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Last hour momentum in the Chinese stock market

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Abstract

Purpose – To capture the last hour momentum over the intraday session, the authors develop a trading strategy for the exchange-traded fund (ETF) that is effective because of the T+0 trading rule. This strategy generates annualized excess return of 9.673%.

Design/methodology/approach – In this study, the authors identify a last hour momentum pattern in which the sixth (seventh) half-hour return predicts the next half-hour return by employing high frequency 2012–2017 data from the China Securities Index (CSI) 300 and its ETF.

Findings – Overall, both the predictability and the trading strategy are statistically and economically significant. In addition, the strategy performs more strongly on high volatility days, high trading volume days, high order-imbalance days and days without economic news releases than on other days.

Originality/value – Noise trading, late-information trading, infrequent rebalancing and disposition effects from retail investors may account for this phenomenon.

Keywords Last hour momentum, Intraday prediction, Chinese stock market, Exchange-traded fund, Information trading

Paper type Research paper

1. Introduction

As the second-largest economy in the world, China has substantially integrated with the global economy over the past three decades. By contrast, the Chinese stock markets are highly different from those in the USA and other developed economies due to its strict capital regulations. In this sense, foreign (domestic) investors have had very few opportunities to invest in Chinese (foreign) stock markets despite the Qualified Foreign Institutional Investor and Qualified Domestic Institutional Investor programs. Moreover, according to the 2018 Shanghai Stock Exchange Statistical Yearbook, retail investors account for 82% of trading. Although the average trading volume for each half-hour exhibits a U-shaped pattern in Figure 1, which is similar to the US stock markets, the average intraday volatility is very similar across the time intervals. The results also provide evidence that retail investors provide most of the liquidity that is a major difference between USA and China.

Beyond that, the uniqueness of its trading rules in the Chinese stock markets, which include short-selling constraints, the "T+1 trading rule" and daily fluctuation limit, profoundly influences investor trading behavior. In particular, the "T+1 trading rule" prohibits investors buying and selling stocks on the same day. Therefore, the best strategy for liquidity is to buy in the today's market close and sell in the next day's market open, which is the main reason for the U-shaped pattern exhibited by intraday volume. Moreover, the "T+1 trading rule" is intended to prohibit the excessive speculative trading that occurred in the early 1990s, when a "T+0 trading rule" was in force. As stated by the authorities, the "T+1 trading rule" protects the interests of retail investors. As proven by theory and the empirical analysis of Guo *et al.* (2012), this regulatory regime reduces price volatility and total

JEL Classification — G11, G14, G17

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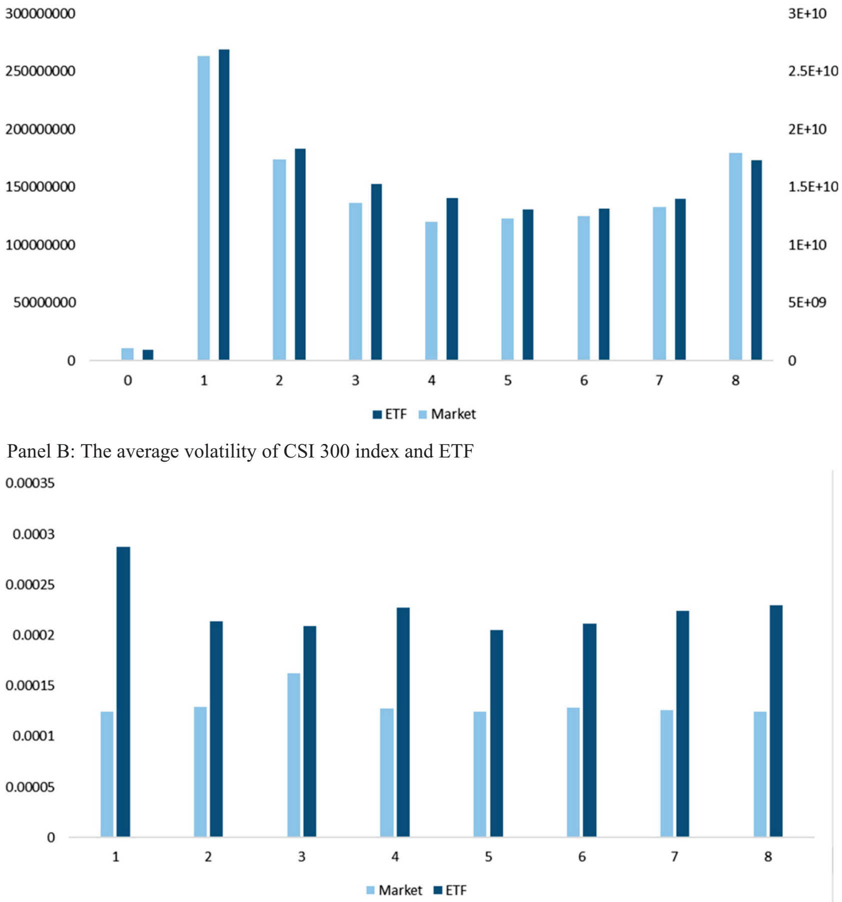
Panel A: The average trading volume of CSI 300 index and ETF



Note(s): Period from May 28, 2012, through December 31, 2017. Label 0 denotes the morning session begins with centralized competitive pricing from 09:15 to 09:25. After the centralized competitive pricing session, each 30-minute period consecutive bidding session is from 9:30am to 3:00pm with labels from 1 to 8 sequentially. The left side axis denotes the average trading volume for CSI 300 index ETF while the right side axis denotes the average trading volume for CSI 300 index. Deep blue denotes the CSI 300 index ETF and light blue denotes the CSI 300 index, respectively

Figure 1.
The average trading volume and volatility of CSI 300 index and ETF for every 30 min

trading volume and enhances the welfare of trend chasers when trend-chasing is predominant. This also explains the similarity of intraday volatility. Therefore, the specific trading rules of the Chinese stock market cause investors to be more motivated to buy at the end of the stock market trading day and sell at the start of trading on the subsequent day. In this paper, we aim to investigate whether this trading pattern brings significant market anomaly in terms of intraday momentum.

Given that trading is dominated by retail investors, the three-factor model constructed by Fama and French (1993) for the US market does not seem to work effectively in the Chinese stock market. Liu *et al.* (2019) suggested an alternative three-factor model that uses the earnings-to-price ratio and book-to-market ratio that functions effectively in the Chinese stock market. Chinese investors emphasize the earnings per share (EPS) ratio because they focus on growth companies that provide superior returns. These stocks tend to be driven by rumors related to their future growth. Because retail investors have limited ability to analyze information regarding companies' growth, most investors just buy on upswings and sell on downswings, which describes as late-information trading. This behavior results in another anomaly of the Chinese stock market: its extreme high herd effect, which lowers long-term stock price momentum (Demirer *et al.*, 2015).

Consequently, the long-term momentum is hardly detected in China instead of short-term reversal. Momentum is a critical factor in asset-pricing models (Carhart, 1997). As such, it is a cornerstone for investigations of financial asset pricing and for the development of investment strategies. Jegadeesh and Titman (1993) revealed cross-sectional momentum across the financial markets in different countries. Subsequently, Griffin *et al.* (2003) provided evidence that the global stock markets exhibit the similar momentum pattern. Furthermore, the time series momentum discovered by Moskowitz *et al.* (2012) evidenced that an asset's future returns can be predicted by its previous 12-month returns positively. In addition, the existence of consistent value and momentum return premia is identified by Asness *et al.* (2013) on the asset class level. In contrast to these studies, which discovered momentum based on monthly frequencies, Gao *et al.* (2018) provide the evidence of the intraday momentum in exchange-traded funds (ETFs). Specifically, the last half-hour return can be predicted based on the first half-hour market return. Motivated by the study of Gao *et al.* (2018), we try to explore the intraday momentum pattern in the Chinese stock market, especially in the last trading hour.

Hereby, we document the first evidence in the literature of last hour momentum. Using intraday data and splitting the daily trading sessions into eight intervals, we discover that the seventh (eighth) half-hour market return can be significantly predicted by its previous half-hour market return. By examining the China Securities Index (CSI) 300, we confirm the existence of last hour momentum for the broad market, and the predictive value of R^2 on the last half-hour return based on the seventh half-hour return is 3.8%. If adding the sixth half-hour return into the predictive regression, the predictive R^2 increases to 4.8%. To confirm this predictability, we perform out-of-sample analysis and discover that the slopes of the predictors are highly persistent and stable. Further, we discover that the predictive power of the predictors increases along with their volatility. For example, when the volatility of seventh half-hour returns is high, the slope is significant and the R^2 value increases to 5.7% for the market index. The predictability is higher for the period of financial turbulence that occurred from June 12, 2015 to February 29, 2016. Considering the financial turbulence as an indicator of market conditions, we also examine the market index to distinguish the market into bull and bear markets. We discover that the predictability is higher in bull markets than in bear markets, especially for the last half-hour. Furthermore, the overall predictability is greater on the no major economic news release days than on the major economic news release days.

To take the advantage of this phenomenon, we employ ETF data to design the trading strategies because retail investors typically must buy the ETF to track the CSI 300 given their level of ability and wealth [1]. Similarly, we determine that the predictability for the ETF is both significant and greater than that of the CSI 300 itself. When considering the ETF's trading activity, we discover that the predictability is higher during high trading volume days and high order-imbalance days than on other days. We develop a market timing strategy to capture last hour momentum. The average annualized return is 12.364% with a standard deviation of 7.629% when trading is started from the sixth half-hour return. The Sharpe ratio is 1.164, which is much higher than the buy-and-holding strategy's Sharpe ratio of 0.427. To maximize returns, we propose a hybrid strategy that generates an annualized return of 21.656% with an even higher Sharpe ratio of 1.685. The ETF trading strategy also outperforms the same strategy based on the market index. This outperformance persists after taking into account of transaction costs. Moreover, we consider a risk aversion factor of 3 and leverage ranging from 0 to 1.5 to construct a mean-variance portfolio. When considering the sixth half-hour return to be a trading signal, we obtain risk-adjusted returns of 5.662% per annum. The hybrid strategy increases the return to 7.246% per annum. Overall, the ETF's returns are still superior to those of the market index.

In addition to using the CSI 300, we examine the CSI Small Cap 500, the Shanghai Composite Index, and the Shenzhen Component Index to test our findings [2] as alternative robustness checks. The results reveal that last hour momentum is both strong and significant regardless of market type. Actually, last hour momentum is stronger in the other market indexes. However, because the ETFs that track the other market indexes are not actively traded, we have to employ the CSI 300 and its tracking ETF in the study rather than the other indexes and their respective ETFs. Furthermore, after identifying the uniqueness of the Chinese stock market, we compare the results to those of studies of the US stock market. As has been documented in the literature on high-frequency asset pricing and retail investor behavior (Aboody *et al.*, 2018; Branch and Ma, 2012; Cushing and Madhavan, 2000), some individual stock's return may show the daily persistence at the same half-hour intervals. We examine this effect by adding the previous day's return into the predictive regression and discover that the results do not change meaningfully. Aboody *et al.* (2018) documented weak persistence of overnight returns but also long-term reversals. Berkman *et al.* (2012) revealed that strong net retail buying on one day will be continuing on the subsequent trading day. Because of the works of "$T+1$ trading rule", the assumption of the existence of overnight return persistence may be correct. However, the empirical results do not appear to support this assumption.

To further robust our study, we replicate the main results of Gao *et al.* (2018), which employ the prior day's closing price to calculate the first half-hour return, which are very similar to those of Gao *et al.* (2018), Chu *et al.* (2019) and Zhang *et al.* (2019). Although Zhang *et al.* (2019) provides the evidence of intraday momentum in the Chinese stock market under the framework of Gao *et al.* (2018), our study is significantly different by uncovering the unique and generalized last hour momentum and present an executable and relevant trading strategy. Specifically, to exclude the overnight return persistence effect, we employ the opening price to calculate first half-hour return. This methodology is an obvious difference from the study of Gao *et al.* (2018) and Zhang *et al.* (2019) that have included the overnight return to make a predication. In addition, the existence of the morning session [3] provides an extremely effective barrier to isolate against overnight information because the opening price reflects such overnight information, which has a significant effect on intraday momentum. Moreover, the existence of the morning session reduces the first half-hour return's predictive value on the last half-hour return, as shown in our analysis. Similar to Lou *et al.* (2019), the first half-hour return shows weak predictability. Instead, the true intraday momentum occurs during the last hour in the Chinese stock market. Furthermore, in contrast to the study of Zhang *et al.* (2019) who only replicates the findings of Gao *et al.* (2018), our study employs the ETFs to develop the profitable strategy to capture the last hour momentum in the Chinese stock market. Because retail investors account for the bulk of trading volume in the Chinese stock markets, our study reveals persistent and significant last hour momentum that does not continue on to the next day's first half-hour.

Three possible explanations can be provided for this phenomenon from the perspective of the stock market microstructure. First, as exhibited in Figure 1, the trading volume of last three half-hour takes more than half of total intraday trading volume. Second, because of the "$T+1$ trading rule", the speculative traders cannot realize their returns in one day, which indicates they have to absorb the overnight risk despite the uncertain return. Third, the irrational trading behaviors from retail investors still dominate the Chinese stock market. These three factors are the key reasons for the last hour momentum revealed in the noise-trading literature (Glostenand and Milgrom, 1985; Admati and Pfleiderer, 1988; Brett, 1988; De Long *et al.*,1989; Bloomfield *et al.*, 2009; Shleifer *et al.*, 1989) and late-information trading literature (Baker and Wurgler, 2016; Hong *et al.*, 2007; Cohen and Frazzini, 2008). Moreover, Bogousslavsky (2016) revealed that investors tend to rebalance portfolios infrequently and at the market close rather than the market open, which explains the intraday momentum.

Overall, the contributions of this paper can be classified as threefold. First, we document the first evidence of last hour momentum that the seventh (eighth) half-hour market return can be significantly predicted by its previous half-hour market return. Second, stepping out of the trading rules in the Chinese stock market, we develop a trading strategy to take advantage of last hour momentum through ETF with an annualized return of 21.656% and a Sharpe ratio of 1.685. Third, by contrast to the study of Gao *et al.* (2018) and Zhang *et al.* (2019), we uncover the unique intraday momentum occurs during the last hour in the Chinese stock market by excluding the overnight return persistence effect.

The remainder of this paper is extended as follows. Section 2 describes the data and the details of the sample. Section 3 provides the main empirical results and possible explanations. Section 4 discusses the trading strategy and explores the economic implications of our research. Section 5 discusses the robustness of the results. Finally, Section 6 concludes this paper.

2. Data and sample selection

We retrieve the tick-by-tick price data from the RESSET database. Specifically, data on the CSI 300 and the ETF that tracks it are employed. The ETF data start from May 28, 2012, so we also employ the same period for the CSI 300 itself. Although investors cannot trade the CSI 300 directly, they can trade its tracking ETF. Moreover, the ETF trades under the "T+0 trading rule" [4]. Therefore, the data period is from May 28, 2012 to December 31, 2017. We also obtain macroeconomic news release dates from the National Bureau of Statistics of China (NBSC). We then obtain every half-hour return from 9:30 a.m. to 15:00 p.m., excluding the break period from 11:30 a.m. to 13:00 p.m. Hereby, total eight half-hour returns are obtained from consecutive bidding session on each trading day.

$$r_j = \frac{p_j}{p_{j-1}} - 1, j = 1, 2, 3, \ldots, 8 \tag{1}$$

where p_j denotes the price at the jth half-hour. To exclude the effect of overnight information, we employ the opening price to compute the first half-hour return after the centralized competitive pricing session [5]. Additionally, we construct the half-hour return volatility to measure the effect on return predictability in two steps. In the first step, the returns are calculated by a tick-by-tick basis within the half-hour [6]. Table 1 reports the descriptive statistics of half-hour returns. In the second step, the half-hour volatility is calculated based on the one-tick returns, which is illustrated in Figure 1.

3. Last hour momentum

3.1 Predictive regression analysis

In this section, we mainly consider the predictability of seventh (sixth) half-hour return on the eighth (seventh) half-hour return in predictive regressions.

$$r_{7,t} = \alpha + \beta r_{6,t} + \epsilon_t \tag{2}$$

$$r_{8,t} = \alpha + \beta r_{7,t} + \epsilon_t \tag{3}$$

Table 1.
Descriptive statistics and predictability

	r_0	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8
Panel A: CSI 300 market index									
Mean	0.051	0.051	0.051	0.048	0.048	0.047	0.050	0.047	0.051
Median	0.051	0.018	0.010	0.021	0.027	0.056	0.034	0.026	0.050
Max	8.134	11.197	11.624	12.551	9.893	7.167	7.387	6.903	6.652
Min	−11.133	−12.191	−10.755	−10.764	−10.044	−9.990	−9.223	−10.610	−8.761
Std	1.586	1.528	1.546	1.528	1.516	1.521	1.441	1.477	1.513
Skewness	−0.784	−0.458	−0.285	−0.090	−0.481	−0.521	−0.505	−0.862	−0.700
Kurtosis	9.768	11.395	12.130	12.431	9.164	8.648	8.915	10.994	8.705
Obs	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426	1,426
Panel B: CSI 300 market index ETF									
Mean	0.053	0.057	0.054	0.051	0.053	0.053	0.055	0.054	0.058
Median	0.000	0.000	0.000	0.000	0.050	0.029	0.029	0.023	0.021
Max	14.912	13.706	14.520	16.389	12.990	9.549	9.635	9.991	10.003
Min	−11.538	−12.054	−10.917	−10.906	−10.283	−11.163	−10.229	−11.709	−9.995
Std	1.606	1.529	1.544	1.538	1.516	1.528	1.478	1.549	1.609
Skewness	−0.312	−0.299	−0.048	0.363	−0.218	−0.409	−0.415	−0.778	−0.512
Kurtosis	14.601	14.267	15.399	17.731	11.623	10.575	11.268	15.134	11.823
Obs	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424

Panel C: Predictability

Predictor	r_6	r_7	r_6 and r_7	r_6	r_7	r_6 and r_7
		CSI 300 market index			CSI 300 market index ETF	
Intercept	−1.666 (2.355)	6.426** (2.618)	6.188** (2.856)	1.904 (2.824)	3.094 (2.844)	3.094 (2.844)
β_{r_6}	14.470*** (3.772)		11.716 (7.163)	21.228*** (4.352)		9.116 (6.453)
β_{r_7}		21.144*** (5.701)	19.775*** (5.774)		19.875** (8.273)	18.343** (8.184)
R^2 (%)	1.7	3.8	4.8	3.6	3.1	3.6

Note(s): Panel A and B report the descriptive statistics of half-hour returns for CSI 300 market index and CSI 300 market index ETF. r_0 denotes the morning session return. $r_j, j = 1, \ldots, 8$ denotes every half-hour return from 9:30 a.m. to 15:00 p.m., excluding the break period from 11:30 a.m. to 13:00 p.m. The first column in each Panel C reports the results of regressing seventh half hour return r_7 on the sixth half-hour return r_6 of the day. The other columns in each panel report the results of regressing eighth half hour return r_8 on the seventh half-hour return r_7 and on the both sixth half hour return r_6 and seventh half hour return r_7 of the day. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

For each trading day t, $r_{6,t}$, $r_{7,t}$ and $r_{8,t}$ represent the sixth, seventh and eighth half-hour return, respectively. Table 1 summarizes the predictive results. Particularly, we employ the CSI 300 as a benchmark of comparison with the ETF. Panel A and B presents the results of the CSI 300 the ETF, respectively. For both the CSI 300 and the ETF, the eighth (seventh) half-hour return is predicted by the seventh (sixth) half-hour return positively at the 1% statistically significant level. In addition, the R^2 is more than 1%, which is much higher than the results of Rapach *et al.* (2013) and Gao *et al.* (2018). It is not a surprise to find the second-to-last half-hour $(r_{7,t})$ as a predictor of the last half-hour return (Gao *et al.*, 2018). Because the "T+1 trading rule" applies, there should be a strong price persistent effect throughout the intraday. However, our later analysis reveals that this strong price persistence is only exhibited in the last hour trading. The value of R^2 based the seventh half-hour return's predictability is more than 3%. This relatively high R^2 is impressive given the usage of high-frequency trading in our analysis.

Given the predictability of r_6 and r_7 individually, we further investigate the joint predictability of r_6 and r_7. Therefore, by extending Eqns (2) and (3), we have the following predictive regression:

$$r_{8,t} = \alpha + \beta_6 r_{6,t} + \beta_7 r_{7,t} + \epsilon_t \tag{4}$$

The third column of Table 1 illustrates the empirical results of joint predictive regression. As expected, only the slopes of β_7 without changing their values are statistically significant at 1% level, which indicates that r_6 and r_8 are independent. The evidence also reveals that the high price persistence exists only for a single half-hour period during the last hour. As indicated in Table 1, the values of the joint R^2s do not increase very much. For the CSI 300, it increases slightly to 4.8%. For the ETF, the joint R^2 is 3.6%, which is almost the same as the individual R^2 and also indicates that the predictability of r_6 and r_8 is irrelevant in the case of the CSI 300 [7].

3.2 Out-of-sample predictability

After the analysis of in-sample estimation, we describe the out-of-sample forecast in this section. As revealed by Welch and Goyal (2008), the predictability suffers instability problems and may vanish under monthly out-of-sample forecast. For the daily time scales, this problem is more common because structural changes occur more frequently than in the longer-term scales. Therefore, to forecast the return for any time t, a recursive estimation window (i.e. an expanding window) is used given the data for time $t-1$. We use the data for the period before January 2, 2014, as our in-sample estimation, and compute the regression coefficients recursively.

To examine whether the last hour momentum has any time trends in different market conditions, we provide the dynamics of the estimated coefficients in Figures 2 and 3. The slopes of r_6 and r_7 are estimated recursively over time. As exhibited in these figures, the slope of r_6 is relatively stable for the entire out-of-sample period except for stock market turbulence period in 2015 [8]. By contrast, the slope of r_7 increases due to the 2015 turbulence. The differences between the CSI 300 and the ETF are minor. Overall, despite the existence of distractions in the predictors, they exhibit relatively stable predictive ability in driving last hour momentum over time.

Following the approaches of Rapach *et al.* (2010), Henkel *et al.* (2011) and Neely *et al.* (2014), we employ the out-of-sample R^2_{os} values to evaluate the forecasting performance. Similar to the definition of R^2, the out-of-sample R^2_{os} can be written as follows:

$$R^2_{os} = 1 - \frac{\sum_{t=1}^{T}\left(r_{7(8),t} - \widehat{r}_{7(8),t}\right)^2}{\sum_{t=1}^{T}\left(r_{7(8),t} - \overline{r}_{7(8),t}\right)^2} \tag{5}$$

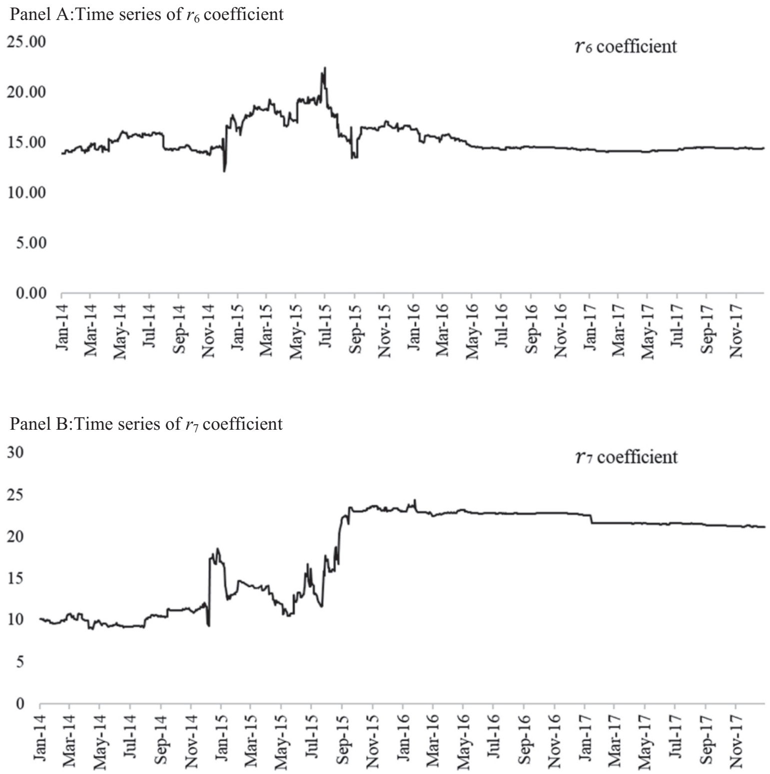
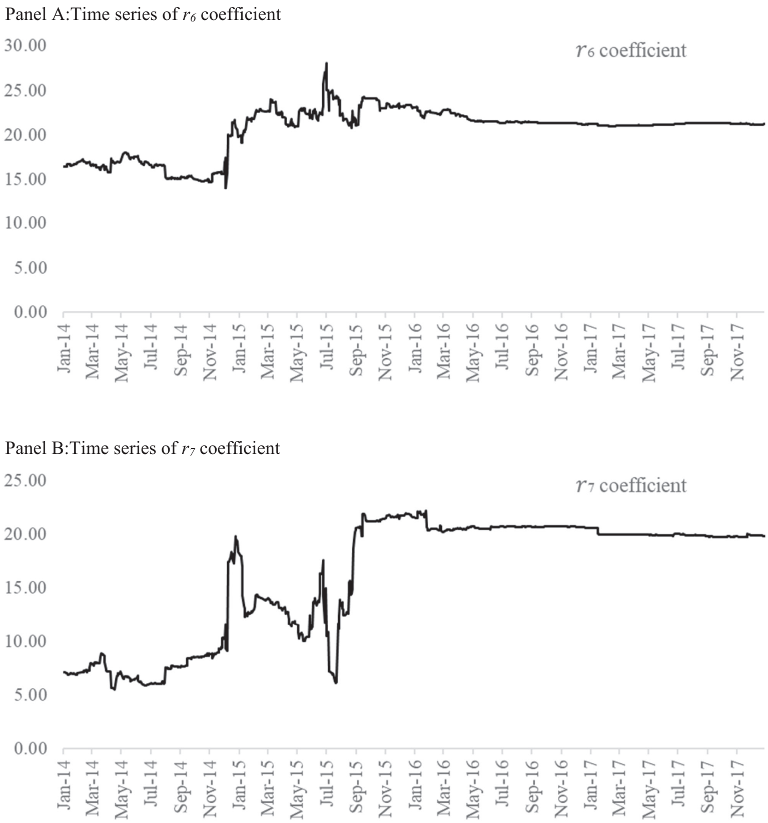


Figure 2.
Time series of r_6 and r_7 coefficients for CSI 300 index

Note(s): The coefficients of *r6* and *r7* are estimated in the predictive regression (2) and (3) recursively over time for the full sample period. *r6* is the half-hour return from 13:30 to 14:00, and r7 is the half-hour return from 14:00 to 14:30

where $\widehat{r}_{7(8),t}$ denotes the forecast seventh (eighth) half-hour return, and $\overline{r}_{7(8),t}$ denotes the historical average forecast. Similarly, to examine how predictability evolves over time, we calculate out-of-sample R^2_{os} values recursively starting from January 2, 2014. Figure 4 displays the time-varying properties of the recursive R^2_{os}. Clearly, a significant time-variation property of the observed predictability is identified. The values of the recursive R^2_{os} of the r_6 predictor peak in 2015 and exhibit a decreasing trend afterward due to the 2015 Chinese stock market turbulence. Consistent with the findings of Welch and Goyal (2008), the Great Moderation period enhances the predictability of numerous return forecasting models even if they perform ineffectively in out-of-sample forecasts. By contrast, the value of the recursive R^2_{os} of the r_7 predictor increases for data after the 2015 Chinese stock market turbulence. The difference between the CSI 300 and the ETF is clear. The ETF exhibits stronger predictability at the sixth half-hour but weaker predictability at the seventh half-hour compared with the index. To summarize, we confirm that the existence of last hour momentum is significant in the ETF and that the last half-hour momentum is stronger in the CSI 300. The last hour momentum of the ETF is due to the strong last half-hour momentum in the CSI 300 because the ETF must ensure that its composition matches that of the CSI 300 before the end of each trading day. The results are also highly consistent with in-sample estimations. Moreover, the



Note(s): The coefficients of *r6* and *r7* are estimated in the predictive regression (2) and (3) recursively over time for the full sample period. *r6* is the half-hour return from 13:30 to 14:00, and r7 is the half-hour return from 14:00 to 14:30

Figure 3.
Time series of r_6 and r_7 coefficients for CSI 300 index ETF

value of R^2_{os} is always positive with average value greater than two, which indicates substantial economic significance even compared with the monthly return forecast in Campbell and Thompson (2008).

3.3 Financial turbulence

The 2015 financial turbulence is an obvious outlier in the sample, and we consider this period separately given that the relevant literature has documented the underperformance of the standard monthly momentum strategy. Therefore, we divide the samples into four subsamples (i.e. the period of financial turbulence, the period excluding the period of financial turbulence, the period prior to the financial turbulence and the period after the financial turbulence) to investigate the effect of the financial turbulence. In Table 2, we summarize the prediction results for both the CSI 300 (Panel A) and the ETF (Panel B). For the period of financial turbulence, only the predictive power of r_7 increases, with a higher R^2 of 8.7% and a larger slope of 33.152 for the CSI 300. However, for the ETF, both the values of the predictive power of r_6 and r_7 increase in slope and R^2. Additionally, the predictive powers of r_6 and r_7 remain independent during the period of financial turbulence.

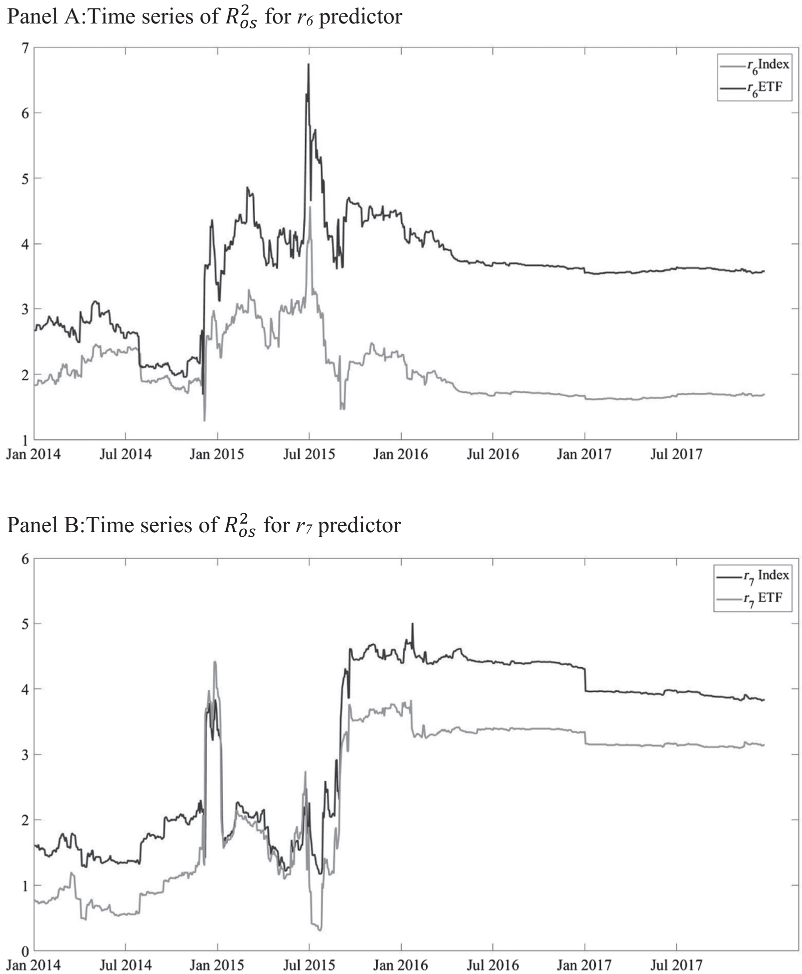


Figure 4.
Time series of R^2_{os} for r_6 and r_7 predictors for CSI 300 index ETF

Note(s): The Ros2 is estimated in the predictive regression (2) and (3) recursively over time for the out of sample period

For a comparison, we also report the prediction results for the period that excludes the financial turbulence, which reveals stronger predictability power of r_6 and weaker predictability power of r_7 for both the CSI 300 and the ETF. Although the slope of r_6 becomes significant, the value of R^2 substantially decreases. The R^2 values are still more than 1.5%, which are higher than those of numerous strong predictors from the monthly frequency. Moreover, the predictive powers of r_6 and r_7 remain independent in the periods that exclude the financial turbulence. Therefore, the last hour momentum for the ETF exists over the entire sample period, regardless of financial turbulence. However, for the CSI 300, financial turbulence may disrupt this pattern on the second last half-hour momentum. By contrast, the last hour momentum persistently exists in the ETF.

Table 2. Predictability and financial turbulence

Predictor	r_6	r_7	r_6 and r_7	r_6	r_7	r_6 and r_7
Panel A: CSI 300 market index						
		Financial turbulence			Excluding financial turbulence	
Intercept	−4.046 (13.556)	−8.568 (14.042)	−8.329 (14.994)	−1.404 (2.142)	8.354** (2.142)	8.259** (2.142)
β_{r_6}	11.111 (7.441)		15.722 (11.597)	16.866*** (3.738)		9.380 (9.167)
β_{r_7}		33.152*** (9.130)	31.799*** (9.830)		11.796*** (5.283)	10.478*** (4.313)
R^2 (%)	1.0	8.7	10.2	2.4	1.3	1.9
		Before financial turbulence			After financial turbulence	
Intercept	−0.476 (3.332)	6.664** (2.855)	6.664** (2.855)	−2.815 (2.375)	11.168*** (2.617)	11.168*** (2.617)
β_{r_6}	18.944*** (3.970)		11.055 (10.948)	7.372 (8.862)		0.823 (8.234)
β_{r_7}		12.708*** (5.965)	10.974** (4.468)		7.522 (11.066)	7.471 (11.406)
R^2 (%)	3.0	1.5	2.5	0.5	0.5	0.5
Panel B: CSI 300 market index ETF						
		Financial turbulence			Excluding financial turbulence	
Intercept	3.808 (13.804)	−10.708 (14.756)	−10.708 (14.756)	1.665 (2.379)	4.988** (2.382)	4.988** (2.382)
β_{r_6}	23.119*** (8.295)		9.785 (10.810)	19.854*** (4.431)		8.265 (8.772)
β_{r_7}		28.121* (16.771)	26.357 (17.275)		13.624** (6.345)	12.310** (5.107)
R^2 (%)	4.2	5.3	5.8	3.2	1.7	2.2
		Before financial turbulence			After financial turbulence	
Intercept	3.332 (3.565)	4.761 (3.565)	4.761 (3.565)	−0.475 (2.547)	5.712** (2.378)	5.712** (2.378)
β_{r_6}	21.879*** (4.817)		9.343 (10.261)	9.001 (8.989)		2.604 (9.286)
β_{r_7}		13.449* (7.413)	11.796** (5.704)		14.604* (7.934)	14.426* (2.604)
R^2 (%)	3.9	1.6	2.4	0.6	1.8	1.8

Note(s): Panel A and B report the predictive regression results for market index and its ETF considering the effect from the financial turbulence during the period from June 12, 2015 to February 29, 2016. For each panel, we consider four subsample period, the financial turbulence period, the period excluding the turbulence, the preturbulence period and postturbulence period, respectively. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

We also divide the sample into pre- and post-turbulence periods to investigate the relationship between last hour momentum and financial turbulence. Interestingly, the predictive power of r_6 is slightly higher for the CSI 300, whereas its slope remains approximately the same for the ETF. The same patterns are also observed for the R^2 values. However, during the postturbulence period, the predictive power of r_7 only exhibits 10% significance. Notably, the postturbulence period has a relatively limited sample size (almost one-third) compared with the preturbulence period, which may be the reason for the insignificance.

3.4 Volatility and volume

Given that the predictive powers of r_6 and r_7 are independent, regardless of the sample period, we only consider the predictive power of r_6 and r_7 separately. Moreover, as indicated in the previous section, financial turbulence has some effects on last hour momentum. As such, we further investigate how volatility influences intraday momentum in general because periods of financial turbulence period are characterized by high volatility (Admati and Pfleiderer, 1988; Lee and Swaminathan, 2000; Murphy and Thirumalai, 2013). Therefore, we sort the sample by the sixth (seventh) half-hour volatility and split the data into two groups: low volatility days and high volatility days. We calculate the volatility based on tick-by-tick returns and half-hour frequency.

Table 3 presents the results for both the CSI 300 Index and the ETF. The predictability of r_6 and r_7 show positive relationship with volatility. For the low-volatility regime, no

Predictor	r_6	r_7	r_6	r_7
Panel A: CSI 300 market index				
	Low volatility		High volatility	
Intercept	−3.665 (2.380)	9.972*** (2.142)	0.238 (4.522)	1.880 (4.998)
β_{r_6}	7.941 (5.435)		15.664*** (4.456)	
β_{r_7}		1.584 (5.677)		26.464*** (6.549)
R^2 (%)	0.4	0.0	2.1	5.6
	Low volume		High volume	
Intercept	−1.618 (2.380)	10.996*** (2.618)	−1.166*** (5.236)	2.737 (6.426)
β_{r_6}	2.818 (5.265)		15.838 (5.482)	
β_{r_7}		10.825** (5.060)		23.757*** (5.918)
R^2 (%)	0.1	0.1	2.1	4.6
Panel B: CSI 300 market index ETF				
	Low volatility		High volatility	
Intercept	−0.785 (1.904)	5.831*** (1.904)	4.474 (4.760)	0.071 (4.998)
β_{r_6}	12.928** (5.016)		22.010*** (4.739)	
β_{r_7}		17.203*** (4.308)		20.305** (9.116)
R^2 (%)	0.9	2.6	4.0	3.2
	Low volume		High volume	
Intercept	0.381 (2.816)	5.426 (3.570)	3.713 (6.188)	−0.095 (5.950)
β_{r_6}	27.759** (10.944)		19.869*** (7.185)	
β_{r_7}		3.095 (5.698)		22.661*** (9.137)
R^2 (%)	4.5	0.1	3.4	4.1

Note(s): Panel A and B report the predictive regression results for market index and its ETF considering the effect from volatility and trading volume. For each panels, the table reports the predictive regressions under different levels of return volatility or trading volume of the sixth half hour or seventh half hour. The half-hour volatility is estimated using tick-by-tick returns with around 350 observations. Both volatility and trading volume are divided into low and high parts based on their median. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

Table 3.
Impact of volatility and volume

significant predictability exists for the CSI 300 with extremely low R^2 values of 0.4 and 0.0%, respectively. For the high-volatility regime, the values of slope and R^2 increase to 2.1% and 5.6%, respectively, for the CSI 300. However, for the ETF, we still obtain significant predictability regardless of the volatility regime, although the predictability increases as the volatility increases. Specifically, given a high volatility at sixth half-hour, the ETF's R^2 increases to 4.0%, more than four times that of the low-volatility regime for the ETF. Critically, different from the CSI 300, the predictive power R^2 of sixth half-hour is lower compared to the predictive power R^2 of seventh half-hour. To summarize, the last hour momentum is highly and positively related to volatility, which is similar to the findings of Zhang (2006), who stated that the stronger persistence of a trend comes after the greater degree of uncertainty.

Moreover, because retail investors are the main liquidity providers in the Chinese stock markets, it is intuitive to expect high trading volumes during bull markets and low trading volumes during bear markets [9]. Thus, it is reasonable to consider trading volume as an alternative indicator of market conditions. Therefore, we sort the trading volume into two parts: low- and high-volume days. For the CSI 300, we confirm that the predictability of r_6 and r_7 is an increasing function of trading volume. However, for the ETF, the trading volumes influence the predictability of r_7 significantly. The significant predictability of r_7 is only observed on days of high trading volume.

3.5 Market condition and liquidity

Although volatility and trading volume can provide insight into the effects of financial turbulence and investor behavior, a further consideration is required for several related issues. To distinguish market conditions more clearly, we employ the CSI 300 level as an anchor to split the sample into bear and bull markets directly. Moreover, unlike trading volume or volatility, retail investor trading style tends to switch according to market conditions due to their irrational behavior. For example, retail investors tend to hold on to losses for too long in bear markets and to sell too early in bull markets. As a result, in the case of the CSI 300, the significant predictability of r_6 disappears during bull markets (as retail investors sell their winners too early). Moreover, bull markets provide higher predictive power than the bear markets (when retail investors hold on to losses for too long) regardless of whether we examine the CSI 300 or the ETF that tracks it. Although Table 4 presents similar predictive results for both the CSI 300 and the ETF, the predictive power of r_6 is still higher for the ETF than for the CSI 300.

Having discovered that different results may exist based on the different classifications of market conditions, we must understand the effect of liquidity on last hour momentum. We compute the Amihud's illiquidity measure (2002) based on the CSI 300 and its tracking ETF over the sixth (seventh) half-hour period. Then, we implement a predictive regression conditional on the low and high Amihud's ratio separately. We observe that liquidity may not be a major concern because the predictive results are similar. In other words, liquidity is abundant for both the market and in the ETF.

3.6 Trading activity

Besides, the data sample also allows us to examine the specific trading activity in the ETF. Therefore, we investigate the specific liquidity measures and order imbalance measure to determine their effects on last hour momentum. Table 5 provides two liquidity measures to implement the predictive regression: the bid–ask spread and the depth. We sort the sample based on the sixth (seventh) half-hour period according to these liquidity measures and split the data into low- and high-liquidity days. As presented in Table 5, for both low- and high-liquidity days, we identify the significantly predictive ability of r_6 although it is slightly

Predictor	r_6	r_7	r_6	r_7
Panel A: CSI 300 market index				
	Bear market		Bull market	
Intercept	−27.608*** (6.902)	9.663*** (2.856)	−1.404 (4.760)	9.187** (4.522)
β_{r_6}	12.877** (6.347)		10.526 (7.952)	
β_{r_7}		20.480** (8.888)		24.394** (8.687)
R^2 (%)	1.4	3.9	0.9	4.0
	Low Amihud		High Amihud	
Intercept	−0.785 (3.332)	6.497 (4.284)	−2.570 (3.094)	5.998** (2.618)
β_{r_6}	13.159*** (4.908)		17.070*** (6.040)	
β_{r_7}		23.948*** (7.887)		16.602*** (5.944)
R^2 (%)	1.5	3.9	2.1	4.1
Panel B: CSI 300 market index ETF				
	Bear market		Bull market	
Intercept	1.951 (3.808)	6.236 (2.856)	1.761 (4.522)	−0.166 (4.760)
β_{r_6}	15.826** (6.986)		24.275*** (7.993)	
β_{r_7}		18.899** (8.271)		20.408** (9.428)
R^2 (%)	2.1	4.6	4.6	2.8
	Low Amihud ratio		High Amihud ratio	
Intercept	7.069** (3.332)	6.426 (4.046)	−3.118 (3.570)	−0.286 (4.998)
β_{r_6}	20.219*** (5.904)		21.869*** (4.396)	
β_{r_7}		17.407*** (8.733)		21.749** (10.862)
R^2 (%)	3.6	2.9	3.5	3.3

Note(s): Panel A and B report the predictive regression results for market index and its ETF considering the effect from market condition and liquidity. For each panels, the table reports the predictive regressions under different levels of market condition or liquidity of the sixth half hour or seventh half hour. The half-hour Amihud illiquidity measure is estimated as the average half hour ratio of the absolute stock return to the dollar trading volume with around 350 observations. The market condition is separated to the bear market and bull market based on the median of market price. The Amihud illiquidity measure is divided into low and high parts according to its median. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

Table 4.
Impact of market condition and liquidity

greater for the former than the latter. By contrast, we only identify the significantly predictive ability of r_7 on high-liquidity days. Consistent with earlier findings, the ETF show higher predictive power of r_6, indicating the effectiveness of rebalancing the portfolio in advance. We plot the trading order imbalance in Figure 5.

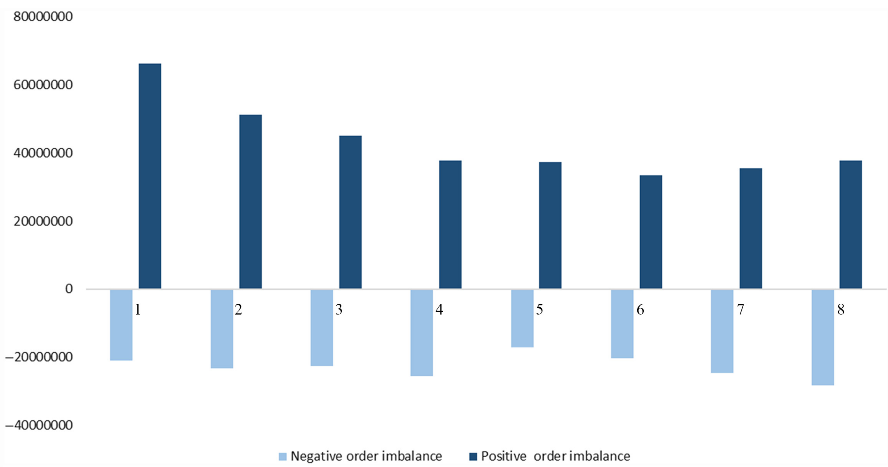
We also consider the effect of order imbalance on the ETF based on two measures. The first measure is the net order imbalance in the sixth (seventh) half-hour period, which is calculated by the difference between buy volume and sell volume. We split the sample by negative and positive order imbalance resulting in two subsets according to the sign of net order imbalance. We then implement predictive regressions on these two subsamples separately. Hereby, the daily ETF order imbalance measure is defined as the ratio of difference between buy volume and sell volume to the sum of them on a given day [10]. Then, the predictive regressions are estimated conditional on low and high order-imbalance days.

As shown in Table 5, for the positive order imbalance days, the predictive ability of r_6 is higher than that of r_7. Moreover, the R^2 value for r_6 is 5.4%, which is almost twice that of r_7. The same pattern can also be observed during high order imbalance days, except the value of R^2 is similar. However, for negative order imbalance days, only the predictive ability of r_6 is significant with an R^2 value of 1.9%. Surprisingly, the predictive ability of r_6 and r_7 is highly similar on high order imbalance days, although the latter has a lower R^2 value than the former.

Predictor	r_6	r_7	r_6	r_7
	Small bid–ask spread		Large bid–ask spread	
Intercept	−1.689 (3.094)	8.496*** (3.094)	5.831 (4.522)	−2.023 (4.046)
β_{r_6}	17.540** (6.937)		22.571*** (5.240)	
β_{r_7}		8.052 (5.464)		24.133*** (9.323)
R^2 (%)	1.9	0.5	4.4	4.6
	Low depth		High depth	
Intercept	−0.381 (3.570)	7.545** (3.808)	4.355 (4.046)	−1.047 (5.474)
β_{r_6}	18.982*** (5.575)		24.874*** (5.791)	
β_{r_7}		3.269 (6.553)		30.070*** (10.382)
R^2 (%)	3.0	0.1	4.6	6.3
	Negative order imbalance		Positive order imbalance	
Intercept	7.449 (5.474)	11.876 (8.092)	−4.974 (4.046)	1.594 (4.046)
β_{r_6}	15.464** (7.529)		29.141*** (6.192)	
β_{r_7}		29.440 (19.417)		15.261** (7.620)
R^2 (%)	1.9	4.8	5.4	2.0
	Low-order imbalance days		High-order imbalance days	
Intercept	−7.497 (4.760)	−2.666 (4.760)	10.877*** (4.522)	8.211* (4.998)
β_{r_6}	17.603** (8.075)		25.024*** (6.971)	
β_{r_7}		17.504 (12.531)		21.942*** (6.850)
R^2 (%)	2.6	2.1	4.6	4.9

Note(s): The table reports the predictive regression results for market index ETF considering the effect from trading activity on the sixth half hour or seventh half hour. Four ratios are provided, that is, average bid–ask spread, average trading depth, the sign of order imbalance and order-imbalance days. The trading depth is defined as $\sum$(Bid Price × Bid Volume + Ask Price × Ask Volume) for each half hour. The order imbalance is defined as buy volume minus sell volume for each half hour. The order-imbalance days is defined as (buy volume – sell volume)/(buy volume + sell volume) for whole trading days. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

Table 5. Impact of ETF trading activity



Note(s): Each 30-minute period is from 9:30am to 3:00pm with labels from 1 to 8 sequentially. Deep blue denotes positive order imbalance and light blue denotes negative order imbalance, respectively

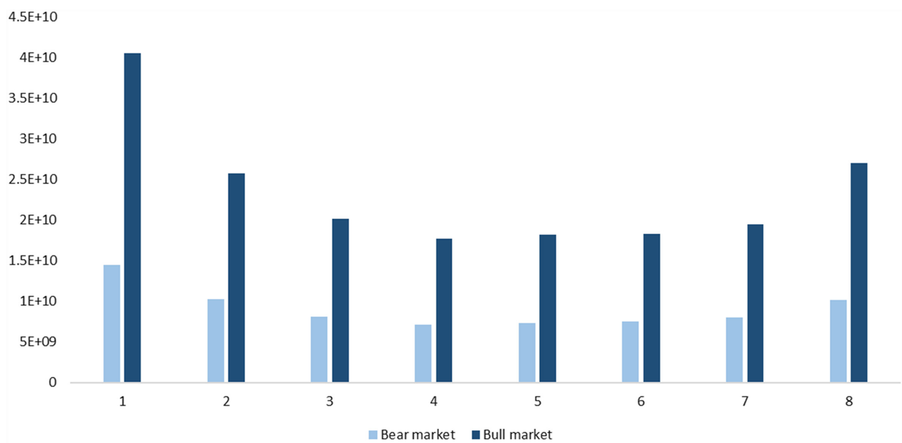
Figure 5. The average trading order imbalance of market for every 30-min according to market condition from May 28, 2012 to December 31, 2017

3.7 Explanations

Our analysis provides strong evidence of last hour momentum both in-sample and out-of-sample periods although slight differences may exist based on the market conditions. To further explore the economic reasons for this phenomenon, we provide three possible explanations below. There are also other possible explanations for this phenomenon, but we leave those explanations for future research.

As illustrated in Figures 1 and 6, for the last three half-hour observations, trading volume accounts for over 50% shares of intraday trading volume with a significant difference based on market conditions. Moreover, because retail investors dominate the market and short selling constraints are in place, trading tends to be higher during bull markets and lower during bear markets. As revealed in Figure 6, trading volume in bull markets is almost three times that of bear markets. As discussed previously, the CSI 300 exhibits extremely high last half-hour momentum, which extends to the last hour for the ETF. Although the last half-hour momentum for the CSI 300 is strong, it is weaker than that of the ETF. Therefore, the first possible explanation for the last hour momentum is the rebalancing effect documented by Bogousslavsky (2016), who argued that investors tend to rebalance their portfolios infrequently near the market close = . Clearly, as the seventh and eighth half-hour returns move in the same direction, a positive correlation between them can be witnessed in the CSI 300. Additionally, since the ETF mimics the index, it is not surprising to observe that this effect occurs earlier for the ETF than for the CSI 300 itself.

As illustrated in Table 5, because liquidity (volatility) weakens the last half-hour momentum, it is reasonable to consider the role of noise trading. Given that retail investors (i.e. noise traders) dominate the Chinese stock market, it is reasonable to expect the existence of a positive relationship between liquidity (volatility) and noise trading (Glostenand and Milgrom, 1985; Admati and Pfleiderer, 1988; Brett, 1988; De Long *et al.*, 1989; Bloomfield *et al.*, 2009). In addition, the results reveal that the persistence of last hour momentum in the ETF is highly dependent on the liquidity (volatility) conditions. A likely reason for the preference among Chinese investors to trade during the last hour is the $T+1$ trading rule. Though the ETF allows the investors to capture the momentum profit in the last hour, Chinese investors still fail to utilize it. Rather than buying the ETF, Chinese investors tend to buy a stock according to their preferences, which they cannot realize returns on it during the same



Note(s): Each 30-minute period is from 9:30am to 3:00pm with labels from 1 to 8 sequentially. Deep blue denotes bull market and light blue denotes bear market, respectively

Figure 6.
The average trading volume of market for every 30 min according to market condition from May 28, 2012 to December 31, 2017

intraday session. In addition, the overconfidence of investors may also explain this phenomenon since speculative traders tends to trust their abilities of stock selecting and earning the excess overnight return. In this sense, the $T+1$ trading rule becomes a barrier to hinder the speculative traders from realizing the excess return in one day. Moreover, as discussed in the section on robustness, no other half-hour time periods exhibit the same pattern as the last hour.

The third explanation is the presence of late-information investors. Understanding the materiality of information takes different lengths of time for different investors. Even when an information release is clear and transparent, retail investors typically do not trade on it at the market open. Nevertheless, information releases from the NBSC usually occur at 9:30 or 10:00 a.m. Considerable time is often needed for market participants to digest this information, especially given that the majority of market participants are retail investors. Investors even sometimes respond to month-old sentiment measures, as revealed in Baker and Wurgler (2016). It takes a month for information to transmit across certain industries, as suggested by Hong *et al.* (2007) and Cohen and Frazzini (2008). As a result, information processing requires days or even months. The optimal trading strategy for retail investors is to trade on the market close, when all the intraday information has been fully digested. It is thus normal to obverse the highest trading liquidity in the last half-hour.

4. Economic significance

4.1 Market timing

Given the existence of last hour momentum, it is our best interest to develop a profitable trading strategy. Hereby, the sixth and seventh half-hour returns are selected to be timing signals to buy the ETF and to sell it in the subsequent half-hour. Since the short-selling constraint applied, we only take a long position when the timing signal is positive. Moreover, as the $T+0$ trading rule applies for the ETF, we can close the long position at the market opening on the intraday session.

If setting the timing signal as the sixth half-hour return r_6, the intraday momentum return is equal to the seventh half-hour return:

$$\eta(r_7) = \begin{cases} r_7, & \text{if } r_6 > 0; \\ 0, & \text{if } r_6 \leq 0. \end{cases} \tag{6}$$

Similarly, if considering the seventh half-hour r_7 as the trading signal, the half-hour momentum return is as follows:

$$\eta(r_8) = \begin{cases} r_8, & \text{if } r_7 > 0; \\ 0, & \text{if } r_7 \leq 0. \end{cases} \tag{7}$$

In addition, because the momentum exists for the last hour of each day, we can maximize our return by implementing the strategies of both $\eta(r_7)$ and $\eta(r_8)$. In other words, we trade the ETF according to the signal: If the seventh half-hour return is negative, we close out the long position; otherwise, we hold the long position until the last half-hour. Mathematically, we have the last hour momentum return as follows:

$$\eta(r_{7,8}) = \begin{cases} (1+r_7)(1+r_8) - 1 & \text{if } r_6 > 0 \text{ and } r_7 > 0 \\ r_7 & \text{if } r_6 > 0 \text{ and } r_7 < 0 \\ 0 & \text{if } r_6 < 0 \end{cases} \tag{8}$$

Table 6 summarizes the descriptive statistics on the three timing strategies' returns for both the CSI 300 and the ETF that tracks it. The sixth half-hour is used as the timing signal to take

	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	Success(%)	Trades
Panel A: Market timing without transaction cost							
$\eta(r_7)$	12.364	7.629	1.164	0.006	8.743	54.65	602
$\eta(r_8)$	15.022	8.231	1.402	−0.017	16.956	57.40	608
$\eta(r_{7,8})$	21.656	10.784	1.685	1.469	13.128	80.86	602
Panel B: Market timing with transaction cost							
$\eta(r_7)$	10.936	7.629	0.977	0.006	8.743	54.65	602
$\eta(r_8)$	13.594	8.231	1.229	−0.017	16.956	57.40	608
$\eta(r_{7,8})$	20.228	10.784	1.553	1.469	13.128	80.86	602
Panel C: Benchmarks							
$\eta(r_7)$	6.483	7.027	0.427	−0.069	8.521	55.54	704
$\eta(r_8)$	12.667	6.365	1.443	−1.500	15.076	59.32	708
$\eta(r_{7,8})$	16.608	9.611	1.366	1.180	11.532	83.12	704
Buy&Hold1	10.860	15.220	0.485	−0.761	8.892		
Buy&Hold2	11.983	16.215	0.524	−0.515	8.967		
Buy&Hold3	11.923	16.215	0.521	−0.515	8.967		

Note(s): The table reports the economic value of the seventh or eighth half-hour market return using r_6, r_7 or both as timing indicators. The timing strategy $\eta(r_7)$ ($\eta(r_8)$) takes a long position in the market when the sixth (seventh) half-hour return is positive while timing strategy $\eta(r_{7,8})$ takes a long position in the market when the sixth half-hour return is positive and continues to hold if the seventh half-hour return is positive. The benchmark represents the same strategies we employed in the ETF trading based on the CSI 300 index. Buy-and-hold involves buying and holding the market on a daily basis based on the close-to-close returns. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (SRatio), skewness, kurtosis, success rate (Success) and trades (Numbers of market timings). The returns are annualized and in percentage. Particularly, the success rate on the strategy $\eta(r_{7,8})$ is calculated based on the conditional probability when $\eta(r_7)$ is success. Buy&Hold1 denotes the strategy based on CSI 300 market index while Buy&Hold2 denotes the strategy based on CSI 300 market index ETF. Buy&Hold3 denotes the strategy based on CSI 300 market index ETF with transaction cost

Table 6.
Market timing

a long position in the seventh half-hour, which generates average annualized return of 12.364% [11]. Alternatively, the seventh half-hour is used as the timing signal, and the average annual return increases to 15.022%. When we combine these two strategies, the last hour momentum annualized return is 21.656%.

To highlight the trading strategies, we provide six alternatives for comparison in Panel C of Table 6. As usual, we employ the CSI 300 half-hour return to mimic the same strategies implemented in the ETF trading, where we obtain annualized returns of 6.483, 12.667 and 16.608%, respectively. Therefore, the trading strategies for the ETF outperform the strategies for the corresponding index. Moreover, as a benchmark, we provide the buy-and-hold strategy for both the CSI 300 return and the ETF return. As illustrated in the final row of Table 6, this generates average annual returns of 10.860% for the CSI 300 and 11.983% for the ETF. Overall, the market timing strategies still outperform for the ETF relative to the CSI 300.

Risk is another crucial issue that we must consider when implementing the market timing strategies. First, the overall market risk (standard deviation) in China is 234.801%. In other words, the risk of the Chinese stock market is higher than that of developed stock markets. Considering the high volatility of Chinese stock markets, we calculate the Sharpe ratio to generate the risk-adjusted returns. As expected, the market timing strategies outperform significantly, with the hybrid strategy exhibiting the highest Sharpe ratio of 0.130. Notably, the hybrid strategy also exhibits positive skewness of 1.469 (i.e. the highest of any other strategy) and kurtosis of 13.128, suggesting that there is high probability of positive returns.

The transaction costs are also considered for the ETF trading strategies. Because trading commissions vary based on the different securities companies, we assume the maximum market trading commission of 0.03% for each trade. Because there is no stamp tax for ETF trading, the total transaction cost for the strategy is 0.06% plus a 5 RMB transfer fee [12]. After deducting the transaction fees from the returns of the market timing strategies, the proposed strategies still outperform the buy-and-hold strategy. The excess return for each strategy compared with itself is 4.453, 0.927 and 3.62%, respectively. If employing the CSI 300 return as a benchmark, we have excess returns of 0.076, 2.734 and 9.368%, respectively. Even if considering the ETF return with transaction costs as the benchmark, the $\eta(r_8)$ and $\eta(r_{7,8})$ strategies still have positive excess returns of 1.671 and 8.305%, respectively.

Finally, the success rate, a ratio of positive returns to total trades, is reported as well [13]. The unconditional probability is over 50%, which cannot be considered as a probability-neutral event. Moreover, the hybrid strategy exhibits conditional probability more than 80%, which not only indicates that the strategy works but also confirms the existence of last hour momentum in the Chinese stock market.

4.2 Utility gains

After discovering that the market timing strategy results in significant improvement in predictability over the benchmark, we consider the economic value of the return forecasts on asset allocations. We construct an optimal portfolio by using the forecast returns on the ETF and the risk-free asset for a mean-variance investor. Following Campbell and Thompson (2008) and Neely *et al.* (2014), the weight of the optimal mean-variance portfolio for intraday t is determined as follows.

$$w_t = \frac{1}{\gamma}\left(\frac{\overline{r}_{7(8),t}}{\overline{\sigma}^2_{7(8),t}}\right), \tag{9}$$

where $\widehat{r}_{7(8),t}$ denotes the forecasts of the seventh (eighth) half-hour stock returns, and $\widehat{\sigma}^2_{7(8),t}$ denotes the forecasts of seventh (eighth) half-hour stock variances, respectively. Specifically, the forecast returns and variances are conditional on information available during the intraday session or before the seventh (eighth) half-hour. The degree of risk aversion γ is set at 3 to represent reasonable risk aversion as suggested by Rapach *et al.* (2010) and Dangl and Halling (2012). We employ a one-year rolling window of historical returns to compute the variance forecasts [14]. Because short selling is forbidden and the use of financial leverage is highly restricted in China, we consider the optimal weight value to range from 0 to 1.5. Therefore, the portfolio intraday return on day t is given as follows:

$$r_{p,t} = w_t r_{7(8),t} + (1 - w_t) r_{f,t} \tag{10}$$

where $r_{f,t}$ is the risk-free rate denoted by the yield on the three-month treasury bill. The realized utility over the out-of-sample period is given as follows.

$$U = \widehat{r}_p - \frac{\gamma}{2}\widehat{\sigma}^2_p \tag{11}$$

where $\widehat{r}_p$ and $\widehat{\sigma}^2_p$ denote the mean and variance of the portfolio, respectively. Hereby, we can estimate the certainty equivalent return (CER) by calculating the difference between realized utility U_2 and U_1. Specifically, we employ the forecasted return $\widehat{r}_{7(8),t}$ to compute U_2 while employ the historical mean forecast $\overline{r}_{7(8),t}$ to compute U_1. Therefore, the CER can be defined as follows:

$$\mathrm{CER} = U_2 - U_1 \tag{12}$$

This interpretation of CER is an additional benefit for an investor when takes advantage of last hour momentum instead of believing the random walk intraday pricing model.

Table 7 presents the results of the analysis of the economic significance. Again, both the CSI 300 and its tracking ETF are examined, and in both cases, the historical average forecast significantly underperforms compared with the forecast using sixth (seventh) half-hour return. For example, if setting the timing signal as seventh half-hour return, the forecast return is 7.344% per annum for the CSI 300 and 10.690% per annum for the ETF. By contrast, for the historical average forecast, the seventh half-hour forecast return declines to 3.398% per annum for the CSI 300 and to 2.416% per annum for the ETF. Although the historical average forecast provides lower forecast variance and a higher Sharpe ratio occasionally, the economic gains are positive and substantial, as indicated by the CER. For the CSI 300, the three strategies capture annualized economic gains of 2.638, 4.275 and 5.795%, respectively. For the ETF, the economic gains are much higher, with values of 5.662, 5.693 and 7.246%, respectively. In other words, the trading strategies for the ETF not only provide economic gains but also beat the market.

The hybrid strategy provides one-hour momentum return, whereas the two individual strategies only capture the half-hour momentum return. Still, the hybrid strategy delivers superior results, which generates an average annual return of 22.877%, a Sharpe ratio of 7.666 and an annualized CER of 7.246%. The results also indicate that the last hour momentum is persistent for each trading day. Combined with the substantial positive skewness and kurtosis values, the results confirm that the last hour momentum is highly persistent and significant. In addition, the hybrid strategy slightly outperforms market timing due to the different asset allocations on each day.

4.3 News releases

Because last hour momentum is very sensitive to trading activity and volatility, we further explore another source of high trading activity and high volatility: major economic news releases (e.g. Savor and Wilson, 2014; Lucca and Moench, 2015; Bernile *et al.*, 2016). Therefore, we investigate whether major economic news release days affect the last hour momentum. We obtain the dataset from the National Bureau of Statistics of China (NBSC) because it is the only institution that provides scheduled news releases in China [15]. In the dataset, we include all the major economic indicator (e.g. Gross Domestic Product (GDP), Consumer Price Index (CPI) and Producer Price Index (PPI)) release days. In addition, after 2017, all the indicators are released before 10:00 a.m. For example, GDP is released at 9:30 a.m., and the purchasing manager index is released at 9:00 a.m. Before 2017, industrial production volume, public (private) fixed asset investment, total retail sales of consumer goods and real estate development and sales were released at 1:30 p.m. Therefore, it is reasonable to consider that all released information is contained in the last hour returns. Due to the available sample size, we include all the major economic release days regardless of the type of information of the releases. We thereby obtain 468 observations of news release days.

Table 8 presents the prediction results based on the predictors of sixth (seventh) half-hour returns for both no news release days and news release days. For the predictors of seventh half-hour returns, the slope of r_7 is highly significant at the 5% level for nonnews release days, whereas the significance disappears for news release days. These results are consistent for both the CSI 300 and the ETF. However, for the predictors of sixth half-hour returns, the R^2 value on the no news release days is higher (lower) for the CSI 300 Index

Table 7. Utility gains

	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	CER(%)
Panel A: CSI 300 market index						
$\bar{r}_7$	3.398	0.033	−0.788	−0.600	0.331	
$\bar{r}_8$	5.073	0.084	19.612	−0.217	0.130	
$\bar{r}_{7,8}$	8.639	0.082	63.942	0.048	0.191	
$\eta(r_7)$	7.344	0.934	4.196	8.790	122.615	2.638
$\eta(r_8)$	11.578	1.222	6.671	5.110	36.992	4.275
$\eta(r_{7,8})$	20.244	1.970	8.539	5.416	43.255	5.795
Panel B: CSI 300 market index ETF						
$\bar{r}_7$	2.416	0.058	−17.363	0.582	0.888	
$\bar{r}_8$	2.385	0.066	−15.663	0.675	0.864	
$\bar{r}_{7,8}$	4.859	0.089	16.137	0.410	0.849	
$\eta(r_7)$	10.690	1.321	5.501	6.334	63.514	5.662
$\eta(r_8)$	10.064	1.153	5.760	5.199	36.976	5.693
$\eta(r_{7,8})$	22.877	2.681	7.255	7.666	89.373	7.246

Note(s): The economic value is estimated by recursively predicting the seventh (eighth) half-hour market return using the sixth (seventh) half-hour return. The predicted returns are used to construct a constrained mean-variance optimal portfolio for a mean-variance investor with a relative risk aversion of three. Portfolio weights are restricted to a range between 0 and 1.5. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (SRatio), skewness, kurtosis and the certainty equivalent gain, CER, calculated as the difference in the certainty equivalent rate of return between the optimal mean-variance strategy using forecasted seventh (eighth) half-hour returns and benchmark using the historical average returns. The returns are annualized and in percentage. The out-of-sample period is from January 1, 2014 to December 29, 2017

Predictor	r_6	r_7	r_6	r_7
Panel A: CSI 300 market index				
	No news release days		News release days	
Intercept	2.047 (3.808)	4.974*** (2.856)	1.856 (3.332)	−0.643 (5.712)
β_{r_6}	22.886*** (4.685)		17.374*** (5.102)	
β_{r_7}		18.629** (9.448)		22.875 (15.881)
R^2 (%)	4.1	3.0	2.4	3.4
Panel B: CSI 300 market index ETF				
	No news release days		News release days	
Intercept	−1.547 (2.856)	6.235 (4.046)	−2.189 (5.712)	6.450 (4.760)
β_{r_6}	13.229*** (4.679)		17.236* (9.060)	
β_{r_7}		23.189** (7.747)		18.046 (11.052)
R^2 (%)	1.6	4.2	1.9	3.1

Note(s): We report the predictive results of sixth (seventh) half-hour return on the seventh (eighth) half-hour return based on the new release days and no news release days. The news is released by the National Bureau of Statistics of China, including GDP, CPI, PPI, and PMI, etc. Most of the news is released before 10:00 a.m. Beijing time. The exceptions only contain industrial production volume, public (private) fixed assets investment, real estate development and sales, and total retail sales of consumer goods before 2017. After 2017, all the news is released before 10:00 a.m. Beijing time. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

Table 8.
Impact of macro-news releases

(ETF) compared with that of the news release days. Similarly, the slope of the sixth half-hour returns is higher for the CSI 300 than that for the ETF, whereas this pattern reverses in the subsequent half-hour. Critically, the slope of r_6 is 17.236, which is significant at the 10% level for the ETF. In other words, the predictors are not significant at the 5% level for the ETF, which suggests that the last hour momentum disappears on news release days. This evidence also confirms that the number of late-information investors is substantial in the Chinese stock market. It is thus not surprising that the market reacts slowly to news releases given that retail investors tend to delay trading due to uncertainty regarding the interpretation of such news.

To investigate whether the news release days provide higher economic gains, we reconsider the previous market timing strategies based on the last hour momentum conditional on news release days. Table 9 presents the results. For the market index, no significance appears to exist for the $\eta(r_7)$ strategy or the $\eta(r_{7,8})$ hybrid strategy. The only huge difference between the days with and without news releases comes from the $\eta(r_8)$ strategy with 3.762% total difference in returns for the CSI 300. Crucially, the difference increases to 9.58% for the ETF. The hybrid strategy generates a return of 23.897% for the no news release days, and the return declines to 17.594% for the news release days. Overall, we find the evidence of stronger economic performance on no news release days, which also suggests that the predominance of late-information investors explains the last hour momentum.

5. Robustness

5.1 Conditional predictability

As indicated in Murphy and Thirumalai (2013), there is much stronger intraday momentum during negative returns' days than the positive returns' days. Besides, because of the short selling constraint, an investigation is required to determine how the last hour momentum

	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis
Panel A: CSI 300 market index					
		No news release days			
$\eta(r_7)$	6.173	6.655	0.417	−0.366	5.953
$\eta(r_8)$	17.778	6.791	2.117	−0.499	18.393
$\eta(r_{7,8})$	15.043	9.060	1.285	0.809	7.927
		News release days			
$\eta(r_7)$	6.511	7.879	0.395	0.272	5.138
$\eta(r_8)$	14.016	7.340	1.446	−0.159	7.129
$\eta(r_{7,8})$	16.949	10.877	1.246	1.589	8.878
Panel B: CSI 300 market index ETF					
		No news release days			
$\eta(r_7)$	12.756	7.847	1.192	0.540	5.061
$\eta(r_8)$	18.520	8.545	1.769	1.172	10.764
$\eta(r_{7,8})$	23.897	11.144	1.839	2.204	11.294
		News release days			
$\eta(r_7)$	11.651	7.235	1.141	−1.239	7.642
$\eta(r_8)$	8.940	7.657	0.724	−2.945	22.071
$\eta(r_{7,8})$	17.594	10.120	1.403	−0.330	6.915

Note(s): The table reports the economic value of the seventh or eighth half-hour market return using r_6, r_7 or both as timing indicators. The timing strategy $\eta(r_7)$ ($\eta(r_8)$) takes a long position in the market when the sixth (seventh) half-hour return is positive while timing strategy $\eta(r_{7,8})$ takes a long position in the market when the sixth half-hour return is positive and continues to hold if the seventh half-hour return is positive. The benchmark represents the same strategies we employed in the ETF trading based on the CSI 300 index. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (SRatio), skewness and kurtosis. The returns are annualized and in percentage

Table 9. Market timing performance based on news

reacts to the signs of the sixth (seventh) half-hour returns. Therefore, we divide the sample into two groups based on their signs and examine their predictability. In particular, because the hybrid strategy outperforms the other strategies, we also consider the predictability of the seventh half-hour returns on the last half-hour returns conditional on the signs of the sixth half-hour returns.

Table 10 presents the results. For the CSI 300, we discover that only the negative seventh half-hour return provides significant predictability with an R^2 value of 4.8%. By contrast, only the positive sixth half-hour return provides significant result for the ETF with an R^2 value of 2.4%. Overall, although a half-hour lag of predictability exists for the different signal signs, the half-hour momentum is much stronger during negative return days than during positive return days. These results are very similar to Murphy and Thirumalai (2013). However, for the ETF, only one insignificant result is identified: the predictability conditional on a positive seventh half-hour return. The hybrid strategy also performs extremely effectively with slope values of 31.992 and 23.103, which are much higher than the same values for the whole sample. In addition, the R^2 values are 4.7% and 4.4%, which are similar to the values of the entire sample period. These results indicate that the strategy based on last hour momentum is robust.

As discussed previously, the rebalancing effect is the key driver of the difference between the CSI 300 and the ETF that tracks it when the market is down. Critically, a possible explanation for the disappearance of last half-hour momentum when the market is up is the disposition effect, which occurs when investors tend to realize gains too quickly during bull markets (Odean, 1998; Coval and Shumway, 2005; Haigh and List, 2005). Given that retail investors dominate the Chinese stock market, the disposition effect should be considered to be

Predictor	r_6	r_7	r_6	r_7	r_7
Panel A: CSI 300 market index					
	$r_6 < 0$	$r_7 < 0$	$r_6 > 0$		$r_7 > 0$
Intercept	−3.261 (6.188)	19.897*** (5.712)	−8.758* (4.760)	12.518*** (3.094)	2.737 (7.616)
β_{r_6}	9.406 (10.529)		22.861*** (7.071)		
β_{r_7}		33.606*** (9.772)		11.173 (8.415)	19.302 (13.336)
R^2 (%)	0.4	4.8	2.4	1.3	2.0
Panel B: CSI 300 market index ETF					
	$r_6 < 0$	$r_7 < 0$	$r_6 > 0$		$r_7 > 0$
Intercept	4.570 (5.236)	13.804** (5.712)	−9.258** (4.284)	5.664 (3.808)	0.333 (11.900)
β_{r_6}	19.307** (6.442)		31.992*** (6.115)		
β_{r_7}		30.264(10.171)**		23.103** (10.638)	17.752 (17.545)
R^2 (%)	1.9	4.0	4.7	4.4	1.5

Note(s): The table reports the predictive results of sixth (seventh) half-hour return on the seventh (eighth) half-hour return conditional on the sign of sixth (seventh) half-hour return. We report the results for CSI 300 market index in Panel A and its ETF in Panel B. Moreover, due to the short-selling constraint, we further consider the predictive results of seventh half-hour return on the eighth half-hour return conditional on the sign of sixth half-hour return, which matches the hybrid strategy. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

Table 10. Conditional predictability

a crucial reason to explain the disappearance of last half-hour momentum. In addition, infrequent rebalancing may also explain the phenomenon because retail investors tend to delay rebalancing near the market close, as suggested by Bogousslavsky (2016). Given that the largest trading volume typically occurs in the last half-hour, this is also a possible explanation.

5.2 Other market indexes and ETFs

The identification of last hour momentum in the CSI 300 and its tracking ETF necessitates an investigation to determine whether the same phenomenon exists in the overall stock market. Thus, we employ the CSI 500, which includes middle- and small-sized companies, and the ETF that tracks it as alternative measures to robust the results. The CSI 300's ETF and the CSI 500's ETF are the most liquid ETFs in the market. We would examine other ETFs to robust the results further, but transactions in other ETFs are too limited, which reduces the applicability of the data. As a result, we only employ two market indexes in the robustness test: the Shanghai Composite Index (SSE) and Shenzhen Composite Index (SZSE). Table 11 presents the results, which reveal that the CSI 500 and the ETF that tracks it exhibit greater last hour momentum than the CSI 300 and its respective ETF. Moreover, the SSE and SZSE exhibit similar results. Critically, r_6 and r_7 jointly predict the last half-hour returns, which indicates that r_6 and r_7 are highly dependent. In turn, the results also strongly suggest that last hour momentum is higher for the ETFs than for the market. Overall, the results are robust.

5.3 Overnight effect

To prove that the last hour momentum is unique, we re-examine the predictability of the first half-hour return on the last half-hour return in Table 12. As illustrated in Panel A, the predictability regressions are insignificant, with R^2 values close to zero. We thereby identify

Table 11. Other market index and ETFs

Predictor	r_6	r_7	r_6 and r_7	r_6	r_7	r_6 and r_7
		CSI 500 market index			CSI 500 market index ETF	
Intercept	−1.666 (2.355)	5.617** (2.618)	5.617** (2.618)	−0.738 (3.332)	6.474 (4.046)	6.449* (3.808)
β_{r_6}	14.812*** (3.094)		25.182*** (7.127)	8.119 (5.400)		25.414*** (6.464)
β_{r_7}		29.556*** (5.294)	26.461*** (5.119)		25.775** (5.726)	23.961*** (5.867)
R^2 (%)	1.8	7.3	11.6	0.6	4.7	8.7
		SSE composite index			SZSE component index	
Intercept	−0.595 (2.142)	10.067*** (2.142)	9.782** (2.380)	−1.571 (2.618)	−3.641 (2.380)	−3.689 (2.380)
β_{r_6}	12.130** (4.684)		15.369** (7.639)	12.696*** (3.676)		17.644*** (6.065)
β_{r_7}		22.689*** (4.997)	21.158*** (5.136)		22.661*** (5.031)	20.653*** (4.837)
R^2 (%)	1.2	4.2	5.8	1.4	4.6	7.1

Note(s): The first column in each panel reports the results of regressing seventh half hour return r_7 on the sixth half-hour return r_6 of the day. The other columns in each panel report the results of regressing eighth half hour return r_8 on the seventh half-hour return r_7 and on the both sixth half hour return r_6 and seventh half hour return r_7 of the day. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

Table 12.
The predictability of first half-hour return and previous day's last half-hour return

Predictor	$r_{1,7}$	$r_{1,8}$	$r_{1,7}$	$r_{1,8}$
Panel A: The predictability of first half-hour return based on opening price				
	CSI 300 market index		CSI 300 market index ETF	
Intercept	−1.975 (2.618)	5.902 (2.856)	1.737 (2.618)	3.308 (2.856)
β_{r_1}	2.053 (3.052)	0.273 (4.160)	3.044 (2.426)	0.997 (4.799)
R^2 (%)	0.1	0.0	0.1	0.0
Panel B: The predictability of first half-hour return based on the previous day's closing price				
Intercept	−1.047 (2.380)	5.355** (2.618)	2.499 (2.380)	3.689 (2.380)
β_{r_1}	2.801 (3.052)	6.428** (3.012)	4.935 (2.127)**	9.969 (2.481)***
R^2 (%)	0.2	1.1	0.7	2.5

Predictor	r_7	r_8	r_7 and r_8	r_7	r_8	r_7 and r_8
Panel C: The predictability of previous day's last half-hour return						
		CSI 300 market index			CSI 300 market index ETF	
Intercept	−1.832 (2.618)	6.616** (2.856)	6.521** (2.856)	1.761 (2.618)	3.213 (2.856)	3.213 (2.856)
β_{r_6}	14.482*** (3.807)		11.431 (7.154)	21.253*** (4.380)		8.960 (6.567)
β_{r_7}		21.111*** (7.881)	19.775*** (5.659)		20.121** (7.881)	18.610** (7.751)
$\beta_{r_{8,\text{lag}}}$	0.746 (6.283)	−6.164 (7.353)	−5.786 (7.249)	3.207 (6.266)	−7.338 (10.685)	−7.219 (10.594)
R^2 (%)	1.7	4.2	5.1	3.7	3.7	4.2

Note(s): The first column in each panel reports the results of regressing seventh half-hour return r_7 on the first half-hour return r_1 of the day. The second columns in each panel report the results of regressing eighth half hour return r_8 on the first half-hour return r_1. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively the unique and robust last hour momentum. We also replicate the results of Zhang *et al.* (2019) with a strong predictive power of first half-hour return, as illustrated in Panel B. However, these studies' values for both slope and R^2 are significantly lower than those of our study. Moreover, using the prior day's closing price to compute the first half-hour return raises the question of overnight return persistence. Intuitively, the overnight return has strong predictive power because overnight information is more than any other half-hour information. For example, overnight information, such as the performance of the US stock market, can significantly influence the performance of the Chinese stock market during the next day. By comparing Panels A and B, we also identify that overnight return is the main driver of predictability on the last half-hour return. Similarly, Lou *et al.* (2019) reveals that momentum profits are relatively high overnight and partially reverse during intraday trading.

In addition, because the literature on the return continuation based on cross-sectional data has documented a high probability of similar returns occurs in the sequence of days (Heston *et al.*, 2010), we must examine the previous day's effect or return continuation effect. Thus, we add the last half-hour return of previous day into the predictability regression as the control variable, and the results are illustrated in Panel C. Clearly, the return continuation effect is low regardless of whether we apply this analysis to the CSI 300 or the ETF. The results also are similar when we employ other indexes. Crucially, the findings are highly different from the intraday pattern in the US stock market. It is reasonable to assume that the trading pattern over the intraday trading in the US stock market is because traders can buy and sell the stock during a single day. However, as to Chinese stock market, evidence for a similar trading pattern in China is low given the application of "T+1 trading rule".

5.4 Other timeframes

Given the uniqueness of the Chinese stock market, we further explore whether intraday momentum may occur during other trading hours. In addition, it is reasonable to assume that the intraday momentum may occur across a half-hour period. Therefore, we implement the prediction regression by employing the half-hour return as the predictor for its next half-hour return. The results are presented in Panel A of Table 13. We find that only the first half-hour return can serve a weak predictor for the first half-hour return at the 10% significant level. We believe this may due to the infrequent (zero) rebalancing effect during the opening hour because the index does not exhibit any significance at all. Overall, the last hour momentum is unique across the trading hours.

Further, we investigate the influence of the "T+1 trading rule" that investors can buy a stock today and sell it on the next day. The results are similar to Aboody *et al.* (2018), who discovered the existence of weak overnight return persistence similar to the findings of Berkman *et al.* (2012). Further, we implement the predictability regression by employing the seventh (eighth) half-hour return as a predictor to make a forecast on the first half-hour return of next day. We summarize the results in Panel B. Specifically, only the last half-hour return has weak predictive power to make a forecast on the first half-hour return of next day [16]. The market index does not exhibit significance, which may also be due to the infrequent (zero) balancing effect in the opening hour. Other indexes also exhibit similar results. Therefore, capturing the last hour momentum requires the ETF as a tool to generate the excess return discussed in this paper because the ETF follows the T+0 trading rule. Other tools to capture the excess return may exist, but we leave investigations of such tools to subsequent research.

Table 13.
The predictability of next half-hour return and overnight

Panel A: The predictability of next half-hour return					
Predictor	$r_{1,2}$	$r_{2,3}$	$r_{3,4}$	$r_{4,5}$	$r_{5,6}$
CSI 300 market index					
Intercept	1.523 (2.856)	−0.571 (2.142)	1.095 (2.856)	5.545 (2.380)	0.571 (2.142)
$\beta_{r_{next}}$	2.416 (3.195)	−8.985 (5.779)	3.864 (6.775)	8.697 (8.387)	−1.066 (3.875)
R^2 (%)	0.1	0.8	0.1	1.1	0.0
CSI 300 market index ETF					
Intercept	1.190 (2.856)	1.357 (2.142)	0.095 (2.618)	6.521*** (2.380)	0.524 (2.380)
$\beta_{r_{next}}$	8.921* (5.178)	−3.629 (5.546)	4.817 (7.253)	6.644 (7.889)	−1.968 (4.344)
R^2 (%)	1.6	0.1	0.1	0.7	0.0

Panel B: The predictability of overnight						
Predictor	r_7	r_8	r_7 and r_8	r_7	r_8	r_7 and r_8
	CSI 300 market index			CSI 300 market index ETF		
Intercept	17.755*** (3.570)	17.612*** (3.570)	17.516*** (3.570)	10.734*** (3.332)	10.424*** (3.332)	10.543*** (3.332)
β_{r_6}	−2.590 (7.382)		−3.397 (7.365)	−5.890 (5.112)		−7.268 (5.714)
β_{r_7}		3.200 (4.956)	3.816 (4.646)		5.789* (3.142)	6.938* (3.560)
R^2 (%)	0.1	0.1	0.1	0.2	0.3	0.6

Note(s): The column in Panel A reports the results of regressing current half-hour return on the next half-hour return of the day. The first column in Panel B reports the results of regressing seventh half hour return r_7 on the first half-hour return r_1 of the next day. The other columns in Panel B report the results of regressing eighth half hour return r_8 on the first half-hour return r_1 and on the both sixth half hour return r_1 and seventh half hour return r_7 of the next day. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust standard errors are in parentheses with the significance value at 1, 5 and 10% level denoted by ***, ** and *, respectively

6. Conclusion

Using high frequency Chinese stock market data, our paper identifies that the sixth (seventh) half-hour return as a predictor for its subsequent half-hour returns, which we term the last hour momentum. The predictability is significant both for the in-sample periods and out-of-sample periods. To capture the economic gains of this phenomenon, we employ the ETF that tracks the CSI 300 as a tool to develop the trading strategy because a trader can buy and sell it during the same intraday session. Then, we reveal that the market timing strategy and asset allocation strategy yield substantial economic gains. The strategy remains profitable after deducting transaction costs. Moreover, we also discover that the last hour momentum is relatively strong on high trading volume days, high volatility days, high-order-imbalance days and days when there are no economic news releases. Furthermore, we demonstrate that the last hour momentum exists for the overall market by employing the SSE and SZSE Composite Indexes. Given the predominance of retail investors in China, retail investor trading behaviors, such as noise trading, late-information trading and trading based on the disposition effect, are theoretically accountable for this phenomenon.

Given the uniqueness of the Chinese stock market, we further explore other possible explanations of the existence of intraday momentum during other trading hours, with negative results. In contrast to US stock market, we determine that the unique and robust last hour momentum in the Chinese stock market. Therefore, a new theoretical model is required to explain the last hour momentum and to identify risk premium factors, especially for the Chinese stock market.

Notes

1. The CSI 300 tracks large cap stocks and the ETF that tracks it trades actively. By contrast, other ETFs are not actively traded, which hinders the ability to develop strategies based on last hour momentum.
2. The CSI Small-cap 500 measures small cap stock performance and its ETF trades actively.
3. The centralized competitive pricing session starts from 09:15 to 09:25. The consecutive bidding session starts from 09:30 to 15:00 with a break from 11:30 to 13:00. The morning session determines the opening price even if trading volume is thin, as illustrated in Figure 1.
4. Most of ETFs in China follow the "T+0 trading rule", especially for the market index ETF.
5. Trading volume during the centralized competitive pricing section is extremely low at less than 1% of total intraday trading volume. By using the opening price to calculate the first half-hour return, we exclude overnight effect as discussed in the relevant literature. This calculation, which is different from Gao *et al.* (2018) and other previous studies, allows us to determine the true intraday momentum.
6. The average tick for the study is five seconds.
7. The situation is similar for the other market indexes.
8. Most listed companies lost two-thirds of their value during the period from June 12, 2015 to February 29, 2016. One-third of the market's value vanished within one month (i.e. from July to August 2015). The 2015 crash was identified as a financial crime by the Chinese government in 2017.
9. There is no significant increase in trading volume during the sample period because retail investors dominate the market.
10. As a mathematical expression, it is equal to (buy volume - sell volume)/(buy volume + sell volume).
11. Annual returns are calculated based on the 238 trading days of each year in China. This is because we close the long positions on each trading day.
12. In our calculation, we ignore the transfer fee because it is too low.

13. There are no zero returns in the analysis.
14. The variance forecast does not change very much even if using two- or three-year windows. A one-year window contains a total of 238 daily observations.
15. We do not include the monetary announcements from Renmin Bank of China since they are not scheduled.
16. In this sense, the application of the "T+1 trading rule" restrains speculative trading behavior in some extent.

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