ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2025.22634

MARKET TIME-SERIES REVERSAL: EVIDENCE FROM CHINA'S MARKET

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Article History:
- received 02 December 2023
- accepted 01 October 2024
- first published online 02 April 2025

Abstract. Upon high-frequency data of China Securities Index 300 (CSI 300) exchange-traded fund and index future contracts, we demonstrate a time-series reversal pattern between the last three-hour returns on current day and those on previous day. Further this reversal is also found in China index future market. This predictability has been illustrated to be both statistically and economically significant, and the significance is stronger on more volatile/higher volume days and non-bearish market state. Extensive regression analysis suggests that the time-series reversal is mainly induced by irrational investor overreaction, not by the lack of liquidity provision. Moreover, the economic value of the reversal pattern is evaluated to yield an outstanding trading performance by executing a market timing strategy.

Keywords: time-series reversal, return predictivity, liquidity, overreaction.

JEL Classification: G11, O16.

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1. Introduction

In addition to the studies for the phenomenon of long-term reversals in stock returns (De Bondt & Thaler, 1985; Jegadeesh, 1990; Jegadeesh & Titman, 1993), considerable efforts have been spent on investigating short-term reversal pattern over the past decades. In index futures markets, intraday price reversal pattern following large price changes at the market opening has been documented in some literature such as by Atkins and Dyl (1990), Fung et al. (2000) and Grant et al. (2005). Lehmann (1990), Lo and Mackinlay (1990) show that contrarian strategies based on weekly returns always obtain significant positive profits. Overnight reversals are also investigated by Stoll and Whaley (1990), Bogousslavsky (2021). It is interesting and naturall that one would ask whether or not such price pattern can be observed at the daily level. This study sheds light on another "anomaly" termed here as time-series reversal pattern, referring to the negative predictability of the return.

The daily time-series reversal pattern in China's market, to the best of our knowledge, has not been fully investigated yet. This paper, in the senses of short-term, seems to provide the first study of time-series reversal and contributes to the existing literature on short-term price reversals to some extent. More specifically, a negative relationship between the last three-hour[1] return in the current day and that in the previous day is identified through various widely-adopted regression analysis (e.g., Gao et al., 2018; Elaut et al., 2018). It's interesting that the utilized regression fails to tell this price reversal when using daily returns, which is one of our findings. Our empirical studies are carried on the tradable CSI 300 ETF (traded on Shanghai Stock Exchange with a ticker symbol of 510300), the most actively traded ETF that tracks the CSI 300 Index. Further, we also investigate and identify the time-series reversal pattern based on China's index future market. In addition, we provide strong out-of-sample evidence of time-series reversals on these financial products.

As for the potential drivers of time-series reversal pattern, two important factors-irrational investor overreaction and liquidity provision are investigated in this paper. As already documented by many pieces of literature (see, e.g., De Bondt & Thaler, 1985; Fung et al., 2000; Grant et al., 2005; Liu et al., 2023), the price reversal is actually a result of irrational investor overreaction in broad financial markets. Other works offer an alternative explanation for price reversals that liquidity provision, measured by bid-ask spreads in transaction prices, are the predominant source of short-term price reversals (Kaul & Nimalendran, 1990; Atkins & Dyl, 1990; Heston et al., 2010; Da et al., 2013). Following these, we test the investor overreaction and liquidity provision hypothesis separately. The empirical analysis finds that time-series reversal pattern is only pronounced in trading days with a higher level of liquidity provision, while the lack of liquidity provision does not cause such a pattern. Furthermore, we find that this reversal pattern occurs only in the trading days with investor overreactions, and this pattern is actually a result of investor overreaction in the market.

To better understand the robustness of time-series reversal pattern, we examine this pattern across different subsamples, a range of return frequencies and various financial assets. The regression analysis shows that the predictability of time-series reversal pattern is positively related to return volatility and trading volume, which is consistent with the findings of Gao et al. (2018). We further analyze the impact of market state on time-series reversal pattern, with a result that the reversal is more pronounced on excluding bearish market states. In addition, time-series reversals are also discerned in the last two-hour and one-hour returns. Investors and fund managers may improve their intraday trading strategies with these empirical findings. From the perspective of trading, the economic significance of overnight reversal pattern is additionally examined through executing a market timing strategy. This strategy using return forecasts generated based on time-series reversal pattern achieves an annualized return of 16.54%, a Sharpe ratio of 0.9 and a success rate of 53.76% on CSI 300 ETF. By contrast, the simple buy-and-hold strategy obtains a return of 10.73%, Sharpe ratio of 0.56 and success rate of 51.51%. Applying this market timing strategy to index future contracts also achieves the substantial economic value of overnight reversal pattern in terms of the trading performances.

There has been a growing body of literature examining reversal and momentum effects within China's market. Chu et al. (2019) demonstrate the presence of both intraday momentum and reversal effects in the Chinese stock market. Similarly, Jin et al. (2020), Yang (2022)

[1] The daily trading sessions are from 9:30 through 11:30am and 13:00pm through 15:00pm.

and Liu et al. (2023) delve into intraday time-series momentum across Chinese Index and ETF, as well as some commodity futures contracts. Our study contributes to the literature by identifying a different type of time-series reversal effect. Furthermore, our findings also extend the realm of investor trading behavior. While many studies attribute reversal effects to investor overreaction and liquidity constraints, our findings suggest that market time-series reversal stems primarily from investor overreaction rather than liquidity provision deficiencies. This enriches existing literature by offering additional insights into the diverse nature of reversal effects. The remainder of this paper is structured as follows. Section 2 describes the data used in the empirical analysis. Section 3 presents the main results on time-series reversal pattern and analyses the potential drivers of this pattern. In Section 4, the robustness of time-series reversal pattern is assessed under various market conditions. Conclusions are in Section 5.

2. Data

To demonstrate time-series reversal pattern in financial markets, empirical studies are carried out using the high-frequency data of CSI 300 ETF, which is traded on Shanghai Stock Exchange with a ticker symbol of 510300. CSI 300 Index is a capitalization-weighted market index, which consists of 300 stocks traded on the Shanghai and Shenzhen Stock Exchanges. The China's stock market is open from 9:30 to 11:30 and 13:00 to 15:00, and 240 one-minute (1-min) returns exist in each trading day. The one-minute frequency data over the period of 2012/05/8 through 2021/11/09 is downloaded from the Wind database (n.d.)[2].

Table 1. Descriptive statistics of one-minute and daily logarithm returns

CSI300 ETF	N	Mean	Min	Max	S.D.	Skew	Kurt	JB
Panel A: Full sample (2012/05/28 to 2021/11/09)								
One-minute return	552000	0.0003	–3.33	2.60	0.0784	0.1582	34.46	2.73e + 7
Daily return	2300	0.0803	–8.47	10.76	1.3325	–0.0942	6.45	3985.14
Panel B: Bearish period (2015/06/01 to 2016/02/28; 2018/02/01 to 2018/12/31)								
One-minute return	96240	–0.0003	–3.33	2. 60	0.1146	0.1973	32.89	4.34e + 6
Daily return	401	–0.0683	–8.47	10.76	2.0500	–0.0999	3.74	234.05

Note: The logarithm returns are multiplied by 100. N: number of one-minute returns. Min: minimum. Max: maximum. S.D.: standard deviation. Skew: skewness. Kurt: kurtosis. JB: Jarque-Bera statistic.

The summary statistics of 1-min and daily returns are presented in Table 1. Considering the sample period featuring stock market crashes (2015/06/01 through 2016/02/28 and 2018/02/01 through 2018/12/31), which are defined as bearish market states in China's stock market, the statistical results for this bearish period is provided in Panel B. First, as Jarque-Bera statistics shown, CSI 300 ETF returns are clearly not normally distributed for both panels A and B (up to 2.73×10^7 in panel A). Second, in terms of 1-min frequency, the positive skewness suggests that large positive returns are considerably more prevalent than large negative returns. This is due to some rare events, such as the release of unexpected monetary policy

[2] Wind is a famous financial and economic database in China.

and COVID-19 crisis (Zhang et al., 2020; Chatjuthamard et al., 2021), which may cause extreme returns in China's stock markets. It is interesting to note that the negative skewness exists in daily returns, which likely reflects the financial crashes in China's financial market during the period of 2015. Third, combining both panels, notably, CSI 300 ETF returns are more volatile and skewed on bearish period than non-bearish period. This result is conceptually consistent with the definition of bearish market.

3. Market time-series reversal: regression analysis and trading strategy

3.1. Predictive regression analysis

To determine the existence of time-series reversal pattern, we consider the simple and effective predictive regression of the last three-hour return of current day on the last three-hour return of previous day:

$$r_{10:30\sim15:00,t} = \alpha + \beta r_{10:30\sim15:00,t-1} + \varepsilon_t, \tag{1}$$

where $r_{10:30\sim15:00,t}$ is the last three-hour return and ε_t is the error term on day t. Notable, there is a break between 11:30 and 13:00 in China's market, which means last three trading hours are ranging from 10:30 to 15:00.

Should be also noted that, to fully detect the reversals, we facilitate predictive regressions using other frequency of returns, such as two-hour and one-hour returns. The detail is in Section 4.2.

Another way to check time-series predictability is to simply focus only on the sign of the predictor. Following Moskowitz et al. (2012), an alternative specification with the sign of lagged three-hour returns as the regressor is also used to examine the robustness of overnight reversal:

$$r_{10:30\sim15:00,t} = \alpha + \beta sign(r_{10:30\sim15:00,t-1}) + \varepsilon_t, \tag{2}$$

where *sign* $(\cdot)$ is the sign function that equals +1 when $r_{10:30\sim15:00,t-1} \geq 0$ and -1 otherwise.

In this study, both regressions are adopted for providing more convincing evidence.

The regression results using last three-hour returns is reported in Panel A of Table 2. Obviously, the last three-hour return of previous day, $r_{10:30\sim15:00,t-1}$, negatively predicts the last three-hour return $r_{10:30\sim15:00,t}$ of day t, with a slope of –0.0904, statistically significant at the 1% level, and an R^2 of 0.776%. Similarly, for the alternative specification with the sign of lagged three-hour returns, it exhibits a negative relationship between $r_{10:30\sim15:00,t}$ and $r_{10:30\sim15:00,t-1}$, with a slope of –0.0008, statistically significant at the 1% level, and R^2 of 0.5206%. From the statistically significant and negative coefficients of $r_{10:30\sim15:00,t-1}$, as well as the sign, it suggests the existence of the time-series reversal pattern in CSI 300 ETF.

Turn to Panel B of Table 2, the daily return of current day, r_t, is regressed on the daily return of previous day, r_{t-1}, or its sign, $sign(r_{t-1})$. The results indicate that there is no significant relation between r_t and r_{t-1}. When adding the first one-hour return into the regressions, it then leads to the disappearance of time-series reversal pattern. The potential explanation

Table 2. Predictability of market time-series reversal

	Panel A			Panel B			Panel C	
Variables	$r_{10:30\sim 15:00,t}$	$r_{10:30\sim 15:00,t}$	Variables	r_t	r_t	Variables	r'_t	r'_t
Intercept	0.0004* (1.8515)	0.0004* (1.7766)	Intercept	0.0008*** (2.7918)	0.0008*** (2.8565)	Intercept	0.0008** (2.7918)	0.0008 (2.8565)
$r_{10:30\sim 15:00,t-1}$	–0.0904*** (–4.3557)		r_{t-1}	0.0210 (1.0085)		r'_{t-1}	0.0210 (1.0085)	
$Sign(r_{10:30\sim 15:00,t-1})$		–0.0008*** (–3.6092)	$Sign(r_{t-1})$		–0.0001 (–0.0339)	Sign(r'_{t-1})		0.0000 (–0.0339)
R^2 (%)	0.7760	0.5206	R^2 (%)	0.0073	0.0023	R^2 (%)	0.0007	0.0000

Note: Panel A reports the results of regressing the last three-hour return of the current day, $r_{t,3}$, on the last three-hour return or its sign of the previous day, $r_{10:30\sim 15:00,\ t-1}$ or *Sign* ($r_{10:30\sim 15:00,\ t-1}$). Panel B reports the results of regressing the return of the current day, r_t (including overnight return), on the return or its sign of the previous day, r_{t-1} or *Sign* (r_{t-1}). Panel C reports the results of regressing the return of the current day, r'_t (excluding overnight return), on the return or its sign of the previous day, r'_{t-1} or *Sign* (r'_{t-1}). Newey-West *t*-statistics are reported in parentheses. Significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from 2012/05/28 through 2021/11/09.

could be from institutional factors and micro-structure effects that opening one-hour returns are considerably more variable than those in other trading sessions, which reflects the information processing at the start of the trading session, and hence the opening hour of daily trading even exhibits a momentum effect. After all, the processing of new information released before the market opens typically takes about one half or one hour, as evident from the high volume in the first trading hour (see Elaut et al., 2018). Once the new information has been incorporated into transaction prices at the first hour, the market cools down and investors begin to correct the significant price change caused by the overreaction in the previous session (see also Gao et al., 2018). In additional, the first half-hour returns is suggested predicting same-half-hour returns on subsequent days by the repetitive institutional traders (Murphy & Thirumalai, 2017), this might be also one more explanation. As emphasized by Gao et al. (2018), the market typically opens at a level that differs from the previous day's close because it reflects new information released before the market opens. The digestion of new information usually takes about 30 minutes, and the high volume and high volatility in the first half hour of trading are the typical phenomenon. In this regard, the first half hours of a trading day is so special. Thus, the traders correct the overreactions formed in the previous day after the first half hour of present trading day.

To completely investigate the relation between daily returns, we consider the close-to-open return, denoted by r_t', which excludes the overnight effect. The regressions are performed on the returns excluding the overnight returns, and the results are reported in Panel C. Apparently, it exhibits almost the same with that using daily return r_t shown in Panel B. Thus, the time-series reversal pattern is significantly observed only between the last three-hour returns whereas insignificant relation appears between daily returns regardless of the overnight factor.

3.2. Out-of-sample predictability

The regression analysis in subsection 3.1 is based on the full sample estimations and it displays in-sample performance, which does not necessarily imply out-of-sample (OOS) predictability. To test the OOS predictability of time-series reversals, the above predictive regressions need expanding windows by adding one trading day. Specifically, the predictive regressions are performed with the data up to day t–1. With the estimated coefficients ($\hat{\alpha}$ and $\hat{\beta}$) and the predictor $r_{10:30\sim15:00,t-1}$, one can generate a forecast of the last three-hour return, $\hat{r}_{10:30\sim15:00,t}$, at day t: $\hat{r}_{10:30\sim15:00,t} = \hat{\alpha} + \hat{\beta} r_{10:30\sim15:00,t-1}$.

In addition, the alternative specification with the sign of lagged three-hour returns as predictor is also used to generate an alternative forecast of the last three-hour return.

With a series of OOS return forecasts, OOS R^2 is estimated to measure OOS predictability:

$$R^2_{OS} = 1 - \frac{MSE_p}{MSE_b}, \tag{3}$$

where $MSE_p = \frac{1}{n}\sum_{i=1}^{n}(r_{10:30\sim15:00,i} - \hat{r}_{10:30\sim15:00,i})^2$ and $MSE_b = \frac{1}{n}\sum_{i=1}^{n}(r_{10:30\sim15:00,i} - \overline{r}_{10:30\sim15:00,i})^2$ refer to the mean square errors. The historical average of the last three-hour return, $\overline{r}_{10:30\sim15:00,i}$, is calculated from the last three-hour returns up to day t–1:

$$\overline{r}_{10:30\sim15:00,t} = \frac{1}{t-1}\sum_{i=1}^{t-1} r_{10:30\sim15:00,i}. \tag{4}$$

To test the significance of the R^2_{OS}, F-statistic of McCracken (2007) are employed:

$$MSE - F = n \cdot \left(1 - \frac{MSE_p}{MSE_b}\right). \tag{5}$$

Table 3. Out-of-sample predictability of market time-series reversal

Variables	OOS R^2	MSE-F
$r_{10:30\sim15:00,t-1}$	0.49%	10.61***
$Sign(r_{10:30\sim15:00,t-1})$	0.63%	13.79***

Note: This table reports the out-of-sample predictability results of the last three-hour of the current day by the last three-hour of the previous day, using a set of recursive regressions. Significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from 2012/05/28 through 2021/11/09.

The OOS predictabilities are tabulated in Table 3. For generating OOS return forecasts using the predictor $r_{10:30\sim15:00,t-1}$, we obtain a significant R^2_{OS} of 0.49%, with an F-statistic of 10.61. Using the sign of the predictor to generate forecasts, a significant R^2_{OS} is obtained as 0.63%, with a F-statistic of 13.79. It is noteworthy that Welch and Goyal (2008) suggest that it is not easy for a predictor to beat the historical average benchmark. Fortunately, from the positive and statistically significant R^2_{OS}, the time-series reversal pattern has better out-of-sample predictability than the historical average benchmark.

3.3. Market timing strategy

To assess the economic significance of applying the time-series reversal pattern, we develop a simple market timing strategy[3] that uses the last three-hour return forecasts as timing signals to trade the market in the last three-hour. Specifically, the timing strategy chooses to take a long position in the market at the end of the first trading hour of the day as long as the last three-hour return forecast is positive, and a short position otherwise. To avoid look-ahead-bias, we only use available data at each trading day to make prediction. The performance of this market timing strategy is benchmarked against a so-called buy-and-hold strategy, which always goes long at the end of the first trading hour. At the end of the trading day, both kinds of strategies liquidate all the open positions. In view of the transaction cost, a reasonable cost is assumed to be 2 bps per round-trip trade with consideration of bid-ask spread and broker fees, as well as the high trading liquidity of the chosen investment underlying. Notably, stamp tax is free for trading ETFs in Shanghai Security Exchange.

Table 4. Performance of market timing strategy based on time-series reversal

Strategy	Mean return	S.D.	S.R.	Success rate
S($r_{10:30\sim15:00,t-1}$)	11.50%	17.28%	0.61	53.76%
S($Sign(r_{10:30\sim15:00,t-1})$)	12.03%	17.28%	0.64	53.12%
Buy and hold	5.69%	17.30%	0.27	51.51%

Note: The performances of two market timing strategies based on time-series reversal and a buy-and-hold trading strategy are reported in this table. The market timing strategy goes long when the last three-hour return forecast is positive, and short otherwise. The buy-and-hold strategy always goes long the last three-hour of the trading day. First strategy S($r_{10:30\sim15:00,t-1}$) relies on the forecasting based on the predictor of $r_{10:30\sim15:00,t-1}$. Second strategy S($Sign(r_{10:30\sim15:00,t-1})$) relies on the forecasting based on the predictor of $Sign(r_{10:30\sim15:00,t-1})$. Mean return: annualized return. S.D.: annualized standard deviation. S.R.: annualized Sharpe ratio. The sample period is from 2012/05/28 through 2021/11/09.

Table 4 reports summary statistics on the trading profits generated from these strategies. The strategy $S(r_{10:30\sim15:00,t-1})$ uses the predictor $r_{10:30\sim15:00,t-1}$ to predict $r_{10:30\sim15:00,t}$ and then makes trading according to the signals. It obtains an annualized return of 11.50%, a Sharpe ratio of 0.61 and a success rate of 53.76%. The strategy $S(sign(r_{10:30\sim15:00,t-1}))$ uses the predictor $sign(r_{10:30\sim15:00,t-1})$ to predict $r_{10:30\sim15:00,t}$ and then trades accordingly. The resultant annualized return is 12.03% with a Sharpe ratio of 0.64 and a success rate of 53.12%. In contrast, the simple buy-and-hold strategy only achieves an annualized return of 5.69%, a Sharpe ratio of 0.27 and a success rate of 51.51%. Overall, the market timing strategy using time-series reversal pattern substantially outperforms the passive buy-and-hold strategy and generates attractive returns in China's stock market.

3.4. Explanations: Irrational overreaction and liquidity provision

The results above (in- and out-of-sample regression) provide strong evidence of time-series reversals in China's market. It is then natural and necessary for us to explore the forces behind this phenomenon.

[3] We here focus on demonstrating the predictability of time-series reversal pattern, rather than emphasising how to establishing a trading strategy like machine learning-based method (see, e.g, Gao et al., 2024).

As aforementioned, there are two potential explanations for the time-series reversal pattern: irrational overreaction and liquidity provision. De Bondt and Thaler (1985) attribute the long-term reversal pattern to irrational investor overreaction. Fung et al. (2000) investigate the US and Hongkong index futures markets and identify an intraday reversal pattern, which is not caused by a bid-ask spread or by panic among investors. They suggest that the irrational investor overreaction may be a potential explanation for this phenomenon. Meanwhile, many other literatures offer an alternative explanation for reversals. Kaul and Nimalendran (1990), Atkins and Dyl (1990) show that liquidity provision, measured by bid-ask spreads in transaction prices, are the predominant source of short-term price reversals. Chordia et al. (2008) find that very short-term predictability is diminished when bid-ask spreads are narrower, suggesting that the lack of liquidity also plays a role in the short-term predictability of returns. In addition, Heston et al. (2010) show that short-term return reversal is driven by temporary liquidity imbalances, and these reversals last for several trading days.

As such, this study investigates the likely drivers of time-series reversal. We adopt the illiquidity indicator from Amihud (2002) (Amihud illiquidity) to measure the lack of liquidity provision, and F-statistics from Klößner et al. (2012) to measure upside overreaction (namely, $F_{\max}$) and downside overreaction (namely, $F_{\min}$). These two overreaction statistics are defined as follows:

$$F_{\max} = \frac{\frac{1}{N}\sum_{n=1}^{N} 2(P_n^h - P_n^o)(P_n^h - P_n^c)}{\frac{1}{N-1}\sum_{n=1}^{N}(R_n - \bar{R})^2}; \tag{6}$$

$$F_{\min} = \frac{\frac{1}{N}\sum_{n=1}^{N} 2(P_n^o - P_n^l)(P_n^c - P_n^l)}{\frac{1}{N-1}\sum_{n=1}^{N}(R_n - \bar{R})^2}, \tag{7}$$

where P_n^o, P_n^h, P_n^l, and P_n^c are open, high, low, and close log-prices for period n; R_n is logarithm return over period n and $\bar{R}$ is the sample mean of these logarithm returns. In particular, the corresponding Amihud illiquidity and overreactions for a trading day are calculated using the one-minute frequency data in the last three-hour of previous trading day.

To formally analyze the relationship between time-series reversal and illiquidity, all trading days are sorted by Amihud illiquidity of the last three-hour on the previous day and split into two groups: low and high illiquidity days. The results are reported in Panel A of Table 5. It is observed that the predictability is statistically significant on low illiquidity days, and insignificant on high illiquidity days, which indicates that time-series reversal pattern is not caused by the lack of liquidity provision. In the same way, all trading days are sorted by F-statistics of upside and downside overreactions of last three-hour in previous day, the analysis results are included in Panel B and C of Table 5 for upside and downside overreactions, respectively. The predictability is statistically significant on high overreaction days, and insignificant on low overreaction days. These findings suggest that time-series reversal pattern is induced by irrational investor overreaction, and does not arise from the lack of liquidity provision.

Table 5. Drivers of time-series reversal

Panel A: *Illiquidity*	High illiquidity day		Low illiquidity day	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	0.0002 (0.7272)	0.0002 (0.7244)	0.0006* (1.8932)	0.0006* (1.7798)
$r_{10:30\sim15:00,t-1}$	–0.0498 (–1.5198)		–0.1161*** (–4.2910)	
$Sign(r_{10:30\sim15:00,t-1})$		–0.0005 (–1.6453)		–0.0011*** (–3.4241)
R^2 (%)	0.1140	0.1485	1.4928	0.9248
Panel B: $F_{\max}$	High $F_{\max}$ day		Low $F_{\max}$ day	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	0.0004 (1.7347)	0.0004 (1.5346)	0.0004 (0.9079)	0.0004 (0.8433)
$r_{10:30\sim15:00,t-1}$	–0.1059*** (–4.5162)		–0.0374 (–0.8309)	
$Sign(r_{10:30\sim15:00,t-1})$		–0.0008*** (–2.8967)		–0.0010** (–2.1738)
R^2 (%)	1.1300	0.4336	0.1151	0.6171
Panel B: $F_{\min}$	High $F_{\min}$ day		Low $F_{\min}$ day	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	0.0005* (1.9037)	0.0005* (1.8297)	0.0000 (0.1893)	0.0001 (0.2583)
$r_{10:30\sim15:00,t-1}$	–0.1166*** (–5.0557)		0.0371 (0.7741)	
$Sign(r_{10:30\sim15:00,t-1})$		–0.0010*** (–4.0176)		0.0000 (–0.0725)
R^2 (%)	1.3732	0.8510	0.1125	0.0010

Note: This table reports the results for an evaluation of the impact of likely driver on time-series reversal. All drivers are calculated from one-minute logarithm return in the last three trading hours of previous day. Newey-West *t*-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from 2012/05/28 through 2021/11/09.

4. Robustness of time-series reversals

Since the time-series reversal pattern may vary with different market conditions, this Section conducts additional regression analysis to test the robustness of time-series reversal pattern along different subsamples, return frequencies and financial asset classes.

4.1. Market conditions

First, due to the influence of volatility on the appearance of time-series price pattern (Wang & Xu, 2015; Kim et al., 2016), we choose volatility as an affecting factor. All trading days are split into two groups based on sorted volatility levels: low volatility days and high volatility days[4].

[4] Specifically, according to Gao et al. (2018), the days with higher (lower) volatility levels than the median of all volatilities are considered as high (low) volatility days.

Note that the volatility of a day is estimated, with the data in last three-hour of previous trading day, as the standard deviation of one-minute logarithm returns. As shown in Panel A of Table 6, the time-series reversal pattern is more significant on high volatility days than low volatility days for both regressions. Hence, the existence of time-series reversal pattern is positively correlated with the volatility. This is consistent with the finding of Gao et al. (2018) that higher volatility would lead to greater predictive power.

Table 6. Time-series reversal under different market conditions

Panel A: *Volatility*	High volatility day		Low volatility day	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	0.0003 (0.7108)	0.0003 (0.6959)	0.0005*** (2.7135)	0.0005*** (2.6265)
$r_{10:30\sim15:00,t-1}$	–0.0931*** (–3.2976)		–0.0723** (–1.9938)	
$Sign(r_{10:30\sim15:00,t-1})$		–0.0012*** (–2.9760)		–0.0004** (–2.1245)
R^2 (%)	0.8528	0.6797	0.2583	0.3048
Panel B: *Volume*	High volume day		Low volume day	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	0.0006 (1.6420)	0.0006 (1.5974)	0.0002 (0.8929)	0.0002 (0.8633)
$r_{10:30\sim15:00,t-1}$	–0.0934*** (–3.4921)		–0.0815** (–2.1459)	
$Sign(r_{10:30\sim15:00,t-1})$		–0.0010*** (–2.7320)		–0.0006** (–2.4234)
R^2 (%)	0.9657	0.5599	0.3128	0.4223
Panel C: *Market state*	Bearish		Non-bearish	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	–0.0012 (–1.3672)	–0.0011 (–1.2845)	0.0007*** (3.5872)	0.0007 (3.4707)
$r_{10:30\sim15:00,t-1}$	–0.1201** (–2.4183)		–0.0742*** (-3.2446)	
$Sign(r_{10:30\sim15:00,t-1})$		–0.0014* (–1.6858)		–0.0007*** (–3.4454)
R^2 (%)	1.1975	0.4584	0.4997	0.5698

Note: This table reports the impacts of return volatility (Panel A), trading volume (Panel B) of the last three-hour and market state (Panel C) on time-series reversal. Newey-West *t*-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from 2012/05/28 through 2021/11/09.

Second, the trading volume is also a second factor affecting the expected which is well documented by many literatures (see Han et al., 2022; Wang, 2021). To examine how trading volume influences the existence of the overnight reversal pattern, we divide all trading days into two groups along trading volume in last three-hour of previous trading day: low-volume days and high-volume days[5]. The related result is in Panel B of Table 6, which tells that

[5] Specifically, according to Gao et al. (2018), the days with higher (lower) volume levels than the median of all volumes are considered as high (low) volume days.

time-series reversal pattern is more significant on high volume days than low volume days. A high trading volume is generally an indication of a high liquidity level for a particular security in the market. This is consistent with the finding of Section 3.4.

Third, the time-series reversal effect may be influenced by market states – bearish and bullish market state – with the outlier in the time series of market returns, since bearish state usually leads to structural changes in market price dynamics (Smith, 2012). It is imperative to understand how market states impacts the predictive power of time-series reversal pattern. In Panel C of Table 6, all trading days are split into two groups: bearish period and non-bearish period (no bullish state during the study period). The result in Panel C suggests time-series reversal pattern during the bearish state. However, this pattern is more significant in non-bearish period in terms of the slopes and R^2. These results demonstrate that the structural changes occurred in markets during the bearish period.

4.2. Return frequencies

It is already demonstrated that using time-series reversal pattern to predict the last three-hour returns is effective in statistical and economic sense. A natural question is whether the observed time-series reversal pattern is robust to the use of different return frequencies. To further test the robustness of time-series reversal pattern, the regression analysis is performed with different return frequencies.

Table 7. Time-series reversal under different return frequencies

	Panel A			Panel B	
Variables	$r_{13:00\sim 15:00,t}$	$r_{13:00\sim 15:00,t}$	Variables	$r_{14:00\sim 15:00,t}$	$r_{14:00\sim 15:00,t}$
Intercept	0.0004* (1.9151)	0.0004** (1.9615)	Intercept	0.0002* (1.7401)	0.0003* (1.8212)
$r_{13:00\sim 15:00,t-1}$	–0.0921*** (–4.1677)		$r_{14:00\sim 15:00,t-1}$	–0.0629*** (–3.0219)	
$Sign(r_{13:00\sim 15:00,t-1})$		–0.0007*** (–3.7382)	$Sign(r_{14:00\sim 15:00,t-1})$		–0.0003** (–2.4040)
R^2 (%)	0.8047	0.5614	R^2 (%)	0.3526	0.2075

Note: This table presents regression results for the return frequency sensitivity analysis. Panel A reports the results of regressing the last two-hour return of the current day, $r_{13:00\sim 15:00,t}$, on the last two-hour return or its sign of the previous day, $r_{13:00\sim 15:00,t-1}$ or $Sign(r_{13:00\sim 15:00,t-1})$. Panel B reports the results of regressing the last one-hour return of the current day, $r_{14:00\sim 15:00,t}$, on the last one-hour return or its sign of the previous day, $r_{14:00\sim 15:00,t-1}$ or $Sign(r_{14:00\sim 15:00,t-1})$. Newey-West t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from 2012/05/28 through 2021/11/09.

In Panel A of Table 7, the last two-hour return of current day, $r_{13:00\sim 15:00,t}$, is negatively predicted by the last three-hour return of previous day, $r_{10:30\sim 15:00,t-1}$, with a slope of –0.0921, statistically significant at the 1% level, and an R^2 of 0.8047%. The alternative specification with the sign of lagged two-hour returns as the regressor confirms this negative relationship between $r_{13:00\sim 15:00,t}$ and $r_{10:30\sim 15:00,t-1}$, with a slope of –0.0007, statistically significant at the 1% level, and an R^2 of 0.5614%.

Panel B reports the results of regressing the last one-hour return of the current day, $r_{14:00\sim15:00,t}$, on the last one-hour return or its sign of the previous day, $r_{14:00\sim15:00,t-1}$. The predictabilities of the last one-hour return and its sign are effective by the slopes and R^2. Time-series reversal pattern in the last one-hour returns still appears, but with less significance than those in the last two-hour and three-hour returns. One potential explanation is that many investors, such as market makers, fund managers and institutional traders, place an enormous emphasis on market close (Cushing & Madhavan, 2000; Foucault et al., 2005), their trading behaviours would cause the high volume and high volatility in the last hour of trading. Overall, overnight reversal pattern is robust with different return frequencies.

4.3. Index futures contracts

Is the existence of time-series reversal pattern unique to the CSI 300 ETF? To answer this question, the regression analysis is performed on three most actively traded index future contracts in this study. These contracts are traded on China Financial Futures Exchange (CFFEX) with the ticker symbols of IF written on CSI 300 Index, IC written on CSI Small-cap 500 Index and IH on SSE 50 Equal Weight Index.

Table 8. Time-series reversal in index future contracts

	IF		IC		IH	
Variables	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$	$r_{10:30\sim15:00,t}$
Intercept	−0.0002 (−0.8240)	−0.0002 (−0.7892)	−0.0003 (−1.0399)	−0.0003 (−0.9715)	−0.0003 (−1.1816)	−0.0003 (−1.2265)
$r_{10:30\sim15:00,t-1}$	−0.0912*** (−3.1999)		−0.1040*** (−3.6500)		−0.0686** (−2.4067)	
$Sign(r_{10:30\sim15:00,t-1})$		−0.0008*** (−3.0818)		−0.0011*** (−3.5230)		−0.0005** (−2.0759)
R^2 (%)	0.7510	0.6911	0.9991	0.9259	0.3890	0.2690

Note: Time-series reversal is examined on the most traded index future contracts in China. IF: index future contract on CSI 300 Index. IC: index future contract on CSI Small-cap 500 Index. IH: index future contract on SSE 50 Equal Weight Index. Newey-West *t*-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from 2016/02/01 through 2021/02/05.

The results are reported in Table 8. The negative relationship between last three-hour return of current day and that of previous day is statistically significant at the 1% level in IF and IC data. Should be noted that, although this relationship still exists in IH data, the predictive ability of time-series reversal pattern becomes weaker in terms of the slope and minimal R^2. Combining with the findings in CSI 300 ETF market makes an overall assertion that time-series reversal pattern is a general phenomenon in China financial market.

To further assess the economic significance of time-series reversal pattern, the simple market timing strategy developed in Section 3.3 is performed on index future contracts. The total transaction cost for trading index futures is also assumed to be 2 bps per round-trip trade with consideration of bid-ask spread, broker fees and the high trading liquidity of the index futures.

Table 9. Performance of market timing strategy on index future contracts

Strategy	Mean return	S.D.	S.R.	Success rate
Panel A: IF				
$S(r_{10:30\sim15:00,t-1})$	16.51%	13.59%	1.07	54.67%
$S(Sign(r_{10:30\sim15:00,t-1}))$	15.69%	13.59%	1.01	54.40%
Buy and hold	–3.96%	13.63%	–0.44	49.23%
Panel B: IC				
$S(r_{10:30\sim15:00,t-1})$	14.62%	16.26%	0.78	52.67%
$S(Sign(r_{10:30\sim15:00,t-1}))$	20.40%	16.23%	1.13	53.31%
Buy and hold	–7.82%	16.28%	–0.60	49.05%
Panel A: IH				
$S(r_{10:30\sim15:00,t-1})$	6.65%	13.34%	0.35	53.38%
$S(Sign(r_{10:30\sim15:00,t-1}))$	11.01%	13.33%	0.68	53.65%
Buy and hold	–5.63%	13.35%	–0.57	46.98%

Note: The performances of two market timing strategies based on time-series reversal and a buy-and-hold trading strategy are reported in this table. The market timing strategy goes long when the last three-hour return forecast is positive, and short otherwise. The buy-and-hold strategy always goes long the last three-hour of the trading day. First strategy $S(r_{10:30\sim15:00,t-1})$ relies on the forecasting based on the predictor of $r_{10:30\sim15:00,t-1}$. Second strategy $S(Sign(r_{10:30\sim15:00,t-1}))$ relies on the forecasting based on the predictor of $Sign(r_{10:30\sim15:00,t-1})$. Mean return: annualized return. S.D.: annualized standard deviation. S.R.: annualized Sharpe ratio. The sample period is from 2016/02/01 through 2021/02/05.

Table 9 reports summary statistics on the trading profits generated from these strategies. As shown in the table, the strategy $S(r_{10:30\sim15:00,t-1})$ applied on IF data obtains an annualized return of 16.51%, a Sharpe ratio of 1.07 and a success rate of 54. 67%. The alternative strategy $S(sign(r_{10:30\sim15:00,t-1}))$ achieves an annualized return of 15.69%, a Sharpe ratio of 1.01 and a success rate of 54.4%. The market timing strategy on IC, as well as IH, produces a similar trading performance as it does on IF. Conversely, the simple buy-and-hold strategy applied on IF, IC and IH data obtains negative annualized returns with success rates less than 50%. Overall, the market timing strategy using time-series reversal substantially outperforms the passive buy-and-hold strategy, and generates attractive returns in China's index future market.

5. Conclusions

This study investigates time-series reversal pattern in China's ETF and Index futures markets. The results show that the last three-hour return on current trading day is negatively predicted by the last three-hour return on previous trading day, and this predictability of time-series reversal pattern is statistically significant using in-sample and out-of-sample. The empirical results provide strong evidence supporting that the time-series reversals actually exist in the markets of CSI 300 ETF and the most actively traded index futures. This finding undoubtedly contributes to existing literature on short-term reversal.

To fully examine the time-series reversal pattern, the robustness across various levels of return frequencies and market conditions is extensively tested. Empirical analysis shows that the existence of time-series reversal pattern is related to return volatility, trading volume and market state. Furthermore, we seek the potential explanations for such reversal pattern and find that the irrational investor overreaction is an explicable factor. In addition, the economic values of this pattern are evaluated through executing the time-series reversal-based market timing strategy developed in this study. The results suggest that such strategy has a superb trading performance and consequently produces substantial economic gains by benchmarking against the buy-and-hold strategy.

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