Finance Research Letters 30 (2019) 83–88

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Intraday momentum and reversal in Chinese stock market

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ARTICLE INFO

Keywords:
Intraday returns predictability
Trading costs
Noise trading

JEL classification:
G11
G14
G17

ABSTRACT

Taking intraday first-half-hour returns as predictor, we find significant intraday momentum and a reversal effect in the Chinese stock market. This momentum and reversal effect is robust even when including previous day returns, overnight returns, and day-of-week effect. We confirm that noise trading is the driving factor that causes the predictability of intraday returns. Although the investment strategy based on the first-half-hour returns can generate abnormal returns, the presence of costs prevents arbitrageur's intervention and makes the intraday returns predictability exist persistently.

1. Introduction

Momentum and reversal are two well-known return patterns. For example, Jegadeesh and Titman (1993), Griffin et al. (2003), Moskowitz et al. (2012), He and Li (2015), and Lim et al. (2018) conducted studies on momentum effect. Lehmann (1990) and Jegadeesh (1990) documented stock market reversal effect. Yang et al. (2018) examined momentum and reversal strategies based on the commodity futures market. But the majority of existing studies were based on low-frequency data. Whether or not such momentum and reversal effect can be found in intraday returns remains an unanswered question. Gao et al. (2018) conducted the first research about the intraday momentum effect on the U.S. market. Similarly, Zhang et al. (2019) and Elaut et al. (2018) documented a significant intraday momentum on Chinese stock market and the ruble market, respectively.

This paper continues to investigate intraday returns predictability in Chinese A-shares market and makes several contributions to existing literature. First, we provide new findings. We find not only intraday momentum in last-half-hour returns but also a reversal effect in the second-half-hour. We further show this reversal effect has economic implications for investment. Second, our results confirm that noise trading drives intraday returns predictability. We find no evidence to show a stronger momentum effect at intraday level on information announcement days. Instead, we find intraday momentum effects are stronger on days of high volume and high liquidity, which is consistent with the noise trading hypothesis. Third, transaction costs hinder the intervention of arbitrageurs. Therefore, we conclude that these costs are the reason for the long-term existence of intraday returns predictability.

The rest of the paper is structured as follows. Section 2 describes our sample. Section 3 discusses the empirical results. Section 4 investigates possible explanations. Section 5 discusses economic significance and transaction costs, and Section 6 concludes our study.

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https://doi.org/10.1016/j.frl.2019.04.002
Received 22 October 2018; Received in revised form 13 January 2019; Accepted 6 April 2019
Available online 08 April 2019
1544-6123/

Table 1
Results of multivariate predictive regressions.

Coefficients	Dependent variables							
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$r_{2,t}$	$r_{3,t}$	$r_{4,t}$	$r_{5,t}$	$r_{6,t}$	$r_{7,t}$	$r_{8,t}$	r_t
β_1	−0.1440***	−0.0237	0.0339*	0.1310***	0.0157	0.0850***	0.1110***	1.2110***
	(−4.621)	(−0.908)	(1.702)	(6.228)	(0.791)	(4.030)	(4.570)	(23.120)
β_2	−0.0161	−0.0755***	−0.0578**	−0.0962***	−0.0585**	−0.0594**	−0.165***	−0.0759***
	(−0.620)	(−2.606)	(−2.201)	(−2.966)	(−2.409)	(−2.368)	(−5.263)	(−3.728)
β_3	0.1200***	0.0425	−0.0043	−0.1570***	−0.0282	−0.0733**	−0.0218	−0.1230
	(3.378)	(1.173)	(−0.148)	(−5.445)	(−1.040)	(−2.394)	(−0.592)	(−1.521)
β_4	0.00072***	0.00037	0.00014	−0.00001	0.00025	0.00016	0.00010	0.00189**
	(2.973)	(1.601)	(0.559)	(−0.0809)	(1.223)	(0.655)	(0.386)	(2.517)
β_5	0.00016	0.00005	0.00002	0.00021	0.00016	0.00005	−0.00040	0.00038
	(0.757)	(0.264)	(0.108)	(0.861)	(0.737)	(0.194)	(−1.577)	(0.644)
β_0	0.00016	−0.00019	−0.00001	0.000166	0.00022**	−0.00004	0.00068***	0.00089***
	(1.401)	(−1.610)	(−0.0345)	(1.412)	(2.115)	(−0.395)	(5.868)	(3.189)

Notes: This table shows the regression results of $r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{i,t-1} + \beta_3 r_{n,t} + \beta_4 D_1 + \beta_5 D_5 + \varepsilon_t$. $r_{i,t}$ is the *i*th half-hour returns on day *t*. $r_{i,t-1}$ is the *i*th half-hour returns on day $t - 1$. $r_{n,t}$ is the overnight returns, which is defined as the opening price of the day t compared to the closing price of day $t - 1$. $D_1 = 1$ if the day is Monday, otherwise 0. $D_5 = 1$ if the day is Friday, otherwise 0. Newey and West (1987) robust *t*-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

2. Sample

Shanghai Composite Index data is used to investigate the intraday returns predictability in this paper. The sample is from 04/04/2015 to 12/31/2015. The data is collected from the CSMAR database. Our sample has at least two advantages. First, the sample period contains two important periods: 2008 global financial crisis and 2015 Chinese stock price crash. Second, a large sample of 10 years can avoid possible structural changes or biased estimates. Chinese stock exchanges operate from 9:30 to 11:30 in the morning, and from 1:00 to 3:00 in the afternoon. To analyze intraday returns predictability, we divide one day into eight half-hour intervals.

3. Empirical results

We conduct the following regression to examine intraday returns predictability.

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

where $r_{i,t}$ ($r_{i,t\text{-}1}$) is the *i*th half-hour returns on day t ($t - 1$). $r_{n,t}$ is the overnight returns, defined as percentage change of the opening price on day t relative to the closing price on previous day. $D_1 = 1$ if it is Monday, otherwise 0. $D_5 = 1$ if it is Friday, otherwise 0. In Eq. (1), the motivation for including $r_{n,t}$, $r_{i,t\text{-}1}$, D_1 and D_5 is as follows. First, the overnight returns capture the arrival of news overnight (Wang et al., 2015). Many of the overnight returns may reflect information surprises (Polk et al., 2018). Second, Heston et al. (2010) shows that the *i*th half-hour returns on day t are significantly correlated with returns in the same time on the previous trading day. Third, the day-of-week patterns have been investigated extensively in different studies. For example, French (1980) finds that stock returns on Monday are significantly less than returns from other days of the week. Therefore, it is possible that $r_{n,t}$, $r_{i,t\text{-}1}$, D_1 and D_5 affect intraday returns patterns.

Table 1 reports the estimated coefficients and Newey and West (1987) robust *t*-statistics. The regression results for daily returns r_t are also listed in the last column. Table 1 indicates a strong correlation between the first-half-hour returns and subsequent half-hour returns. For example, the β_1 for the second-half-hour returns is negative (−0.1440), which is significant at the 1% level. The result suggests significant reversal between the first- and second-half-hour returns. The β_1 for the fifth-, seventh-, and eighth-half-hour returns are 0.131, 0.085, and 0.111, respectively. These coefficients are all significant at the 1% level. There is also a significant positive correlation between daily returns and first-half-hour returns, with a coefficient of 1.211 and *t*-statistic of 23.12. Overall, these results indicate that there are significant intraday momentum and reversal effects in the Chinese stock market.

4. Explanations

Gao et al. (2018) provided two possible explanations for intraday momentum: the portfolio rebalancing effect and the late-informed investors' effect. In this section, we argue that neither hypothesis explains the intraday returns predictability observed in this paper. Then, we present our noise trading hypothesis.

4.1. The portfolio rebalancing effect

If the portfolio rebalancing effect is true, the predictive ability of first-half-hour returns only exists that day. This is due to the fact

Table 2
The intraday portfolio rebalancing effect.

Depend variable	Coefficient			
	β0	β1	β2	β3
$CR_{[1,4],\,t}$	0.000379*(1.652)	0.0990***(2.584)	−0.0612**(−2.168)	0.927***(15.90)

Notes: The regression model is $CR_{[1,4],\,t} = \beta_0 + \beta_1 r_{1,t-1} + \beta_2 CR_{[1,4],\,t-1} + \beta_3 r_{n,t} + \varepsilon_{[1,4],\,t}$. $CR_{[1,4],\,t}$ is cumulative returns from first half-hour to fourth half-hour on day *t*. $r_{1,t-1}$ is the first half-hour returns on day $t-1$. $r_{n,t}$ is the overnight returns on day t. Newey and West (1987) robust t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

that investors delay their transaction to near closing according to the portfolio rebalancing effect (Gao et al., 2018). We use the following regressions at longer horizons to test this possible explanation:

$$CR_{[1,4],t} = \beta_0 + \beta_1 r_{1,t-1} + \beta_2 CR_{[1,4],t-1} + \beta_3 r_{n,t} + \varepsilon_{[1,4],t}, \tag{2}$$

where $CR_{[1,4],\,t}$ ($CR_{[1,4],\,t-1}$) is cumulative returns from first-half-hour to fourth-half-hour on day t ($t-1$) and $CR_{[1,4],\,t-1}$ is for controlling the significant correlation between a given time returns and returns in the same time on previous day. $r_{1,t\text{-}1}$ is the first-half-hour returns on day $t-1$. $r_{n,t}$ is the overnight returns. We have a major finding in Table 2: the coefficient for β1 is significantly positive at the 1% level. This result shows that the momentum generated by the first-half-hour returns could spill over to the next day. It seems that the intraday returns predictability is unlikely to be the result of investors delaying trading on that day.

4.2. The late-informed investors' effect

If the predictability of intraday returns comes from late-informed investors, information is an important factor that drives returns predictability. Therefore, such predictability should be stronger in news-release samples than in non-news-release samples as reported by Gao et al. (2018). Thus, we study the effect of macroeconomic news announcements on intraday returns predictability. We focus on two announcements: announcement from the National Bureau of Statistics about macroeconomic indicators (such as GDP and CPI) and announcement from the People's Bank of China (such as the adjustment of monetary policy). This paper divides the sample into news-release days and non-news-release days. If the announcement date occurs during non-trading hours, the next trading day is regarded as the news-release day.

$$r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{i,t-1} + \beta_3 r_{n,t} + \beta_4 MA_t + \beta_5 (MA_t \times r_{1,t}) + \varepsilon_t, \tag{3}$$

where MA is the announcement dummy variable. $MA = 1$ if it is a news-release day, otherwise 0. The β_5 is to capture the interaction between r_1 and MA. Table 3 shows the estimate β_5 is not significant in all cases. The t-statistic for $r_{8,t}$ is only 1.183, which is insignificant at the 10% level. These results are inconsistent with the findings of Gao et al. (2018). Thus, the evidences from Table 3 are inconsistent with the late-informed investors' effect.

4.3. Noise trading hypothesis

De Long et al. (1989) found that stock prices respond to not only news but also noise trading. We confirm that the intraday returns

Table 3
Macro Announcement Effects.

Coefficients	Dependent variables							
	$r_{2,t}$	$r_{3,t}$	$r_{4,t}$	$r_{5,t}$	$r_{6,t}$	$r_{7,t}$	$r_{8,t}$	r_t
β1	−0.161***	−0.0147	0.0229	0.134***	0.0206	0.0824***	0.0960***	1.185***
	(−4.363)	(−0.491)	(1.003)	(5.349)	(0.891)	(3.256)	(3.325)	(19.49)
β2	−0.0152	−0.0758***	−0.0579**	−0.0964***	−0.0594**	−0.0599**	−0.163***	−0.0757***
	(−0.590)	(−2.622)	(−2.185)	(−2.972)	(−2.454)	(−2.407)	(−5.206)	(−3.729)
β3	0.122***	0.0439	−0.00329	−0.157***	−0.0268	−0.0731**	−0.0203	−0.115
	(3.573)	(1.208)	(−0.112)	(−5.465)	(−0.988)	(−2.379)	(−0.553)	(−1.442)
β4	−0.000234	0.000109	5.01e-05	−0.000134	0.000199	−0.000289	0.000179	−0.000135
	(−1.118)	(0.528)	(0.255)	(−0.567)	(1.116)	(−1.378)	(0.862)	(−0.254)
β5	0.0509	−0.0317	0.0313	−0.00766	−0.0167	0.00888	0.0410	0.0693
	(1.496)	(−0.801)	(1.273)	(−0.214)	(−0.562)	(0.228)	(1.183)	(0.919)
β0	0.000398***	−0.000132	0.00001	0.000239**	0.000254***	0.000079	0.000566***	0.00137***
	(3.371)	(−1.214)	(0.115)	(2.080)	(2.633)	(0.715)	(6.226)	(4.952)

Notes: The regression model is $r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{i,t-1} + \beta_3 r_{n,t} + \beta_4 MA_t + \beta_5 (MA_t \times r_{1,t}) + \varepsilon_t$. $r_{1,t}$ is the *i*th half-hour returns on day *t*. $r_{i,t-1}$ is the *i*th half-hour returns on day $t-1$. $r_{n,t}$ is the overnight returns, which is defined as the opening price of the day *t* compared to the closing price of day $t-1$. MA is macro announcement dummy variable. $MA = 1$ if it is news-release day otherwise 0. Newey and West (1987) robust t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Intraday returns predictability and volume.

Coefficients	Dependent variables							
	$r_{2,t}$	$r_{3,t}$	$r_{4,t}$	$r_{5,t}$	$r_{6,t}$	$r_{7,t}$	$r_{8,t}$	r_t
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β1	−0.173***	−0.0179	0.0586***	0.111***	0.00552	0.0725***	0.0851***	1.144***
	(−6.067)	(−0.608)	(2.837)	(5.020)	(0.253)	(3.109)	(3.045)	(19.62)
β2	−0.0191	−0.0751***	−0.0534**	−0.101***	−0.0585**	−0.0599**	−0.164***	−0.0837***
	(−0.767)	(−2.603)	(−2.101)	(−3.065)	(−2.389)	(−2.403)	(−5.388)	(−4.078)
β3	0.117***	0.0458	0.00189	−0.161***	−0.0296	−0.0757**	−0.0264	−0.126
	(3.153)	(1.303)	(0.0686)	(−5.492)	(−1.138)	(−2.488)	(−0.770)	(−1.565)
β4	0.000509**	0.000159	−0.000106	0.000601***	0.000060	−0.000063	0.000008	0.00131**
	(2.268)	(0.709)	(−0.516)	(2.668)	(0.301)	(−0.318)	(0.0405)	(2.448)
β5	0.0820*	−0.0225	−0.0784	0.0592*	0.0309	0.0398	0.0780**	0.193***
	(1.855)	(−0.562)	(−0.210)	(1.778)	(0.856)	(1.363)	(2.267)	(2.724)
β0	0.000157	−0.000143	0.000089	0.000006	0.000278***	−0.000001	0.000593***	0.000889***
	(1.575)	(−1.455)	(0.792)	(0.0525)	(2.962)	(−0.00653)	(6.446)	(3.391)

Notes: The regression model is $r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{t-1} + \beta_3 r_{n,t} + \beta_4 HighVol_t + \beta_5(HighVol_t \times r_{1,t}) + \varepsilon_t$. $r_{i,t}$ is the ith half-hour returns on day t. $r_{i,t-1}$ is the ith half-hour returns on day $t-1$. $r_{n,t}$ is the overnight returns, which is defined as the opening price of the day t compared to the closing price of day $t-1$. *Highvol* is a trading volume dummy variable. *Highvol* = 1 if trading volume is greater than the sample mean, otherwise 0. Newey and West (1987) robust t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

predictability is not driven by news in last section. Therefore, it is possible that noise trading drives intraday returns predictability.

4.3.1. Intraday returns predictability and volume

High trading volume is the indicator of noise trading (Sun et al., 2016; Odean, 1998). Noise traders' investments are susceptible to stock price short-term change. When the first-half-hour returns of that day are positive (negative), noise traders often follow the trend and implement a buying (selling) strategy because of the well-known herd effect. As a result, the intraday returns are predictable. The following regression is used to test the noise-trading hypothesis:

$$r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{t-1} + \beta_3 r_{n,t} + \beta_4 HighVol_t + \beta_5 (HighVol_t \times r_{1,t}) + \varepsilon_t, \tag{4}$$

where *Highvol* is a dummy. When the trading volume of day t is greater than the sample mean, the *Highvol* is 1, otherwise 0. The interaction is to capture whether the predictive power of first-half-hour returns depend on trading volume. The results of Table 4 show that coefficient β_5 is significantly positive in the second-, fifth-, and eighth-half-hour returns and daily-returns regression. This is consistent with the expectation of noise trading.

4.3.2. Intraday momentum and liquidity

We also consider how liquidity affects intraday returns predictability. This allows us to further identify whether noise trading drives intraday returns predictability. Existing literature shows a positive relationship between noise trading and liquidity (Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988). Generally, the increase in noise trading can reduce adverse selection, and thus market liquidity is improved. Therefore, noise trading positively affects market liquidity (Bloomfield et al., 2009). If noise trading drives intraday returns predictability, the fact that intraday returns predictability depends on liquidity should be observed.

$$r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{t-1} + \beta_3 r_{n,t} + \beta_4 HighLiquidity_t + \beta_5 (HighLiquidity_t \times r_{1,t}) + \varepsilon_t,\ i = 2, 3, \ldots, 8 \tag{5}$$

where *HighLiquidity* is a dummy. When the liquidity of day t is greater than the sample mean, *HighLiquidity* is 1, otherwise 0. Relative spread and quote depth are used as a proxy for liquidity. The interaction is to capture whether the predictive power of the first-half-hour returns depends on liquidity. Table 5 reports the relationship between intraday returns predictability and relative spread. The results show that the coefficient β_5 is statistically significantly positive in the following cases: the second-, fifth-, and eighth-half-hour returns and daily returns. The most significant estimate for β_5 is the daily returns regression with a t-statistic of 2.479. In the case of the eighth-half-hour, the t-statistic is 2.019, which is significant at the 5% level. Table 6 reports the relationship between intraday returns predictability and quote depth. Table 6 finds that the coefficient β_5 is statistically significantly positive in the following cases: the second- and eighth-half-hour returns and daily returns. The most significant estimate for β_5 is also the daily returns regression with a t-statistic of 2.907, which is significant at the 1% level. For the eighth-half-hour regression, the t-statistic is 2.085, which is also significant at the 5% level. Taken together, the evidences from Tables 5 and 6 confirm that the hypothesis that noise trading drives the returns predictability by the first-half-hour returns is true.

5. Economic significance and trading costs

Unlike the U.S. $T+0$, China uses a $T+1$ settlement cycle for A-shares. This means that investors cannot sell stocks they bought that day. Therefore, we cannot implement the strategy from Gao et al. (2018). Instead, we construct two investment strategies. One is

Table 5
Intraday returns predictability and relative spread.

Coefficients	Dependent variables							
	$r_{2,t}$	$r_{3,t}$	$r_{4,t}$	$r_{5,t}$	$r_{6,t}$	$r_{7,t}$	$r_{8,t}$	r_t
β_1	−0.176***	−0.0348	0.0444*	0.100***	0.0183	0.0890***	0.0745**	1.119***
	(−4.535)	(−1.056)	(1.814)	(3.475)	(0.762)	(3.234)	(2.408)	(18.32)
β_2	−0.0194	−0.0766***	−0.0568**	−0.0968***	−0.0589**	−0.0592**	−0.163***	−0.0773***
	(−0.770)	(−2.638)	(−2.149)	(−3.042)	(−2.432)	(−2.272)	(−5.171)	(−3.772)
β_3	0.122***	0.0437	−0.00340	−0.158***	−0.0273	−0.0729**	−0.0224	−0.118
	(3.569)	(1.216)	(−0.115)	(−5.499)	(−0.995)	(−2.393)	(−0.617)	(−1.504)
β_4	0.000635***	0.000097	0.000009	0.000352	0.000002	−0.000219	−0.000261	0.000711
	(3.265)	(0.497)	(0.0418)	(1.606)	(0.0140)	(−1.105)	(−1.358)	(1.322)
β_5	0.0572*	0.0201	−0.0219	0.0587*	−0.00573	−0.00625	0.0733**	0.173**
	(1.741)	(0.622)	(−0.912)	(1.717)	(−0.225)	(−0.212)	(2.019)	(2.479)
β_0	−0.000094	−0.000173	0.000031	−0.000042	0.000307**	0.000140	0.000771***	0.000825*
	(−0.575)	(−1.061)	(0.159)	(−0.217)	(1.992)	(0.875)	(4.979)	(1.921)

Notes: The regression model is $r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{t-1} + \beta_3 r_{n,t} + \beta_4 LowRQS_t + \beta_5(LowRQS_t \times r_{1,t}) + \varepsilon_t$. $r_{i,t}$ is the *i*th half-hour returns on day *t*. $r_{i,t-1}$ is the *i*th half-hour returns on day $t-1$. $r_{n,t}$ is the overnight returns, which is defined as the opening price of the day t compared to the closing price of day $t-1$. *LowRQS* is a dummy variable. $LowRQS = 1$ if relative quoted spread is less than the sample mean, otherwise 0. Newey and West (1987) robust t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Intraday returns predictability and quote depth.

Coefficients	Dependent variables							
	$r_{2,t}$	$r_{3,t}$	$r_{4,t}$	$r_{5,t}$	$r_{6,t}$	$r_{7,t}$	$r_{8,t}$	r_t
β_1	−0.164***	−0.0281	0.0510***	0.125***	0.00499	0.0786***	0.0973***	1.170***
	(−5.715)	(−1.042)	(2.584)	(5.401)	(0.231)	(3.508)	(3.738)	(20.83)
β_2	−0.0166	−0.0771***	−0.0528**	−0.0975***	−0.0595**	−0.0589**	−0.165***	−0.0792***
	(−0.660)	(−2.662)	(−2.095)	(−2.985)	(−2.423)	(−2.349)	(−5.380)	(−3.910)
β_3	0.114***	0.0434	0.00622	−0.158***	−0.0338	−0.0758**	−0.0271	−0.131*
	(3.042)	(1.218)	(0.220)	(−5.444)	(−1.365)	(−2.459)	(−0.781)	(−1.663)
β_4	0.000164	0.000320	0.000343*	0.000338*	−0.000300	−0.000007	−0.000099	0.000777
	(0.768)	(1.623)	(1.680)	(1.690)	(−1.612)	(−0.0377)	(−0.575)	(1.553)
β_5	0.111**	0.0178	−0.111	0.0308	0.0683	0.0375	0.0766**	0.225***
	(2.447)	(0.330)	(−0.152)	(0.994)	(1.502)	(1.215)	(2.085)	(2.907)
β_0	0.000284**	−0.000195*	−0.000059	0.000108	0.000387***	−0.000006	0.000646***	0.00111***
	(2.575)	(−1.848)	(−0.500)	(0.834)	(3.746)	(−0.0562)	(6.644)	(3.843)

Notes: The regression model is $r_{i,t} = \beta_0 + \beta_1 r_{1,t} + \beta_2 r_{t-1} + \beta_3 r_{n,t} + \beta_4 HighDepth_t + \beta_5(HighDept_t \times r_{1,t}) + \varepsilon_t$. $r_{i,t}$ is the *i*th half-hour returns on day t. $r_{i,t-1}$ is the *i*th half-hour returns on day $t-1$. $r_{n,t}$ is the overnight returns, which is defined as the opening price of the day t compared to the closing price of day t - 1. *HighDepth* is a dummy variable. $HighDepth = 1$ if quoted depth is greater than the sample mean, otherwise 0. Newey and West (1987) robust t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

the momentum-reversal strategy (MR-Strategy); the other is the momentum strategy (M-Strategy). Both are based on first-half-hour returns (r_1) as trading signal. The former uses the second-half-hour returns reversal effect, while the latter does not. For MR-Strategy, if $r_1 > 0$, we take a long position at the end of the second half-hour. If the r_1 on next day is still positive, we continue to hold. If the r_1 on next day is negative, we close the position at the end of the second half-hour. For M-Strategy, if $r_1 > 0$, we take a long position at the end of the first half-hour. If the r_1 on next day is still positive, we continue to hold. If the r_1 on next day is negative, we close the position at the end of the first-half-hour.

Table 7 reports the results of the above two strategies. Table 7 also reports the results of the buy-and-hold strategy (BH-Strategy) as a benchmark. Table 7 shows that MR-Strategy has the best performance because the average annual returns are 30.44%, which exceeds 23.28% of BH-strategy. The Sharpe ratio (SR) of MR-Strategy is 0.19, which is greater than 0.04 of BH-Strategy's SR. These results show that the MR-Strategy does not only obtain abnormal market returns, but it also bears lower risks.

The results from Table 7 also indicate that there is a difference in the economic meaning between MR-Strategy and M-Strategy. For example, the average returns of M-Strategy are 19.65%, which is less than 30.44% of the MR-Strategy. This result confirms that the intraday reversal effect is very important for transaction timing in the economic sense. Although the M-Strategy only gets the lowest average annual returns, the SR of M-Strategy is 0.12, which is still greater than 0.04 of BH-Strategy. This finding means that the M-Strategy bears lower risk than BH-Strategy.

Although M-Strategy can obtain abnormal returns of 7.16% over the BH-Strategy, it is based on zero transaction costs. MR-Strategy has frequent transactions, as shown in Table 7. The number of average annual transactions is 120. Therefore, in investment practice, costs have to be considered. The cost of A-share transactions is mainly composed of commission and stamp taxes. Both costs change over time. Taking the current situation as an example, trading commission is about 0.03%, which is levied bilaterally. The

Table 7
Returns and Sharpe Ratio of alternative investment strategies.

	MR-strategy			M-strategy			BH-strategy	
	Returns%	Trade times	SR	Returns%	Trade times	SR	Returns%	SR
2005	8.13	91	0.10	−5.98	91	−0.07	−8.33	−0.01
2006	69.53	112	0.50	63.07	112	0.46	130.43	0.26
2007	95.45	122	0.45	71.16	122	0.36	96.66	0.14
2008	−42.77	124	−0.23	−73.79	124	−0.37	−65.39	−0.14
2009	61.77	122	0.29	53.27	122	0.26	79.98	0.14
2010	6.95	128	0.07	−5.98	128	−0.05	−14.31	−0.04
2011	5.15	128	0.05	−0.71	128	−0.01	−21.68	−0.08
2012	14.51	134	0.16	13.33	134	0.15	3.17	0.02
2013	8.46	132	0.07	3.54	132	0.03	−6.75	−0.02
2014	43.86	115	0.27	38.89	115	0.25	52.87	0.17
2015	63.88	116	0.31	59.29	116	0.31	9.41	0.03
Average	30.44	120	0.19	19.65	120	0.12	23.28	0.04

Notes: MR-Strategy: if the first-half-hour returns are positive, we take a long position at the end of the second-half-hour. If the first-half-hour returns on next day are still positive, we continue to hold. If the first-half-hour returns on next day are negative, we close the position at the end of the second-half-hour. M-Strategy: if the first-half-hour returns are positive, we take a long position at the end of the first-half-hour. If the first-half-hour returns on next day are still positive, we continue to hold. If the first-half-hour returns on the day are negative, we close the position at the end of the first-half-hour. BH-Strategy: buy at the beginning of the sample period until the end of the sample period. SR is Sharpe ratio.

stamp tax is 0.1%, which was unilaterally collected for sellers. Therefore, the cost of a buying and selling transaction together is about 0.16%. The annual average cost of MR-Strategy is 9.6%, which is greater than 7.16% abnormal returns obtained by MR-Strategy. This means that MR-Strategy does not bring abnormal returns after including transaction costs.

6. Conclusion

The presence of momentum and reversal effects challenges the efficient market hypothesis. Taking intraday first-half-hour returns as predictor, we find not only significant intraday momentum but also a reversal effect. This momentum and reversal effect is robust even when considering previous day returns, overnight returns, and day-of-week effect. Our results indicate that the momentum generated by the first-half-hour returns could spill over to the next day. This result confirms that intraday returns predictability is not driven by the portfolio rebalancing effect. Also, we have no evidence that intraday returns predictability is stronger in news-release days than in non-news-release days. We confirm that noise trading is the driving factor that causes the predictability of intraday returns. Using intraday first-half-hour returns as predictor can generate significant abnormal returns, however transaction costs prevent arbitrageurs' intervention and makes intraday returns predictability exist persistently.

Acknowledgments

The authors would like to acknowledge the financial support of Jiangsu Social Science Fund Project in 2018, China (No. 18GLB001), Major Program of the Philosophy and Social Science Fund of Education Department of Jiangsu Province, China (No. 2018SJZDI071), and National Statistical Science Research Project, China (No. 2018LY36).

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