	0.012586	-0.014274	0.003338	-0.284358	4.667695
	r_7	0.000083	0.000255	0.016750	-0.014255	0.003805	0.109733	4.630016
	r_8	0.000222	0.000447	0.012484	-0.013451	0.003418	-0.513082	4.604207
CSI 300	r_{whole}	0.001219	0.001200	0.059500	-0.078800	0.013440	-0.442310	7.717854
	r_{half1}	0.000979	0.000363	0.031528	-0.024341	0.007760	0.386659	4.817651
	r_{half2}	0.000133	0.000200	0.023166	-0.036223	0.006833	-0.592425	6.432477
	r_1	0.000532	0.000192	0.027384	-0.017415	0.005028	0.597069	5.729558
	r_2	0.000116	0.000069	0.014615	-0.015204	0.003624	-0.213471	4.918249
	r_3	0.000145	0.000019	0.012897	-0.017865	0.003333	-0.286310	5.259460
	r_4	0.000191	0.000284	0.014800	-0.014047	0.003627	-0.041571	5.172580
	r_5	-0.000158	-0.000231	0.026080	-0.016932	0.003652	0.427748	10.655160
	r_6	-0.000027	0.000091	0.009549	-0.012853	0.002797	-0.285612	5.024450
	r_7	0.000100	0.000166	0.013343	-0.014038	0.003299	0.260668	5.046910
	r_8	0.000224	0.000404	0.007780	-0.010498	0.002808	-0.539167	4.186700

Descriptive statistics show that the average value of the entire day's returns is positive, and the first half of the day's returns and the second half of the day's returns are also positive. From the perspective of specific half-hour earnings, the fifth and sixth half-hour earnings are negative, the remaining six and a half hours are positive, and the first half-hour has the highest rate of return. In terms of standard deviation, high returns in the first half hour correspond to higher standard deviations, but higher returns in the last half hour correspond to lower standard deviations. A positive excess kurtosis value proves that the distributions of all given return series have thick tails.

3.4 Full-day and half-day yield correlation

In order to explore the correlation of intraday data of Chinese stock market, this paper first performs regression on r_{whole} , r_{half1} and r_{half2}, and the results are shown in Table 2.

Table 2. Regression results of full-day and half-day returns

	β			R^2		
	The Shanghai Composite Index	Shenzhen Component Index	CSI 300	The Shanghai Composite Index	Shenzhen Component Index	CSI 300
$r_{whole,t-1} \rightarrow r_{whole,t}$	0.0377 (0.8292)	0.0193 (0.4253)	0.0146 (0.3204)	0.001419	0.000374	0.000212
$r_{half2,t-1} \rightarrow r_{half1,t}$	0.0689 (1.4178)	0.0098 (0.1911)	0.0296 (0.5750)	0.004136	0.000075	0.000683
$r_{half1,t} \rightarrow r_{half2,t}$	0.1294*** (3.0899)	0.1187*** (2.9902)	0.1009*** (2.5409)	0.019305	0.018102	0.013137
$r_{whole,t-1} \rightarrow r_{half1,t}$	0.0094 (0.3655)	0.0246 (0.9121)	0.0119 (0.4544)	0.000276	0.001716	0.000427
$r_{whole,t-1} \rightarrow r_{half2,t}$	-0.0534** (-2.2481)	-0.0492** (-2.0754)	-0.0551*** (-2.3953)	0.010334	0.008821	0.0170

Judging from the regression results of the first, second and fourth rows of Table 2, the daily rate of return of the previous day and the full-day rate of return of the next day, the rate of return of the second half of the previous day and the rate of return of the first half of the next day And there is no significant relationship between the full-day return on the previous day and the first half-day return on the following day.

Judging from the regression results in the third row, there is a correlation between the first half-day rate of return and the second half-day rate of return, and the regression coefficient is 0.1294, which means that the first-half-day rate of return has a positive impact on the second-half-day rate of return. There is an intraday momentum effect between the two indices, which is confirmed in the regressions with the three indices as samples, and all of them are significant at the 1% level.

From the regression results of the fifth row, there is a correlation between the daily rate of return of the previous day and the rate of return of the second half of the next day. The regression coefficient is -0.0534, which means that the daily rate of return of the previous day has a similar effect on the rate of return of the second half of the next day. Negative effects, this result is also confirmed in the regression with the three indices as samples, which are significant at the 1% and 5% levels.

3.5 Half-hourly return correlation

Next, this paper further explores the correlation between intraday half-hour returns. Since the opening time of the Chinese stock market is in the morning and afternoon, considering the concentration of investors and the digestion of information when the market is closed. In this part of the regression test, this paper mainly focuses on four special half-hours, namely the first half-hour of the morning period and the last half-hour of the morning period, the first half hour of the afternoon period and the last half hour of the afternoon period. Table 3 presents the regression results for these four special half-hourly returns.

Table 3. Regression results of half-hour returns

	β			R^2		
	The Shanghai Composite Index	Shenzhen Component Index	CSI 300	The Shanghai Composite Index	Shenzhen Component Index	CSI 300
$r_{1,t} \rightarrow r_{4,t}$	0.0163 (0.4871)	-0.0049 (-0.1537)	0.0109 (0.0327)	0.000489	0.000049	0.000232
$r_{1,t} \rightarrow r_{5,t}$	0.1011*** (3.0491)	0.0950*** (2.9317)	0.1069*** (3.2780)	0.018809	0.017413	0.021676
$r_{1,t} \rightarrow r_{8,t}$	0.0533* (1.9331)	0.0285 (1.1279)	0.0271 (1.0731)	0.007646	0.002616	0.002369
$r_{4,t} \rightarrow r_{5,t}$	8.07E-05 (0.0017)	0.0021 (0.0451)	-0.0203 (-0.4455)	0.000000	0.000004	0.000409
$r_{4,t} \rightarrow r_{8,t}$	0.0926** (2.4867)	0.0837 (2.3301)	0.0794 (2.2711)	0.012590	0.011071	0.010523
$r_{8,t-1} \rightarrow r_{1,t}$	0.0564 (0.7645)	-0.0003 (-0.0044)	0.0028 (0.0351)	0.001206	0.000000	0.000003
$r_{8,t-1} \rightarrow r_{4,t}$	-0.0121 (-0.2206)	-0.0301 (-0.5274)	-0.0128 (-0.2195)	0.000101	0.000574	0.000100
$r_{8,t-1} \rightarrow r_{5,t}$	-0.0662 (-1.2097)	-0.0159 (-0.2732)	-0.0647 (-1.0975)	0.003015	0.000154	0.002483
$r_{8,t-1} \rightarrow r_{8,t}$	-0.0177 (-0.3915)	-0.0238 (-0.5255)	-0.0187 (-0.4137)	0.000317	0.000570	0.000353

From the regression results in Table 3, at the 1% confidence level, there is a positive correlation between the first half-hour rate of return and the fifth-hour rate of return, which is also consistent with the first half-hour rate of return and the fifth half-hour return are the highest of the day and the results are consistent with the positive correlation between the first and second half-day returns. Except for the results in the second row, the regression results of the rest of the series are not significant, which indicates that there is no significant correlation between the half-hour returns, whether it is the intraday data of the current day or the intraday data of the previous day and the next day.

Table 4. Out-of-sample regression results

	β			R^2			R^2_{OS}		
	The Shanghai Composite Index	Shenzhen Component Index	CSI 300	The Shanghai Composite Index	Shenzhen Component Index	CSI 300	The Shanghai Composite Index	Shenzhen Component Index	CSI 300
$r_{1,t} \rightarrow r_{5,}$	0.1011*** (3.0491)	0.0950*** (2.9317)	0.1069*** (3.2780)	0.018809	0.017413	0.021676	0.8416 [0.1467]	0.9992 [0.1203]	0.5453 [0.1582]

Although the correlation regression results between the first half-hour return r_1 and the fifth half-hour return r_5 are significant in-sample, but out-of-sample R^2_{OS} is not significant, so future returns cannot be predicted recursively.

3.6 Refine the model

Next, this paper improves the above univariate model and adds new explanatory variables. First, considering the impact of the previous day's yield and overnight yield, investors further digest the previous day's information or overnight information, and their emotions are reflected in the stock price of the next day; secondly, considering whether the trading day is Monday or Friday, and The corresponding dummy variables are added to the model. The expanded model is as follows:

$$r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{i,t-1} + \beta_3 r_{n,t} + \beta_4 D_1 + \beta_5 D_5 + \varepsilon_t \tag{4}$$

Where $r_{i,t}$ ($r_{i,t-1}$) represents the return rate of the ith half-hour on day t (t-1), $r_{n,t}$ represents the overnight return rate, defined as the percentage change of the opening price on day t relative to the closing price of the previous day, D_1 and D_5 is a dummy variable, if the day is Monday, then $D_1 = 1$, otherwise take 0, similarly if the day is Friday, then $D_5 = 1$, otherwise take 0.

Table 5. Regression results after perfecting the model

	$r_{2,t}$	$r_{3,t}$	$r_{4,t}$	$r_{5,t}$	$r_{6,t}$	$r_{7,t}$	$r_{8,t}$	r_t
β_1	-0.1357*** (-4.313)	-0.11193*** (-3.566814)	-0.057004* (-1.686141)	0.048281 (1.393378)	-0.032137 (-1.194593)	-0.061624** (-2.083695)	-0.038352 (-1.449755)	1.166613*** (12.58735)
β_2	-0.0516 (-1.247)	-0.058492 (-1.346549)	-0.023600 (-0.543332)	-0.063897 (-1.445261)	-0.032899 (-0.749130)	-0.062344 (-1.492600)	-0.002762 (-0.067722)	-0.010252 (-0.309687)
β_3	0.117693*** (10.13026)	0.082360*** (7.114174)	0.092527*** (7.419828)	0.058472*** (4.570273)	0.063843*** (6.441145)	0.101189*** (9.277679)	0.105506 (10.81807)	1.103641*** (19.01032)
β_4	0.000511 (1.512667)	0.000370 (1.100678)	0.000152 (0.416408)	-0.000112 (-0.301448)	-0.000122 (-0.420981)	-0.000675 (-2.114529)	0.000373 (1.316753)	0.001051 (1.022724)
β_5	-0.000310 (-0.899238)	1.58E-06 (0.004601)	-0.000918** (-2.489832)	9.25E-05 (0.244156)	0.000435 (1.478422)	0.000870*** (2.691384)	-2.91E-05 (-0.100612)	-0.000247 (-0.235614)
R^2	0.186917	0.102827	0.120163	0.063968	0.085770	0.175546	0.206334	0.490571
R^2_{OS}	16.4405*** [0.00001291]	7.911834*** [0.00116873]	10.512970*** [0.00022985]	12.632313*** [0.00029612]	8.3253296*** [0.000552617]	-3.424737 [0.10235806]	18.96832*** [0.0000605]	32.764409*** [0.0000000214]

Table 5 shows that the new model outperforms the univariate model. Horizontally, β_1 and β_3 are highly significant, that is, the first half-hour rate of return and overnight rate of return has a high explanatory power for other half-hour rates of return. From the regression coefficient, the β of the first half-hour returns are mostly negative, and the absolute value gradually decreases over time, which indicates that there is a reversal effect in the day, that is, the first hour returns are high It is very likely that the yield on the trading day will be negative in the next half hour.

The first half-hour has a positive coefficient on the full-day rate of return, that is, the first half-hour has a positive impact on the full-day rate of return, and there is an intraday momentum effect between the first half-hour and the full-day rate of return. The last row is the out-of-sample R^2_{OS} for these regressions, and it can be found that compared to the univariate model, the refined model is still applicable out-of-sample for most regressions, especially when the dependent variable is an integer The p-value for out-of-sample R^2_{OS} is only 0.0000000214 for daily returns. Therefore, using this model to make predictions is statistically valid.

3.7 Economic significance

In order to test whether the measurement results can achieve excess returns in the market, that is, whether there is economic significance. This paper constructs two investment strategies based on the regression results.

The first is the MR Strategy. The specific operation of this strategy is that if the rate of return in the first half hour is positive, we will go long at the end of the second half hour. If the first half hour return of the next day is still positive, we will continue to hold. If the first half hour of the next day is negative, we will close the position at the end of the second half hour.

The second is M-Strategy, which works by taking a long position at the end of the first half hour if the return in the first half hour is positive. If the first half hour return of the next day is still positive, we will continue to hold. If the first half hour of the day is negative, we will close the position at the end of the first half hour.

The BH-Strategy strategy, as a comparison, refers to buying at the beginning of the sample period until the end of the sample period.Table 6 lists the returns that can be obtained by following the above strategies.

Table 6. Return on investment strategy

	MR-strategy		M-strategy		BH-strategy
	Returns%	Trade times	Returns%	Trade times	Returns%
2019	10.36%	129	9.83%	129	21.70%
2020	30.62%	119	28.87%	118	12.74%
2021	8.56%	97	7.6%	96	2.21%
Average	16.51%	115	15.43%	114	12.22%

The results in Table 6 show that MR-Strategy and M-Strategy differ in an economic sense, but this difference is small in terms of three-year average returns. The average yield of M-Strategy is 15.43%, which is lower than 16.51% of MR-Strategy. The results show that MR-Strategy and M-Strategy can achieve more returns than BH-Strategy, and according to Chu (2019)[3], if the sample time is extended, this return gap will continue to increase. But it is based on zero transaction costs. MR-Strategy trades frequently, with an average of 115 (114) trades per year, so in investment practice, costs must be considered. The cost of A-share trading mainly consists of commission and stamp duty. Both costs will change over time. Taking the current situation as an example, the transaction commission is about 0.03%, which is levied bilaterally. Stamp duty is 0.1%, levied unilaterally by the seller. Therefore, the total cost of a buy and sell transaction is about 0.16%. The average annual cost of MR-Strategy and M-strategy is 9.6%, which is greater than the excess return obtained by MR-Strategy. This means that MR-Strategy and M-strategy will not deliver excess returns after including transaction costs.

4. Conclusion

This paper studies the predictability of intraday returns in China's stock market, and draws the following conclusions.

First of all, there is an intraday momentum effect between the first half of the daily rate of return and the second half of the rate of return. This effect has passed the test of the three indices and is highly significant. After using the univariate model regression, it is found that only the first half hour in the sample is within the sample. There is a significant positive relationship between returns and returns in the fifth half-hour (first half-hour in the afternoon), and the correlations between the remaining half-hours are not significant or strong. However, an out-of-sample test of this correlation found that the intraday momentum does not exist, so the univariate model cannot be used for prediction purposes.

Second, after perfecting the model, it can be found that there is an intraday momentum effect between the first hour and the full-day return, and there is a reversal effect between the first half hour and the other half hours. This intraday momentum effect has an economic impact on investing, and it was further discovered after the portfolio was constructed.

Third, although the intraday momentum effect has economic significance, transaction costs hinder the intervention of arbitrageurs, and investors cannot obtain excess returns after considering transaction costs. It is therefore concluded that these costs are responsible for the long-term predictability of intraday returns.

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