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Intraday momentum and stock return predictability: Evidence from China

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ABSTRACT

Using the high-frequency data from the Chinese stock market, this paper documents an intraday momentum that the first and/or second-to-last (seventh) half-hour returns can significantly predict the last half-hour return both in- and out-of-sample. Furthermore, this intraday momentum yields substantial economic gains from both the asset allocation and market timing perspectives. The intraday momentum findings are not only theoretically explained by the trading behavior of infrequent rebalancing or late-informed investors, but also consistent with the empirical evidence of a U-shaped volume pattern and significantly more useful information contained in the first and seventh half-hour returns. Due to a 90-min lunch break in the Chinese stock market, we find that the market return in the morning also significantly predict the return in the afternoon.

1. Introduction

The seminal work of Jegadeesh and Titman (1993) finds a well-known momentum strategy that buying past winners and selling past losers generate significantly positive returns over 3- to 12-month holding periods. In contrast to this cross-sectional momentum, Moskowitz et al. (2012) and Neely et al. (2014) demonstrate the time-series momentum for stock returns at the monthly frequency. Furthermore, a recent study by Gao et al. (2018) documents an intraday momentum that the first half-hour return positively predicts the last half-hour return in the U.S. stock market. Based on the intraday momentum, Sun et al. (2016) and Renault (2017) document that high-frequency investor sentiment can predict the intraday stock return. Along the same lines, this paper investigates the return predictability of the intraday momentum for the Chinese stock market.

Two major reasons motivate us to explore the intraday momentum in the Chinese stock market. First, with rapid growth of China's economy, international investors pay growing attention to the Chinese stock market. Financial researchers are thus interested in investigating the return predictability for the Chinese stock market. For example, Goh et al. (2013) explore the relationship between the U.S. economic variables and Chinese stock return, and find that the U.S. economic variables show significant predictive power for periods after China's admission into the WTO. Using intraday data, Narayan et al. (2015) and Narayan and Sharma (2016) show that order imbalances and S&P500 futures returns, respectively, successfully predict Chinese stock returns at some specific trading frequency.[1]

The second motivation is based on the special trading mechanism of the Chinese stock market. Specifically, the trading time of the U.S. stock market is from 9:30 to 16:00 (Eastern Time), while the trading time of the Chinese stock market is from 9:30 to 11:30 (Beijing Time) in the morning and from 13:00 to 15:00 in the afternoon. The different trading time may lead to quite different intraday momentum patterns between the U.S. and the Chinese markets. Sun et al. (2016), Renault (2017), and Gao et al. (2018) investigate the intraday return predictability of the U.S. stock market by dividing each daily return into thirteen half-hour returns. However, there are only eight half-hour returns on each trading day in the Chinese stock market. More importantly, the Chinese market has a 90-min lunch break, in which investors may learn new information or process early information, thereby influencing the intraday momentum. Hence, the special trading mechanism of the Chinese stock market also stimulates us to explore its intraday momentum.

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[1] The two articles are related to our paper as we all explore the return predictability for the Chinese stock market from an intraday perspective. However, our paper investigates the intraday momentum, while Narayan et al. (2015) focus on order imbalances and Narayan and Sharma (2016) explore the role of the U.S. stock futures returns. In addition, see Cakici et al. (2015), Ni et al. (2015), Xue and Zhang (2017), Chen et al. (2017), and Jiang et al. (2018), among others, for more related studies on Chinese stock return predictability from either cross-sectional or time-series perspective.

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In this paper, we use the representative Shanghai composite index to measure the Chinese market return. The last half-hour market return is predicted by the first and/or second-to-last (i.e., seventh) half-hour return. In our empirical analysis, we provide several remarkable findings.

First, in terms of the in-sample analysis, either of the first and seventh half-hour returns triumphantly predicts the last half-hour return with a significantly positive regression slope and a high predictive R^2 that is far larger than 1%. In particular, using the two predictors jointly to forecast the last half-hour return generates an impressive R^2 of 4.5%, which is nearly twice as high as the one found by Gao et al. (2018) in the U.S. market. Furthermore, we observe a consistent pattern for out-of-sample performance. The first half-hour return individually yields an out-of-sample R^2 (R^2_{OS}) of 2.080%, which is statistically significant at the 1% based on the Clark and West (2007) test. Surprisingly, the seventh half-hour return individually yields a higher R^2_{OS} of 2.876%, which is different with the U.S. finding of Gao et al. (2018). Finally, the two momentum predictors, namely the first and seventh half-hour returns, are found to contain complementary information for predicting the last half-hour return, thereby generating an impressive R^2_{OS} of 4.545%. Such a high value not only roughly equals the sum of the individual R^2_{OS}s, but also is at least twice as large as the U.S. ones found by Gao et al. (2018).

Second, to explore the effects of return volatility and trading volume on the intraday momentum, we sort all the trading days into high, medium, and low terciles according to their first half-hour realized volatility or trading volume, and calculate the R^2_{OS} statistics separately for each tercile. Similarly, we divide the trading days into a high group and low group according to the Amihud illiquidity measure. The empirical evidence shows that the intraday momentum is stronger on high volatility days, median trading volume days, and low liquidity days. In addition, this intraday predictability is fluctuant during the global financial crisis (GFC) and our intraday momentum is concentrated in the non-GFC period. This is opposite to the U.S. finding of Gao et al. (2018). We also find that the role of economic variables in forecasting intraday returns is scarce relative to the significant role of our intraday momentum.

Third, we examine the economic significance of the intraday momentum from both the asset allocation and market timing perspectives. The last half-hour return forecasts based on the intraday momentum generate noteworthy economic gains for a mean-variance investor who allocates between equities and risk-free bills. Assuming that an investor with a relative risk aversion coefficient of three is restricted to take equity weight between −0.5 and 1.5, she can realize a certainty equivalent return (CER) of 30.472% and a Sharpe ratio of 3.204 by using both the first and seventh half-hour returns to forecast the last. Such high economic values are remarkable, because the prevailing historical average benchmark only delivers a CER of 17.969% and a Sharpe ratio of 1.582. The asset allocation results are robust to alternative risk aversion coefficients and alternative portfolio constraints. In terms of market timing, using the signs of the two predictors to trade the market also generates a high Sharpe ratio of 2.540, while the Always Long strategy yields a lower Sharpe ratio of 1.582 and the Buy-and-Hold strategy yields the lowest Sharpe ratio of 0.410. Note that consistent with the statistical evidence, our economic significance is substantially stronger than the U.S. one of Gao et al. (2018).

Fourth, due to a 90-min lunch break in the Chinese stock market, an investor may use the market return in the morning to predict the market return in the afternoon. For this consideration, we further investigate the return predictability of this half-day momentum. The out-of-sample results show that the half-day predictability is also both statistically and economically significant, though there is a decline relative to our previous half-hour predictability. Since the period of the fifth half-hour return covers the lunch break, this predictor may contain more useful information. Given this, we examine the last half-hour return predictability by using the fifth half-hour return. However, we do not obtain any forecasting gains from statistical or economic perspective.

Finally, our interesting findings of the intraday momentum can be explained by the trading behavior of either investors who infrequently rebalance their portfolios due to the slow-moving of capital (see Bogousslavsky, 2016), or late-informed investors who learn or process new information slowly and have to trade near the market close so as to tally the net asset values of mutual funds, calculate portfolio returns, or avoid overnight risk (see, e.g., Cushing and Madhavan, 2000). The two theoretical explanations are supported by some empirical evidence. First, the high trading volume concentrates in the first and last half hours, thus displaying a U-shape. This evidence suggests that investors are more willing to trade in the first and last half hours. Second, forecast encompassing tests of Harvey et al. (1998) show that the first and seventh half-hour returns provide significantly more information useful for predicting the last half-hour return than the remaining half-hour returns. Moreover, the useful information cannot be effectively extracted by the approaches of mean combination and principal component analysis.

Our paper is related to the work of Gao et al. (2018). In contrast, we provide several new findings and contributions. First, we apply the U.S. market intraday momentum of Gao et al. (2018) to the Chinese stock market and find stronger intraday moment effect relative to the U.S. market. Furthermore, we provide some explanations about the stronger effect in China based on our empirical evidence. Specifically, this is because the U.S. market intraday momentum is concentrated in the short GFC period, while the Chinese market intraday momentum is concentrated in the long non-GFC period. This is also because the Chinese stock market typically exhibits higher volatility and low liquidity than the U.S. market and the intraday momentum is found to be positively related to volatility and illiquidity. Second, the second-to-last half-hour return is more powerful for predicting the last half-hour return than the first half-hour return, which is opposite to the corresponding finding of Gao et al. (2018). Third, we perform the forecast encompassing test of Harvey et al. (1998) and document that the first and seventh half-hour returns contain significantly more useful forecasting information than the remaining half-hour returns. This empirical evidence supports one of our theoretical explanations regarding late-informed investors. Fourth, we further investigate the half-day momentum due to the special 90-min lunch break in the Chinese markets. The half-day return predictability is also both statistically and economically significant despite a decline relative to the half-hour return predictability. In addition, the fifth half-hour return including the information in the lunch break has no predictive ability.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 presents the empirical analysis. Section 4 investigates the economic significance of the intraday momentum. Section 5 details a series of extensions and robustness checks. Finally, Section 6 concludes.

2. Data

We use Shanghai composite index to calculate the intraday returns of the Chinese stock market as Shanghai composite index typically represents the overall the Chinese stock market.[2] Both the intraday price and volume data are available from the CSMAR database. The sample period spans from January 4, 2000 through December 30, 2016.

To investigate the intraday return predictability of the Chinese stock market on each trading day *t*, we calculate the first half-hour return using

[2] In terms of the data of equity index, there is an issue for opening prices due to delayed openings for some individual stocks. However, this issue has no impact on our empirical results because we do not rely on the opening prices in this study. Furthermore, in the Chinese stock market, the data of equity index are more available, reliable, and longer than that of other tradable assets such as ETF and futures. For these considerations, we follow Welch and Goyal (2008), Rapach et al. (2010), Neely et al. (2014), and Jiang et al. (2017), among others, and use the equity index data to study the return predictability.

previous trading day's closing price at 15:00 (Beijing Time) and this trading day's price at 10:00, and then every half-hour return from 10:00 to 15:00. Particularly, the fifth half-hour return is calculated by the price at 11:30 and the price at 13:30 because there is a 90-min lunch break from 11:30 to 13:00 in the Chinese stock market. Consequently, we obtain a total of 8 half-hour returns per day,

$$r_{j,t} = \frac{p_{j,t}}{p_{j-1,t}} - 1, \quad j = 1, \cdots, 8, \tag{1}$$

where $p_{j,t}$ is the price at the j-th half-hour and $p_{j-1,t}$ is the price at the previous half-hour. Note that $p_{0,t}$ is the previous day's price at the last half-hour (15:00). In other words, we use the previous trading day's closing price as the starting price when calculating the first half-hour return on day t, i.e., $p_{0,t} = p_{8,t-1}$, so that the first half-hour return contains the information released after the previous day's market close.

To further examine the impact of return volatility on return predictability, we follow Gao et al. (2018) and calculate the first half-hour volatility using the 1-min returns. More specifically, we first compute the returns minute by minute within the first half-hour. Then, we calculate the realized volatility of the first half-hour by summing the squared 1-min returns. Similarly, we obtain the first half-hour trading volume by summing the 1-min volume within the first half-hour.

3. Empirical analysis

3.1. Predictive regression analysis

Motivated by Gao et al. (2018), we use the following predictive regression model to examine the in-sample predictability of the intraday momentum.

$$r_{8,t} = \alpha + \beta_1 r_{1,t} + \varepsilon_t, \tag{2}$$

where $r_{8,t}$ and $r_{1,t}$ are the eighth (i.e., last) half-hour return and the first half-hour return, respectively, on trading day t, and ε_t is an error term with mean equal to zero.

The first column in Table 1 reports the in-sample estimation results of the predictive regression in Eq. (2). The first half-hour return r_1 has a positive slope of 0.082 that is statistically significant at the 1% level, and generates an in-sample R^2 of 1.9%. Such a high predictive R^2 is impressive, not only because almost all monthly predictors have lower R^2s (see, e.g., Rapach and Zhou, 2013) but also because the R^2 from the U.S. intraday stock return is smaller (see Gao et al., 2018).

Gao et al. (2018) also find that the second-to-last half-hour return can positively predict the last half-hour return. With this in mind, we further run a time-series regression of $r_{8,t}$ on a constant and the second-to-last (i.e., seventh) half-hour return $r_{7,t}$,

$$r_{8,t} = \alpha + \beta_7 r_{7,t} + \varepsilon_t. \tag{3}$$

The second column in Table 1 reports the in-sample estimation results using the predictor of the seventh half-hour return. The seventh half-hour return r_7 predicts the last half-hour return r_8 with a positive slope of 0.182, statistically significant at the 1% level, and an in-sample R^2 of 2.9%. It is clear that the slope, Newey and West (1987) t-statistic, and predictive R^2 of the seventh half-hour return are substantially larger than those of the first half-hour return. This is, the intraday momentum of the seventh half-hour return is stronger than that of the first half-hour return, which is opposite to the finding from the U.S. stock market (see Gao et al., 2018).

Since r_1 and r_7 can predict r_8 individually, we wonder how do they predict r_8 jointly? For this motivation, we estimate the bivariate predictive regression of $r_{8,t}$ on a constant and both predictors of $r_{1,t}$ and $r_{7,t}$,

$$r_{8,t} = \alpha + \beta_1 r_{1,t} + \beta_7 r_{7,t} + \varepsilon_t. \tag{4}$$

The third column in Table 1 reports the in-sample predictive results using both predictors of r_1 and r_7. It is of interest that the slopes just change a little bit from their individual regression values. Furthermore, the joint R^2 is as high as 4.5%, which is nearly close to the sum of the individual R^2s. The evidence indicates that r_1 and r_7 are roughly independent and complementary in predicting the last half-hour return r_8, which is consistent with the finding from Zhang et al. (2018b) that the predictors with low correlation can provide complementary information that helps to enhance predictive ability.

In conclusion, the in-sample results demonstrate the existence of the intraday momentum not only between r_1 and r_8 but also between r_7 and r_8. Furthermore, the latter intraday momentum pattern is more pronounced. More importantly, r_1 and r_7 contain complementary information useful for forecasting the last half-hour return r_8.

3.2. Out-of-sample forecasting performance

The in-sample analysis of the intraday momentum is based on the entire sample estimation. However, at the monthly frequency, Welch and Goyal (2008) document that a long list of macroeconomic predictors suffers from an instability problem and their in-sample predictability is probably due to over-fitting issue, so that their predictability largely vanishes out-of-sample. That is, in-sample predictability does not necessarily imply out-of-sample predictability. Furthermore, out-of-sample forecasting is more useful in practical application as out-of-sample return forecasts can help financial practitioners to make their future investment decision. Therefore, out-of-sample forecasting is a more stringent test for return predictability. Given this, we focus on out-of-sample tests in the following empirical analysis.

To generate out-of-sample forecasts of the last half-hour return, we use a recursive (expanding) estimation window, as in Rapach et al. (2010), Neely et al. (2014), and Gao et al. (2018), among others. Specifically, we divide the entire sample consisting of T observations into an in-sample portion consisting of the first m observations and an out-of-sample portion consisting of the last q observations. For example, when we use regression (2), the first out-of-sample forecast of the eighth half-hour return is given by

$$\widehat{r}_{8,m+1} = \widehat{\alpha}_m + \widehat{\beta}_{1,m} r_{1,m+1}, \tag{5}$$

where $\widehat{\alpha}_m$ and $\widehat{\beta}_{1,m}$ are the ordinary least squares (OLS) estimates of α and β_1, respectively, in regression (2) generated by regressing $\{r_{8,t}\}_{t=1}^{m}$ on a constant and $\{r_{1,t}\}_{t=1}^{m}$. The next out-of-sample forecast is calculated as

$$\widehat{r}_{8,m+2} = \widehat{\alpha}_{m+1} + \widehat{\beta}_{1,m+1} r_{1,m+2}, \tag{6}$$

where $\widehat{\alpha}_{m+1}$ and $\widehat{\beta}_{1,m+1}$ are generated by regressing $\{r_{8,t}\}_{t=1}^{m+1}$ on a constant and $\{r_{1,t}\}_{t=1}^{m+1}$. Proceeding in this manner through the end of the out-of-sample period, we can obtain a series of q out-of-sample forecasts of the eighth half-hour return, $\{\widehat{r}_{8,t}\}_{t=m+1}^{T}$. Using a similar manner, we can also generate the out-of-sample based on regressions (3) and (4). As in

Table 1
In-sample predictability.

Predicator	(1)	(2)	(3)
	r_1	r_7	r_1 and r_7
β_1	0.082*** (5.601)		0.076*** (5.077)
β_7		0.182*** (6.694)	0.173*** (6.429)
Intercept	0.064*** (10.360)	0.060*** (9.236)	0.064*** (10.198)
R^2	0.019	0.029	0.045

This table reports the in-sample results of regressing the last half-hour return r_8 on the first half-hour return r_1 and/or the seventh half-hour return r_7. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January 4, 2000 to December 30, 2016.

Gao et al. (2018), our in-sample period spans from January 4, 2000 through December 31, 2004, consisting of 1197 observations over five years. As a result, we obtain a desirable trade-off between an initial in-sample estimation period that has enough observations to precisely estimate parameters and an out-of-sample period that has a relatively long length for forecast evaluation.

Following the convention in return forecasting (see, e.g., Campbell and Thompson, 2008; Rapach et al., 2010; Zhu and Zhu, 2013; Neely et al., 2014; Huang et al., 2015; Narayan and Bannigidadmath, 2015; Narayan and Gupta, 2015; Rapach et al., 2016; Jiang et al., 2017; Gao et al., 2018; Narayan et al., 2018; Wang et al., 2018; Zhang et al., 2018a), we use the out-of-sample R^2 statistic to evaluate the out-of-sample predictive accuracy of the forecasting model of interest relative to the prevailing historical average benchmark, which is calculated as $\overline{r}_{8,t+1} = 1/t\sum_{k=1}^{t} r_{8,t}$. The seminal study of Welch and Goyal (2008) finds that the historical average is very difficult to be outperformed by many popular predictors. The out-of-sample R^2 statistic is given by

$$R_{OS}^2 = 1 - \frac{\sum_{t=m+1}^{T}(r_{8,t} - \widehat{r}_{8,t})^2}{\sum_{t=m+1}^{T}(r_{8,t} - \overline{r}_{8,t})^2}, \tag{7}$$

where $r_{8,t}$, $\overline{r}_{8,t}$, and $\widehat{r}_{8,t}$ are the actual return, historical average, and return forecast, respectively, of the last half-hour on trading day t, and m and T are the lengths of the initial estimation period and entire sample period, respectively.

The R_{OS}^2 statistic measures the reduction in mean squared forecast error (MSFE) for the return forecast relative to the prevailing historical average. To further ascertain whether a forecasting model yields a statistically significant improvement in MSFE, the Clark and West (2007) statistic is employed. Specifically, the Clark and West (2007) statistic tests the null hypothesis that the MSFE of the benchmark model is less than or equal to the MSFE of the forecasting model of interest against the alternative hypothesis that the MSFE of the benchmark model is greater than the MSFE of the forecasting model of interest. Mathematically, the Clark and West (2007) statistic is calculated by first defining

$$f_t = (r_{8,t} - \overline{r}_{8,t})^2 - (r_{8,t} - \widehat{r}_{8,t})^2 + (\overline{r}_{8,t} - \widehat{r}_{8,t})^2. \tag{8}$$

By regressing $\{f_s\}_{s=m+1}^{T}$ on a constant, we can obtain the Clark and West (2007) statistic that is equivalent to the t-statistic corresponding to the constant. Furthermore, a p-value for the one-sided (upper-tail) test is readily obtained with the standard normal distribution.

Panel A of Table 2 reports the overall out-of-sample forecasting performance using the first half-hour return r_1, the seventh half-hour return r_7, and both of them. Consistent with the in-sample estimation results, the first half-hour return individually yields the R_{OS}^2 of 2.080% and the seventh half-hour return individually yields a higher R_{OS}^2 of 2.786%. When we use the two predictors jointly, the R_{OS}^2 achieves the highest value of 4.545%, which is roughly equal to the sum of the individual R_{OS}^2s. This evidence suggests that the out-of-sample predictive power of r_1 and r_7 is also complementary. In addition, it is clear that all the R_{OS}^2s are statistically significant at the 1% level. Moreover, these sizeable R_{OS}^2s not only match or exceed those at the monthly frequency but also are at least twice as large as the U.S. ones found by Gao et al. (2018).

Overall, we find the intraday return predictability in the Chinese stock market due to the presence of the intraday momentum. Compared to the U.S. stock market, the Chinese intraday return predictability is substantially stronger. In addition, the second-to-last (i.e., seventh) half-hour return exhibits a more powerful predictive ability to forecast the last half-hour return than the first half-hour return in the Chinese stock market, which is, however, opposite in the U.S. stock market (see Gao et al., 2018).

Table 2
Out-of-sample predictability.

Predictor	Panel A: Overall performance	Panel B: Subsamples divided by the global financial crisis			
		GFC	Excluding GFC	Before GFC	After GFC
r_1	2.080***	0.590**	2.633***	3.262***	2.332***
r_7	2.786***	2.135**	3.027***	0.517*	4.226***
r_1 and r_7	4.545***	2.474***	5.314***	3.469***	6.194***

This table reports the out-of-sample R-square in percentage, R^2_{OS} (%). The last half-hour return r_8 is recursively predicted by the first half-hour return r_1 and/or the seventh half-hour return r_7. Particularly, Panel A reports the R^2_{OS}s with respect to the entire out-of-sample period. Panel B reports the R^2_{OS}s for subsample periods that are divided by the global financial crisis (GFC). The period of GFC, the period excluding GFC, the period before GFC, and the period after GFC are considered. Statistical significance for R^2_{OS} statistic is based on the p-value for the Clark and West (2007) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

3.3. Global financial crisis

The monthly momentum strategy is found to perform poorly during the recent global financial crisis (GFC). It is thus interesting to examine how well the intraday momentum performs in this crisis. Similar with the related studies (see, e.g., Rapach et al., 2010; Neely et al., 2014; Huang et al., 2015; Jiang et al., 2017; Wang et al., 2018), we calculate the R_{OS}^2 statistic separately for the period of GFC, the period excluding GFC, the period before GFC, and the period after GFC,

$$R_{OS,c}^2 = 1 - \frac{\sum_{t=m+1}^{T} I_t^c (r_{8,t} - \widehat{r}_{8,t})^2}{\sum_{t=m+1}^{T} I_t^c (r_{8,t} - \overline{r}_{8,t})^2} \text{ for } c = \text{GFC, excluding GFC, before GFC, after GFC}, \tag{9}$$

where I_t^c is an indicator that takes a value of one when the trading day t belongs to the period of c and zero otherwise.

Panel B of Table 2 reports the R_{OS}^2s for the four periods that are divided based on the GFC. First, we can see that the intraday momentum is greatly stronger during the non-GFC period than during the GFC period. This evidence is consistent with the finding of the standard monthly momentum but opposite to the U.S. intraday momentum of Gao et al. (2018). Second, the intraday momentum for the pre-crisis period is mainly concentrated in the first half-hour return, while we observe the intraday momentum in both the first and seventh half-hour returns for the post-crisis period. Overall, the intraday predictability of the first half-hour return only exists during the non-GFC period, while the intraday predictability of the seventh half-hour return disappears before the GFC, arises during the GFC, and further strengthens after the GFC.

3.4. The impacts of volatility, volume, and liquidity

First, to explore the impact of return volatility on the intraday momentum, we sort all the trading days, according to their first half-hour realized volatility, into three terciles: high, medium, and low volatility days. Consistent with Eq. (9), we calculate the R_{OS}^2 statistic separately for high volatility days ($R_{OS,\text{high}}^2$), median volatility days ($R_{OS,\text{median}}^2$), and low volatility days ($R_{OS,\text{low}}^2$),

$$R_{OS,c}^2 = 1 - \frac{\sum_{t=m+1}^{T} I_t^c (r_{8,t} - \widehat{r}_{8,t})^2}{\sum_{t=m+1}^{T} I_t^c (r_{8,t} - \overline{r}_{8,t})^2} \quad \text{for } c = \text{high, median, and low}, \tag{10}$$

where I_t^{high} ($I_t^{\text{median}}, I_t^{\text{low}}$) is an indicator that takes a value of one when the trading day t belongs to the high (median, low) volatility group and zero otherwise.

Panel A of Table 3 reports the R_{OS}^2s under different levels of return

Table 3
The impacts of volatility, volume and liquidity on out-of-sample predictability.

Predictor	Panel A: Volatility			Panel B: Trading volume			Panel C: Illiquidity	
	High	Median	Low	High	Median	Low	High	Low
r_1	2.232***	2.022***	0.450*	0.739***	3.906***	0.450*	5.201***	−0.057*
r_7	2.929***	2.541***	1.858***	3.402***	3.265***	0.955**	5.676***	0.804**
r_1 and r_7	4.855***	4.123***	2.196***	3.685***	6.830***	2.996***	9.439***	1.191***

This table reports the out-of-sample R-square in percentage, R^2_{OS} (%), under different levels of volatility (Panel A), trading volume (Panel B), or illiquidity (Panel C). The last half-hour return r_8 is recursively predicted by the first half-hour return r_1 and/or the seventh half-hour return r_7. In Panel A, the first half-hour volatility is estimated using 1-min returns. Then, all the trading days are ranked into three terciles by their first half-hour volatility: high, medium, and low. In Panel B, to take into account the increasing trading volume over time, we also rank the trading days into high, medium, and low terciles by their first half-hour trading volume year by year, and then combine each volume tercile across all years to form three volume groups. In Panel C, we further rank the trading days into two groups according to their Amihud illiquidity measure. Statistical significance for R^2_{OS} statistic is based on the p-value for the Clark and West (2007) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

volatility. Two important findings emerge. First, compared to the R^2_{OS}s over the entire out-of-sample period, we observe a similar pattern in each volatility tercile. That is, the seventh half-hour return yields a higher R^2_{OS} than the first half-hour return, and the joint R^2_{OS} based on the two predictors achieves the highest value. Second and more importantly, the intraday momentum appears to have a positive relationship with volatility. Higher volatility will result in greater predictability. This interesting finding is consistent with the empirical results of Zhang (2006) that the greater the uncertainty, the stronger the persistence of a trend. In our context, the larger the volatility, the stronger the intraday momentum.

Second, to explore the impact of trading volume on the intraday momentum, we also sort the trading days into high, medium, and low volume terciles by their first half-hour trading volume year by year due to the increasing trading volume over time. Then, we obtain three volume groups by combining each volume tercile across all years. Similar to the definition in Eq. (10), we calculate the R^2_{OS} statistic separately for high volume days ($R^2_{OS,\text{high}}$), median volume days ($R^2_{OS,\text{median}}$), and low volume days ($R^2_{OS,\text{low}}$).

Panel B of Table 3 reports the R^2_{OS}s under different levels of trading volume. The impact of trading volume on the intraday momentum seems to be mixed. Overall, the intraday momentum is relatively strong during the median volume days, suggesting that extreme volume reduces the intraday return predictability.

Third, to explore the impact of liquidity on the intraday momentum, we sort all the trading days into a high group and a low group according to their stock liquidity. Following Amihud (2002), we compute the illiquidity measure as the ratio of the absolute stock return to the dollar trading volume. Therefore, the high (low) illiquidity group contains the trading days with low (high) liquidity. Similar to the definition in Eq. (10), we calculate the R^2_{OS} statistic separately for high illiquidity days ($R^2_{OS,\text{high}}$) and low illiquidity days ($R^2_{OS,\text{low}}$).

Panel C of Table 3 reports the R^2_{OS}s for the high and low illiquidity days. It is evident that the intraday momentum is greatly stronger for high illiquidity (less liquidity) days. This is intuitive as predictive information is more difficult to exploit when stock market lacks liquidity.

3.5. The role of economic variables

Extensive literature studies the role of economic variables in forecasting monthly stock returns (see, e.g., Campbell and Thompson, 2008; Welch and Goyal, 2008; Rapach et al., 2010; Goh et al., 2013; Pettenuzzo et al., 2014). Given this, we follow Sun et al. (2016) and further investigate the role of economic variables in forecasting intraday returns. Welch and Goyal (2008) recommend 14 widely used economic variables at monthly frequency. In this study, we rely on two of them, risk-free interest rate and stock return realized volatility, which are available at daily frequency in China. We separately incorporate risk-free interest rate, realized volatility, or both of them into the predictive regression models (2), (3), and (4). That is, we forecast the last half-hour return depending on both the intraday momentum and economic variables.

Table 4 reports the R^2_{OS}s when we further consider the role of two popular economic variables. The out-of-sample forecasting results are comparable when we include or exclude the economic variables. Moreover, there is a slight decline in R^2_{OS} when we incorporate the economic variables. This evidence suggests that the role of economic variables is scarce and the two economic variables can hardly explain or impact the intraday momentum, which is consistent with the finding of Sun et al. (2016).

3.6. Explanations

Both the in- and out-of-sample tests above provide convincing evidence on the intraday momentum of the Chinese stock market from a statistical perspective. It is interesting to explore what economic driving forces are behind it. To this end, we provide two explanations, as in Gao et al. (2018).

First, Bogousslavsky (2016) proposes a model of infrequent rebalancing that can explain the predictability pattern in the intraday stock returns. Specifically, Bogousslavsky (2016) theoretically shows that our intraday momentum can be driven by some investors' infrequent rebalancing to their portfolios. These investors simply delay their rebalancing trading to near the market close instead of market open probably because of the slow-moving of capital. Intuitively, trading in the last half-hour in the same direction as the first half-hour would result in a positive correlation between the two half-hour returns, thus generating the intraday momentum pattern.

Second, the intraday momentum is probably driven by the presence of late-informed investors. Let us consider a trading day with good news

Table 4
The role of economic variables.

Predictor	Risk-free rate	Volatility	Risk-free rate and Volatility
r_1	1.988***	2.068***	1.977***
r_7	2.728***	2.771***	2.714***
r_1 and r_7	4.436***	4.528***	4.419***

This table reports the out-of-sample R-square in percentage, R^2_{OS} (%), when we further consider the role of two popular economic variables (i.e., risk-free interest rate and stock return volatility). The last half-hour return r_8 is recursively predicted by one of the predictors given in the first column (the first half-hour return r_1, the seventh half-hour return r_7, or both of them) and one of the predictors given in the first row (risk-free rate, volatility, or both of them). Statistical significance for R^2_{OS} statistic is based on the p-value for the Clark and West (2007) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

released before the market open. Some investor may react quickly and buy equities promptly in the first half-hour, delivering a positive first half-hour return. However, some other investors who are late-informed may receive the news later or process the news too tardily to react in the first half-hour. Some empirical evidence supports the presence of late-informed investors. For example, Baker and Wurgler (2006) and Huang et al. (2015) find that investors still react to month old sentiment measures. In addition, Cohen and Frazzini (2008) show that in the presence of the constraint of investor attention, stock prices do not promptly incorporate news, and information transmission can last up to a month. Hence, information processing can easily take more than a whole day. If the late-informed investors chase to buy equities, the last half-hour is a relatively good choice because it is the highest liquid period since the first half-hour. Intuitively, buying in the same direction as the first half-hour can deliver a positive return in the last half-hour, therefore generating the positive correlation between the two half-hour returns, i.e., the intraday momentum.

Fig. 1 plots the trading volume pattern from the first half-hour to the last. We can clearly see a U-shape, in which the first and the last half hours have considerably higher trading volume than the remaining half hours. From an economic point of view, the U-shaped pattern of trading volume results from the digestion of new information in the first half-hour and the desire of trading in the last half-hour for avoiding overnight risk or for settlement. To support the two explanations, we also provide the evidence regarding the other half-hour returns in Section 5.3.

Finally, we also provide two potential explanations for the stronger intraday momentum in the Chinese market. First, Gao et al. (2018) document that the intraday momentum for the U.S. stock market is concentrated in the financial crisis. On the contrary, as evidenced in Section 3.3, the intraday momentum for the Chinese stock market is concentrated in the non-GFC period. The non-GFC period is greatly longer than the GFC period, which probably results in the stronger intraday momentum in the Chinese market. Second, Gao et al. (2018) and our study both provide evidence that the intraday momentum increases with the increase of volatility and decrease with the increase of liquidity. We learn from the financial common sense that the Chinese stock market exhibits higher volatility and lower liquidity than the U.S. market. For example, the first half-hour realized volatility for the Chinese stock market is 0.874 (in percentage), while the first half-hour realized

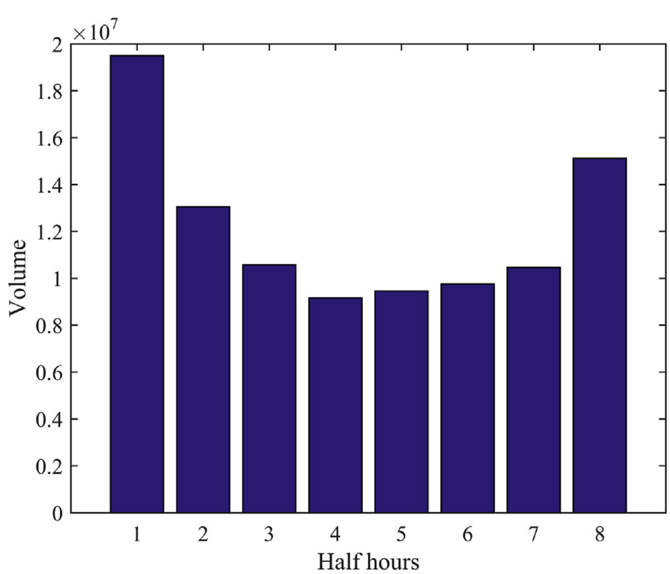

Fig. 1. Average 30-min trading volume in eight half-hour intervals. For each 30-min interval, this plot shows the average trading volume for Shanghai Composite Index throughout the entire sample period from January 4, 2000 through December 30, 2016. Each half-hour interval is labeled from 1 to 8 sequentially on the x-axis.

volatility for the U.S market (S&P 500 index) during the same sample period is 0.236, which is much smaller.[3] Furthermore, the public data of the Oxford-Man Institute's Realized Library show that the volatility of the Chinese market is larger not only than that of the U.S. market but also than those of most international stock markets.[4] Therefore, the stronger intraday momentum in the Chinese market can be also attributed to its high volatility and low liquidity (high illiquidity).

4. Economic significance

In this section, we further measure the economic value of our intraday momentum from both the asset allocation and market timing perspectives. Timing strategies only use the signs of the predictors r_1 and r_7, while asset allocation exercises utilize both the signs and magnitudes of predictors to forecast the expected last half-hour returns.

4.1. Asset allocation

Following Campbell and Thompson (2008), Rapach et al. (2010), Neely et al. (2014), Rapach et al. (2016), and Gao et al. (2018), among others, we compute the certainty equivalent return (CER) for a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills using the last half-hour return forecasts. At the end of the second-to-last half-hour, the investor optimally allocates the weight of equities during the last half-hour on trading day t as

$$w_t = \frac{1}{\gamma}\frac{\widehat{r}_{8,t} - r_{f,t}}{\widehat{\sigma}^2_{8,t}}, \tag{11}$$

where γ is the investor's coefficient of relative risk aversion, $\widehat{r}_{8,t}$ and $r_{f,t}$ denote the last half-hour return forecast and risk-free rate, respectively, on day t, and $\widehat{\sigma}^2_{8,t}$ denotes a variance forecast of the last half-hour returns. Similar to Campbell and Thompson (2008), Rapach et al. (2010), Neely et al. (2014), and Rapach et al. (2016), we estimate the volatility forecast using a one-year moving window of past returns for the last half-hour.[5] In addition, we restrict w_t to lie between 0 and 1.5 to preclude short sales and to allow no more than 50% leverage (see, e.g., Campbell and Thompson, 2008; Rapach et al., 2010; Neely et al., 2014; Jiang et al., 2017). To be more realistic, we also impose a relatively loose constraint on portfolio weights, where w_t is restricted to lie between −0.5 and 1.5, implying that the investor is allowed to short or borrow 50% on margin (see also Rapach et al., 2016; Gao et al., 2018).

The investor who uses Eq. (11) to allocate her wealth can realize the portfolio return of

$$R_t = w_t r_{8,t} + (1 - w_t) r_{f,t} \tag{12}$$

on trading day t. With respect to the entire out-of-sample period, the realized CER is given by

$$CER = \overline{R}_p - 0.5\gamma\sigma^2_p, \tag{13}$$

where $\overline{R}_p$ and σ^2_p are the mean and variance, respectively, of the portfolio returns over the out-of-sample evaluation period. The CER gain is computed as the difference between the CER for the investor when she employs one of the last half-hour return forecast and the CER when she

[3] The intraday data of S&P 500 index are available from the Thomson Reuters Tick History Database.

[4] The data of the Oxford-Man Institute's Realized Library are available at https://realized.oxford-man.ox.ac.uk/.

[5] The results of asset allocation are similar for other reasonable window sizes of volatility estimation. For the sake of brevity, we do not report the robust results, but they are available upon request.

just depends on the prevailing historical average forecast, so that it can be interpreted as the portfolio management fee that the investor would be willing to pay to have access to the return forecast in instead of the simple mean forecast.

Table 5 reports the asset allocation results. Panel A of Table 5 presents the economic values when equity weights are restricted to the range from 0 to 1.5. The historical average forecasts $\bar{r}_8$ generate the lowest average portfolio return of 20.388% per annum. In contrast, the first half-hour return r_1 and the seventh half-hour return r_7 individually yields much higher average return, reaching roughly 25% per annum. Consistent with the statistical evaluation above, r_7 yields a slightly higher average return than r_1. Furthermore, combining the two predictors, r_1 and r_7, delivers the highest average return of 29.156% per annum.

Of course, it is necessary to take risk into account. Surprisingly, the last half-hour return forecast with a higher average portfolio return consistently generates a lower standard deviation. In particular, the historical average forecasts $\bar{r}_8$ generate the highest standard deviation of 12.698% and combining the two predictors generates the lowest standard deviation of 9.539%. Consequently, the rank of the used return forecasts for portfolio performance does not change after considering risk. Specifically, the Sharpe ratio and CER of the historical average forecasts are lowest, whereas combining r_1 and r_7 to predict r_8 yields the largest Sharpe ratio and CER. Again, r_7 yields slightly higher values of Sharpe ratio and CER than r_1. Finally, the sizeable and positive CER gains also demonstrate the impressive economic values of our intraday momentum.

Panel B of Table 5 presents the economic values when equity weights are restricted to the range from −0.5 to 1.5. Under this relatively loose constraint, we obtain a stronger performance. More importantly, we find that the results are robust to alternative portfolio constraints.

Overall, the mean-variance investor who switches from using a random walk model to using the intraday momentum can realize sizable economic gains. In addition, a notable finding is that our economic gains based on the Chinese stock market are substantially greater than the ones based on the U.S. stock market found by Gao et al. (2018), which is consistent with the previous results of statistical evaluation.

4.2. Market timing

Instead of using both the signs and magnitudes of the predictors to forecast the last half-hour returns in asset allocation exercises, we use only the signs to form timing strategies. In contrast to asset allocation, market timing has an appealing advantage that the investor's relative risk aversion is free. In the market timing test, we follow Gao et al. (2018) and use the first and seventh half-hour returns as timing signal to trade the market during the last half-hour. More specifically, we will take a long position in the market at the beginning of the last half-hour if the timing signal is positive, and take a short position otherwise. It is worthy to note that the long or short position should be closed at the end of the last half-hour on each trading day.[6]

First, we use the first half-hour return r_1 as the trading signal. Consequently, the market timing strategy based on the signal of r_1 on trading day t will realize a return in the last half-hour as

$$\eta(r_1) = \begin{cases} r_8, & \text{if } r_1 > 0; \\ -r_8, & \text{if } r_1 \le 0. \end{cases} \tag{14}$$

Second, when using the seven half-hour return r_7 as the trading signal on day t, we can realize a return in the last half-hour as

$$\eta(r_7) = \begin{cases} r_8, & \text{if } r_7 > 0; \\ -r_8, & \text{if } r_7 \le 0. \end{cases} \tag{15}$$

Third, combining r_1 and r_7, we take a long position only if both of the two returns are positive, and take a short position only if both of them are negative. Otherwise, we choose to stay out of the market. Consequently, the realized return can be calculated as

$$\eta(r_1, r_7) = \begin{cases} r_8, & \text{if } \ r_1 > 0 \text{ and } r_7 > 0; \\ -r_8, & \text{if } \ r_1 \le 0 \text{ and } r_7 \le 0; \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

Finally, we also consider two benchmark strategies. The first benchmark is the Always Long strategy, in which we always take a long position at the beginning of the last half-hour and close it at the end. The second is the prevailing Buy-and-Hold strategy, where we buy equities at the beginning of the sample period, and hold it until the end of the whole sample period.

The market timing results are reported in Table 6. The two benchmark strategies exhibit relatively low economic values. In particular, the prevailing Buy-and-Hold strategy generates the smallest average return and the greatest standard deviation, thereby leading to the lowest Sharpe ratio of 0.410. In contrast, all of the three timing strategies based on our

Table 5
Asset allocation.

Predictor	Avg Ret (%)	Std Dev (%)	Sharpe ratio	CER (%)	CER gain (%)
Panel A: Equity weights are restricted to lie between 0 and 1.5.					
$\bar{r}_8$	20.388	12.698	1.582	17.969	–
r_1	24.838	10.647	2.305	23.138	5.169
r_7	25.473	10.121	2.488	23.936	5.967
r_1 and r_7	29.156	9.539	3.026	27.791	9.822
Panel B: Equity weights are restricted to lie between −0.5 and 1.5.					
$\bar{r}_8$	20.388	12.698	1.582	17.969	–
r_1	25.953	10.842	2.367	24.190	6.221
r_7	27.627	10.364	2.637	26.016	8.047
r_1 and r_7	31.885	9.860	3.204	30.427	12.458

This table reports the results of asset allocation exercise. The economic values are based on a mean-variance investor with a relative risk aversion of three who allocates between equities and risk-free bills using the last half-hour return forecasts. The last half-hour return r_8 is recursively predicted by the first half-hour return r_1 and/or the seventh half-hour return r_7, or the historical average $\bar{r}_8$. In particular, we report the average return (Avg Ret), standard deviation (Std Dev), Sharpe ratio, certainty equivalent return (CER), and CER gain of the realized portfolio returns, which are annualized and in percentage. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

Table 6
Market timing.

Timing strategy	Avg Ret (%)	Std Dev (%)	Sharpe ratio
$\eta(r_1)$	15.641	8.452	1.816
$\eta(r_7)$	15.574	8.453	1.808
$\eta(r_1,r_7)$	15.607	6.030	2.540
Always Long	13.689	8.465	1.582
Buy-and-Hold	11.545	27.478	0.410

This table reports the market timing results. The timing strategies of $\eta(r_1)$ and $\eta(r_7)$ take a long position in the market if r_1 and r_7, respectively, are positive, and a short position if the corresponding returns are negative. The joint strategy of $\eta(r_1,r_7)$ trades only when both r_1 and r_7 have the same sign – takes a long position when both are positive and a short position when both are negative. The benchmark of Always Long is to invest in the market during the last half-hour on each trading day, while the Buy-and-Hold benchmark is to buy and hold the market throughout the sample period. For each timing strategy, we report the average return (Avg Ret), standard deviation (Std Dev), and Sharpe ratio. The returns are annualized and in percentage.

[6] Note that the Chinese stock market has a T+1 trading rule that investors are not allowed to buy equities and then sell them within a same day. Hence, it is difficult to implement the market timing strategy in the Chinese stock market. However, we still employ the market timing test for the consideration of referential meaning. Furthermore, it becomes feasible to take a short position since the Chinese market implements a new rule of securities margin trading in 2010.

Table 7
Out-of-sample performance from 2010 to 2016.

Predictor	R^2_{OS} (%)	CER gain (%)	Sharpe ratio
r_1	2.099***	6.016	2.055
r_7	4.349***	8.615	2.415
r_1 and r_7	6.071***	13.563	3.157

This table reports the out-of-sample performance, in which the initial estimation period is from January 4, 2000 through December 31, 2009, while the out-of-sample period is from January 4, 2010 through December 30, 2016. In terms of statistical evaluation, we report the R^2_{OS} in percentage. Statistical significance for R^2_{OS} statistic is based on the p-value for the Clark and West (2007) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. From an asset allocation perspective, we report certainty equivalent return (CER) gain and Sharpe ratio of the realized portfolio returns, which are annualized and in percentage. Specifically, the CER gain and Sharpe ratio are calculated based on a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills. The equity weights are restricted to lie between −0.5 and 1.5.

intraday momentum deliver substantially higher economic values. In particular, the $\eta(r_1, r_7)$ strategy using both the signs of the first and seventh half-hour returns have the highest Sharpe ratio of 2.540. The evidence suggests that our intraday momentum can also generate positive economic gains from the market timing perspective.

5. Robustness and extensions

In this section, we present a number of extensions and robustness checks to further investigate and validate the main findings presented in Sections 3 and 4.

5.1. Alternative forecasting windows

Rossi and Inoue (2012) and Inoue et al. (2017) argue that the arbitrary choices of estimation window sizes may result in quite different out-of-sample results in practical applications. Therefore, the initial estimation window size plays an important role in out-of-sample evaluation. With this in mind, we further use a different forecasting window, where the initial estimation period is from January 4, 2000 through December 31, 2009, while the out-of-sample period is from January 4, 2010 through December 30, 2016. It is worthy to note that the global financial crisis is incorporated in the out-of-sample period of the first forecasting window above and in the in-sample period of the second forecasting window here, so that we can examine the robustness of our previous findings for the impact of the global financial crisis.

Table 7 reports the out-of-sample results for the new forecasting window, where equity weights are restricted to the range between −0.5 and 1.5.[7] In short, we find a robust result that our intraday momentum still generates considerable forecasting gains from both statistical and economic perspectives. Particularly, using the seventh half-hour return to predict the last half-hour return exhibits stronger predictive power than using the first half-hour return, and using the two predictors jointly further improve the out-of-sample forecasting performance. A slight difference is that the forecasting gain using the seventh half-hour return relative to using the first half-hour return is much greater after the global financial crisis than the one before the global financial crisis.

To further investigate out-of-sample forecasting performance based on either estimation window sizes, we plot the time-series differences between the cumulative squared forecast error (CSFE) for the benchmark forecast of historical average and the CSFE for the forecasts based on the intraday momentum in Fig. 2. The informative graphical device provides

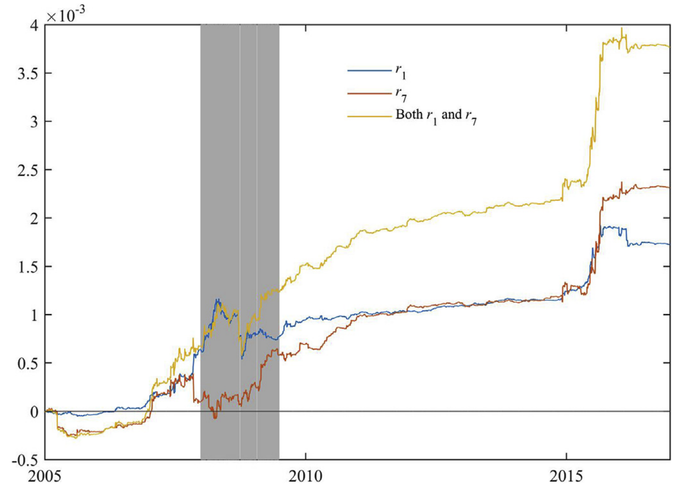

Fig. 2. Cumulative squared forecast errors of the intraday momentum forecasts against the historical average benchmark forecasts. The solid lines recursively depict the time-series differences between the cumulative squared forecast error (CSFE) for the benchmark forecast of historical average and the CSFE for the forecasts based on the intraday momentum, including the first half-hour return r_1, the seventh half-hour return r_7, and both of them. Vertical bar depicts the period of the global financial crisis. The sample period is from January 4, 2005 through December 30, 2016.

a visual impression about the consistency of each momentum model's out-of-sample performance over time. When one of the curves in Fig. 2 increases, the corresponding momentum model outperforms the benchmark model, whereas the opposite holds when a curve decreases. As evidenced in Fig. 2, the curves of our intraday momentum models generally change with a positive slope despite a fluctuation during the global financial crisis. This suggests that the intraday momentum can commonly lead to a positive return predictability over time. Furthermore, consistent with the previous results, the curve based on both the first and seventh half-hour returns increases more rapidly than the curves based on the individual predictors.

5.2. Alternative risk aversion choices

Our previous analysis of asset allocation is based on the assumption that the mean-variance investor has a relative risk aversion coefficient of $\gamma = 3$. To investigate the sensitivity of our results to this parameter, we further consider three reasonable values of risk aversion coefficient, namely, $\gamma = 2$, 4, and 6.

Table 8 provides the asset allocation results for alternative risk aversion coefficients, where equity weights are restricted to the range between −0.5 and 1.5.[8] In short, we observe a consistent pattern as shown in Table 5. That is, our asset allocation results are robust to alternative risk aversion choices.

5.3. Other half-hour returns

Does the intraday momentum exist between the last half-hour return and other half-hour returns? To answer this question, we present the out-of-sample performance for each half-hour return in Table 9. Specifically, we generate the individual forecasts by regressing the last half-hour return on a constant and each return separately from the first half-hour to the seventh half-hour. In contrast to the first and seventh half-hour return, the individual returns from the second half-hour to the sixth show extremely poor out-of-sample performance from both statistical and

[7] The results are similar when we restrict portfolio weights to lie between 0 and 1.5. To save space, we omit the results, but they are available upon request.

[8] Again, we obtain similar results when portfolio weights are constrained to lie between 0 and 1.5.

Table 8
Asset allocation under alternative risk aversion coefficients.

Predictor	Avg Ret (%)	Std Dev (%)	Sharpe ratio	CER (%)	CER gain (%)
Panel A: Risk aversion coefficient of $\gamma = 2$					
$\bar{r}_8$	20.388	12.698	1.582	18.775	–
r_1	25.740	10.929	2.328	24.545	5.770
r_7	27.757	10.488	2.618	26.657	7.882
r_1 and r_7	31.800	9.945	3.168	30.810	12.035
Panel B: Risk aversion coefficient of $\gamma = 4$					
$\bar{r}_8$	20.388	12.698	1.582	17.163	–
r_1	26.128	10.729	2.408	23.826	6.663
r_7	27.681	10.265	2.668	25.573	8.411
r_1 and r_7	31.975	9.754	3.248	30.072	12.910
Panel C: Risk aversion coefficient of $\gamma = 6$					
$\bar{r}_8$	20.110	12.508	1.584	15.417	–
r_1	26.487	10.499	2.495	23.180	7.763
r_7	27.591	10.060	2.713	24.555	9.138
r_1 and r_7	31.638	9.532	3.288	28.912	13.495

This table reports the results of asset allocation exercise under alternative risk aversion coefficients. Panels A, B, and C provide the results for investors' risk aversion coefficients of 2, 4, and 6, respectively. The economic values are based on a mean-variance investor who allocates between equities and risk-free bills using the last half-hour return forecasts. Equity weights are constrained to lie between −0.5 and 1.5. The last half-hour return r_8 is recursively predicted by the first half-hour return r_1 and/or the seventh half-hour return r_7, or the historical average $\bar{r}_8$. In particular, we report the average return (Avg Ret), standard deviation (Std Dev), Sharpe ratio, certainty equivalent return (CER), and CER gain of the realized portfolio returns, which are annualized and in percentage. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

Table 9
Out-of-sample performance using each half-hour return.

Forecasting model	R^2_{OS} (%)	CER gain (%)	Sharpe ratio
r_1	2.080***	6.221	2.367
r_2	−0.021	−0.063	1.621
r_3	−0.006	−0.519	1.556
r_4	−0.083	−2.046	1.466
r_5	−0.095**	−1.139	1.607
r_6	0.034*	1.757	1.837
r_7	2.786***	8.047	2.637
r_1 and r_7	4.545***	12.458	3.204
Mean combination	1.503***	2.230	1.804
Principal component	1.363***	5.561	2.296

This table reports the out-of-sample performance using each half-hour return. In particular, the mean combination forecast is computed as the equal-weighted average of the seven individual forecasts based on the first seven half-hour returns. We also generate the principal component forecast by regressing the last half-hour return on a constant and the first principal component extracted from the first seven half-hour returns. In terms of statistical evaluation, we report the R^2_{OS} in percentage. Statistical significance for R^2_{OS} statistic is based on the p-value for the Clark and West (2007) test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. From an asset allocation perspective, we report certainty equivalent return (CER) gain and Sharpe ratio of the realized portfolio returns, which are annualized and in percentage. Specifically, the CER gain and Sharpe ratio are calculated based on a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills. The equity weights are restricted to lie between −0.5 and 1.5. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

economic perspectives. Most of them yield negative R^2_{OS}s and CER gains, suggesting that the historical average benchmark outperforms these predictors. The sixth half-hour return generates positive R^2_{OS} and CER gain, while these values are substantially smaller than the ones based on the first and/or seventh half-hour return.

Motivated by the related literature on return predictability (see, e.g., Rapach et al., 2010; Neely et al., 2014), we further consider two popular forecasting models. First, the mean combination forecast is computed as the equal-weighted average of the seven individual forecasts based on the first seven half-hour returns. Second, we also generate the principal component forecast by regressing the last half-hour return on a constant and the first principal component extracted from the first seven half-hour returns. The results of the two forecasting models are also reported in Table 9. Although the two forecasting models using all the information from the first seven half-hour returns yield better out-of-sample performance than not only the predictors from the second to the sixth half-hour returns but also the historical average benchmark, they are still outperformed by the first and seventh half-hour returns. The superior predictability of the first and seventh half-hour returns support the explanations of infrequent rebalancing and late-informed investors.

Furthermore, to compare the information content of each half-hour return for predicting the last half-hour return, we perform forecast encompassing tests. Harvey et al. (1998) propose a statistic for testing the null hypothesis that one forecast encompasses another forecast against the alternative hypothesis that the forecast does not encompass the other forecast.[9]

Table 10 reports the p-values of forecast encompassing tests. It is clear that the last half-hour return forecasts based on the first and seventh half-hour returns encompass the forecasts based on either of the remaining half-hour returns, whereas the forecasts based on either of the remaining half-hour returns do not encompass the forecasts based on the first or seventh half-hour return. This finding suggests that the first and seventh half-hour returns can provide additional information that is useful for forecasting the last half-hour returns beyond the information already contained in the remaining half-hour returns. On the contrary, the remaining half-hour returns do not contain information that is useful for forecasting the last half-hour returns beyond the information already contained in the first or seventh half-hour return. Moreover, the evidence from forecast encompassing tests supports our previous explanation regarding late-informed investors.

5.4. Half-day momentum

A feature of the trading mechanism in the Chinese stock market is that there is a 90-min lunch break from 11:30 to 13:00 (Beijing Time). Given this, we wonder whether some useful information is released during the lunch break. As evidenced in Table 9, the return in the fifth half-hour incorporating the lunch break yields negative R^2_{OS} and CER gain, suggesting that the information released in the lunch break is of little importance to investors who focus on the trading in the last half-hour. In addition, due to the presence of the special lunch break, we presume that some investors may trade the market in the afternoon according to the market performance in the morning. If so, there is probably a half-day momentum in the Chinese stock market. To explore the half-day momentum, we run a predictive regression of the afternoon return $r_{aft,t}$ on a constant and the morning return $r_{mor,t}$,

$$r_{aft,t} = \alpha + \beta_{mor} r_{mor,t} + \varepsilon_t. \tag{17}$$

Table 11 reports both the in- and out-of-sample results of the half-day momentum. The in-sample estimation results show that the morning return positively predicts the afternoon return with a slope of 0.103, statistically significant at the 1% level, and a notable R^2 of 1.3%. In spite of a decrease in R^2 relative to the half-hour momentum, the evidence from the half-day momentum is also impressive (see Rapach and Zhou, 2013). Furthermore, we obtain a consistent finding in the out-of-sample forecasting performance. The forecasting strategy based on the half-day momentum significantly surpasses the prevailing historical average

[9] For more details about forecast encompassing tests, see Harvey et al. (1998).

Table 10
Forecast encompassing tests.

Predictor	r_1	r_2	r_3	r_4	r_5	r_6	r_7
r_1	–	0.325	0.477	0.485	0.172	0.216	0.000
r_2	0.000	–	0.109	0.111	0.023	0.030	0.000
r_3	0.000	0.127	–	0.207	0.026	0.052	0.000
r_4	0.000	0.066	0.089	–	0.026	0.027	0.000
r_5	0.000	0.017	0.017	0.027	–	0.006	0.000
r_6	0.000	0.043	0.069	0.062	0.012	–	0.000
r_7	0.005	0.633	0.668	0.651	0.344	0.527	–

The table reports *p*-values for the Harvey et al. (1998) statistic for seven half-hour returns. The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the last half-hour return forecast based on one of the predictors given in the first column encompasses the forecast based on one of the predictors given in the first row, against the alternative hypothesis that the forecast given in the first column does not encompass the forecast given in the first row. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

Table 11
Half-day momentum.

Panel A: In-sample estimation results		
β_{mor}	*t*-stat	R^2
0.103***	5.165	0.013
Panel B: Out-of-sample performance		
R^2_{OS} (%)	CER gain (%)	Sharpe ratio
0.633***	7.201	2.066

This table reports the in- and out-of-sample results of the half-day momentum. We run a predictive regression of the afternoon return $r_{aft,t}$ on a constant and the morning return $r_{mor,t}$, $r_{aft,t} = \alpha + \beta_{mor} r_{mor,t} + \varepsilon_t$. For the in-sample results, we report the coefficient estimate of β_{mor}, its Newey and West (1987) robust *t*-statistic (*t*-stat), and predictive R^2. For the out-of-sample results, we first report the R^2_{OS} in percentage. Statistical significance for R^2_{OS} statistic is based on the *p*-value for the Clark and West (2007) test. From an asset allocation perspective, we also report certainty equivalent return (CER) gain and Sharpe ratio of the realized portfolio returns, which are annualized and in percentage. Specifically, the CER gain and Sharpe ratio are calculated based on a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills. The equity weights are restricted to lie between −0.5 and 1.5. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The initial estimation period is from January 4, 2000 through December 31, 2004, while the out-of-sample period is from January 4, 2005 through December 30, 2016.

benchmark from both statistical and economic perspectives. Overall, we find significant return predictability of the half-day momentum possibly due to the presence of the lunch break in the Chinese stock market.

6. Conclusion

This paper demonstrates the existence of the intraday momentum in the Chinese stock market. Both the first and second-to-last (i.e., seventh) half-hour returns can significantly predict the last half-hour return. The return predictability based on the intraday momentum is statistically significant both in- and out-of-sample. Compared with the intraday results for the U.S. stock market found by Gao et al. (2018), the intraday predictability of the Chinese stock market is substantially stronger. Another different finding is that the second-to-last half-hour return is more useful for predicting the last half-hour return than the first one in the Chinese stock market. In addition, we find that the intraday momentum is stronger over high volatility days, median trading volume days, and low liquidity days. Furthermore, this intraday predictability is unstable during the GFC period and much stronger during the non-GFC period. We also document that two popular economic variables can hardly explain or impact the intraday momentum. Finally, we conduct the exercises of asset allocation and market timing from an economic perspective. Using the intraday momentum to allocate asset and time the market both generates sizeable economic gains.

Theoretically, the intraday momentum is probably caused by the trading behavior of investors who infrequently rebalance their portfolios due to the slow-moving of capital, or late-informed investors who learn or process news slowly and have to trade near the market close. We provide some empirical evidence in support of the theoretical explanations. First, the trading volume displays a U-shape, indicating that investors are more likely to trade in the first and last half-hour. Second, forecast encompassing tests show that the first and seventh half-hour returns provide more information useful for predicting the last half-hour return than the remaining half-hour returns.

Since the Chinese stock market has a special trading mechanism of 90-min lunch break from 11:30 to 13:00 (Beijing Time), we further explore the half-day momentum. The return in the morning significantly predicts the return in the afternoon both in- and out-of-sample. Furthermore, an investor who learns information from the morning return to trade in the afternoon can realize substantial economic gains.

Finally, we provide some practical implications based on our empirical findings of the intraday momentum. Since the intraday momentum yields significantly positive economic gains, we suggest that investors should pay attention to the intraday momentum (i.e., the first and seventh half-hour return), especially, for high volatility and illiquid trading days. However, investors need not to exploit the information during the lunch break because of its uselessness. In terms of policymakers and market regulators, they should attempt to abolish the T+1 trading rule in the Chinese stock market. This is because the special trading rule makes the Chinese market inefficient and prevents investors employing the appealing intraday momentum.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.econmod.2018.08.009.

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