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Does the $T+1$ rule really reduce speculation? Evidence from Chinese Stock Index ETF

Xinyun Chen[a], Yan Liu[b], Tao Zeng[c]

[a]*Department of Finance, Economics and Management School, Wuhan University, Wuhan, Hubei, China*
[b]*Center for Economic Development Research, Department of Finance, Economics and Management School, Wuhan University, Wuhan, Hubei, China*
[c]*School of Economics, Academy of Financial Research, Zhejiang University, Hangzhou, Zhejiang, China*

Abstract

Stock market in China is subject to the $T+1$ rule, which requires investors to hold the asset for at least 1 day before selling. This rule was initially imposed in the mid-1990s, replacing the previous $T+0$ rule, to prevent excessive speculative trading. Given the considerable changes in China's financial market over the past 20 years, it is controversial whether the $T+1$ rule should be replaced by the $T+0$ rule in today's market. In this paper, we empirically test the effect of the $T+1$ rule on market speculation. To identify potentially different impacts of the $T+1$ and $T+0$ rule, we choose a unique pair of CSI 300 ETFs, one subject to the $T+1$ rule while the other to the $T+0$ rule. Based on an error correction model, we develop an empirical methodology to test intraday speculation in the ETF price. Our empirical results show that, at least under current market condition, the $T+1$ rule reduces the price efficiency and spurs more speculation when the market liquidity is not in a shortage.

Key words: CSI 300 ETF; Speculation; $T+0$; $T+1$; Trading rules

JEL classification: G10, G12, G18

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1. Introduction

Among the major stock markets around the world, China's stock market is the only one that adheres strictly to the so-called $T + 1$ trading rule until now.[1] In both Shanghai Stock Exchange and Shenzhen Stock Exchange, investors cannot sell shares of stocks or funds that are bought on the same day. Historically, the $T + 1$ rule was imposed in the mid-1990s to prevent excessive speculative trading and to protect retail investors. In recent years, more and more industrial practitioners and academic researchers are advocating elimination of the $T + 1$ rule and adoption of the $T + 0$ rule (shares can be bought and sold on the same day). They argue that China's stock market condition is no longer the same as in the 1990s, with the market depth increased significantly and greater presence of institutional investors. Moreover, in principle, the $T + 0$ rule will improve market liquidity over the $T + 1$ rule, and the adoption of the $T + 0$ rule will bring China's stock market more in line with the international standards. Finally, recent theories of market speculation, for example Scheinkman and Xiong (2003), Xiong (2013), demonstrate that under investor belief heterogeneity, trading restrictions are conductive to speculation instead of preventing it. Against these arguments, China's regulatory agencies are still concerned with potential risk of excessive speculation under the $T + 0$ rule and hence are cautious to change the $T + 1$ rule.[2]

Reflecting upon the opposite views, we attempt to provide a set of empirical evidences on the potentially distinct effects of the $T + 1$ versus $T + 0$ rule upon China's stock market, including their impacts upon market speculation, and in this way, we are able to provide more meaningful information for the policy debate on trading rules. Our empirical strategy consists of testing *directly* the market effects – especially those related to speculation – of the two trading rules. This helps us avoid the ambiguous notion of improved market condition and assess how much validity is left in the old wisdom about pro-speculation effect of the $T + 0$ rule insisted by adherents to the $T + 1$ rule, as the market condition does change considerably over the past two decades.

There are two identification challenges that such a research strategy has to confront. The first is on data limitations. On the one hand, the $T + 0$ rule was only adopted before 2001 in several segments of China's stock market,[3] and from 2001 up to now, there is no sample observation on individual stock trading under the $T + 0$ rule for a direct comparison between the two trading rules. In addition, the current market condition is fundamentally different from

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[1] We relegate more details to Section 3.1.

[2] See *China Financial Stability Report* 2014 (pp. 89–91) and 2016 (pp. 58–60) for the regulators' opinion on $T + 0/T + 1$ trading rules.

[3] The $T + 0$ rule was adopted in the A-share market from December of 1992 to December of 1994, and in the B-share market until December of 2001.

that before 2001; thus, it is of little use to compare the market trading behaviour of the current $T + 1$ rule to that of the former $T + 0$ rule. On the other hand, although most international markets adopt the $T + 0$ rule, again they are different from China's market along many other aspects. Consequently, it is intricate, if not entirely impossible, to differentiate the impacts of $T + 1/T + 0$ rules by comparing market trading samples from China to those from other markets. The second challenge is related to speculative trading, a key element in the question we want to address. Conceptually, speculation is a trading phenomenon with two intertwined elements: buying-for-selling behaviour and price deviation from fundamental value.[4] Empirically, however, it is typically difficult to distinguish buying-for-selling trading from other trading behaviour, and to measure the fundamental value properly.

Our research design addresses both challenges. Our first contribution is the utilisation of a *unique* data sample to overcome the data limitation discussed above. In specific, we use minute-level trading data of two stock index ETFs in China, Huatai and Jiashi,[5] over the period of October 2014 to September 2015, which covers the 2015 Chinese stock market crash.[6] The two ETFs both track the CSI 300 stock index,[7] and they are almost identical in all aspects except one *critical* difference. Huatai adopts the 'cross-market' $T + 0$ rule while Jiashi adopts the $T + 1$ rule from their creations in 2012 to now.[8] The unique difference in the trading rules enables us to identify potentially differential market impacts associated with the $T + 0/T + 1$ rules in a simple and clear manner, which is generally impossible to achieve by *any* other data sample in China's stock market. To our best knowledge, we are the first to exploit this feature of the Huatai ETF to study the implications of $T + 0$ trading rule in China's stock market.

Our second contribution is on the empirical modelling and measure of speculation. Most empirical works use volatility and its variants to measure

[4] The original articulation of speculation is due to Keynes (1936, ch. 12) and subsequently elaborated by Harrison and Kreps (1978) and Morris (1996).

[5] Huatai and Jiashi are listed in Shanghai Stock Exchange and Shenzhen Stock Exchange, respectively, with tick number 510300 and 159919. Although they are listed and traded in separate exchanges, investors have equal access to both exchanges so there is no issue of market segmentation.

[6] Chinese stock market doubled in less than a year and reached the recent peak in June 2015, followed by a sudden crash from June to July 2015.

[7] CSI 300 index covers 300 stocks traded in both Shanghai Stock Exchange and Shenzhen Stock Exchange, and the selected stocks have both large market capitalisation and high liquidity. CSI 300 is by far the most representative stock index for China's stock market.

[8] More institutional details are relegated to Section 3. To be clear, Huatai is the only $T + 0$ ETF in the class of stocks and related securities in China, while there are other $T + 1$ ETFs similar to Jiashi. However, Jiashi has the largest size and the most active trading among all $T + 1$ ETFs.

speculation, yet it is unclear how to distinguish the speculative component of trading volatility from the nonspeculative one. Instead of using volatility, we focus on the second aspect of speculation, namely the price deviation from fundamental. The ETF sample we use makes the measure of fundamental value straightforward. The two ETFs we consider are designed to mirror the CSI 300 index, and as the index is directly observable in real time, it can be readily used as the measure of fundamental value for the ETFs. In this article, we shall measure the price deviation of the ETF with respect to the index in a cointegration framework. Intuitively, when the market is efficient with little speculative trading, the ETF price and the index should be cointegrated, with the pricing error sequence being stationary around 0. However, when speculative trading is active, the pricing error becomes significant and persistent, thus represents a structural change in the cointegration relation. In detail, we use the error correction representation to model the cointegration between the ETF and the index, and introduce a 'speculation' term in the error correction model to capture persistent pricing error. We estimate the error correction model and test the existence of the speculation term for the two ETFs for each trading day. This allows us to empirically test the impact of $T + 1/T + 0$ trading rules on (intraday) speculation.

We obtain three main results. First, correction to price deviation under the $T + 0$ rule is faster than under the $T + 1$ rule. Second, before the market crash in mid-June of 2015, speculation under the $T + 1$ rule is more frequent than under the $T + 0$ rule. Third, during the market crash in June and July of 2015, speculation increases both under the $T + 0$ and $T + 1$ rule, but to a greater extent for the latter case. These findings indicate that, under the same market condition, the $T + 1$ and $T + 0$ trading rules do have different impact on speculation. Our result is consistent with the recent theory of speculation featuring trading restrictions and belief heterogeneity, even in the absence of information asymmetry among investors. The intuition is as follows: when there is a trading restriction, pessimistic investors may be unable to express their negative valuation through trading, which leaves the market price reflecting only the valuation of optimistic investors. In a dynamic setting, such price deviation will induce speculative trading, which in turn may feedback into the price deviation due to trading restriction. In our setting, compared with Huatai under the $T + 0$ rule, the $T + 1$ rule prohibits the intraday cross-market trading for Jiashi, which then leads Jiashi to be more prone to speculation.

We stress that our results are obtained under the *current* market condition, and they are not implying ineffectiveness of $T + 1$ rule as an impediment to speculation back to early days of Chinese stock market in the 1990s. Both market investor composition and market liquidity change significantly over the past two decades. In the 1990s, the predominant force in the market consisted of retail investors, who are more prone to speculative behaviour. Furthermore, the market-wide liquidity at that time was far from the current level. When the market liquidity is low, small trading imbalance can cause large price sway. In fact, in our empirical analysis, we find that, after the market crash in July 2015 with liquidity dropping by more than 60 percent, the performance of Huatai was no longer better than Jiashi.

In summary, our empirical study shows that the $T + 0$ rule reduces ETF price deviation and helps contain speculative trading, which is suggestive of the counter-speculation effect of the $T + 0$ rule under the current market condition. Nonetheless, we stress that our analysis is confined to recent index ETF trading sample, and we are cautions to make policy recommendation regarding adoption of the $T + 0$ rule over the entire market. Arguably, the benefit of the $T + 0$ rule depends on investor composition and market liquidity, among many other factors. As a result, it is necessary to scrutinise more widely the relevant factors across Chinese stock market before making decision on lifting the $T + 1$ rule.

The rest of the article is organised as follows: Section 2 reviews briefly related works; Section 3 describes institutional details, including in particular the trading rules of the two ETFs; Section 4 presents the empirical model and methodology; Section 5 reports the empirical results; and lastly, Section 6 summarises the empirical findings and concludes.

2. Related works

There are a few papers on China's $T + 1$ trading rule. Liu and Ye (2008) apply event study methods on a sequence of trading rule changes before 2006, including the $T + 0/T + 1$ switches for A/B shares, convertible bonds and options. They conclude that the $T + 0$ rule increases market liquidity and pricing efficiency, and does not increase price volatility. Ge and Ye (2009) analyse the daily price amplitudes for A shares from 1992 to 1996 and for B shares from 1996 to 2008, and conclude that the $T + 1$ rule reduces stock volatility. Wu and Qin (2015) take the 2001 adoption of the $T + 1$ rule for B shares as a quasi-natural experiment, and use DID method to illustrate that the switch to the $T + 1$ rule increases price volatility and market spread, and also decreases trading volumes and price efficiency. These papers are subject to some common problems. First, their data samples are for the early period of Chinese stock market. Second, they do not measure speculation directly. Finally, their empirical methodologies typically suffer from identification problems like confounding variables.[9]

One study that addresses identification problems and uses more recent data is Bian and Su (2010). The paper compares the prices of a set of stocks and the corresponding warrants in the Chinese stock market over 2005–2008. Trading in warrants is subject to the $T + 0$ rule while trading in stocks is subject to the $T + 1$ rule. According to the standard Black–Scholes option pricing theory, stock price can be derived from the option price. Based on this relationship,

[9] For example, in the DID set-up of Wu and Qin (2015), they have not controlled many other policy changes contemporary to the trading rule switch, such as changes in accessibility to B shares by domestic investors.

Bian and Su (2010) take the stock price implied by the warrant price as the hypothetic $T + 0$ price and the price observed in the stock market as the $T + 1$ price. This approach overcomes the data limitation that there is no overlapping period of the $T + 0$ and $T + 1$ trading rules in China's stock market, and in principle is better at controlling confounding factors. They interpret the $T + 0/T + 1$ price difference as a liquidity premium, but do not explore the implications on market speculation.[10] In addition, Yu and Xiong (2011) also note the different trading rules for stocks and warrants in China, but do not test formally the implications of the trading rules.

Different from the above empirical works, Guo *et al.* (2012) build a theoretic model with a single manipulator, illustrating that the $T + 1$ rule could effectively limit manipulation behaviour and hence improve the welfare of retail investors. In the model, the manipulator faces no competition, and the retail investors are trend traders who follow the price trend blindly. Such a set-up is likely to be at odds with ETF trading where institutional investors dominate. Using an agent-based model, Cheng *et al.* (2011) suggest that in a market with more rational investors, the $T + 0$ rule in fact improves market liquidity and efficiency.

Our empirical methodology is related to the literature on price deviation of ETFs. Hasbrouck (2003) builds a cointegration model for S&P500 index, and the corresponding futures and ETFs. The objective of Hasbrouck (2003) is to study the lead–lag relationship between these assets and hence is different from ours, yet our empirical formulation shares the same basic cointegration structure. Richie *et al.* (2008) and Marshall *et al.* (2013) document arbitrage opportunities caused by price disparities among S&P500 index, ETFs and futures.

3. Institutional details and data description

3.1. *The* $T + 1$ rule in stock markets

As mentioned in Introduction, China's stock market is the only major market in the world that adheres strictly to the $T + 1$ rule until now. To be precise, the $T + 1$ trading rule is not unique to China. In the United States, according to the FINRA Rule 4210 'Margin Requirements', investors need to maintain a $25,000 balance in the trading account once he or she is identified as a 'pattern day trader',[11] which effectively puts a limit on stock selling, albeit a mild one.

[10] One potentially difficulty with this approach is the validity of the BS option pricing formula to Chinese warrant market. Chang *et al.* (2013) show that Chinese warrant market over this period is far from the prediction of the BS option pricing theory. This difficulty is partially addressed subsequently in Bian *et al.* (2015) by examining different option pricing theories.

[11] Roughly speaking, an investor is identified as a pattern day trader if the investor executes day trade in 4 days of a week, where day trade refers to the behaviour of selling out stocks purchased on the same day.

For another example, the stock market regulatory agency in Taiwan did not lift restrictions on day trading and switch to the $T + 0$ rule until 2014.[12]

However, as there is no systematic information on the $T + 1$ versus $T + 0$ rule worldwide, we conduct a manual search through links of major stock exchanges provided by 'Day Trade the World' website.[13] We identify no market adopting the $T + 1$ rule except for China.

3.2. Trading rules of the two ETFs

To understand the difference in the two ETFs in their trading rules, we first briefly describe the general trading mechanism of an ETF. An ETF is traded on two markets: the primary market and the secondary market. In the primary market, institutional investors (or qualified retail investors with enough wealth) can create or redeem ETF shares from the fund. In the secondary market, institutional and retail investors can buy and sell ETF shares with each other. Besides, in the primary market, creations and redemptions of ETF shares are generally in kind with baskets of underlying stocks. Investors need to deposit a basket of stocks to the fund to create ETF shares and receive a basket of stocks back after redemption. On the contrary, in the secondary market, investors can buy and sell ETF shares in cash.

Both ETFs, Huatai and Jiashi, were established in May 2012 and have been the two most liquid ETFs tracking CSI 300 index in China ever since. They adopt different trading rules as summarised in detail in Table 1.

Investors in Huatai can create shares on the primary market and then sell them in the secondary market, or buy shares in the secondary market and then redeem them on the primary market on the same trading day, which constitutes $T + 0$ trading. However, for Jiashi, investors must hold the ETF shares for at least one trading day, before selling or redeeming, which constitutes $T + 1$ trading. Therefore, when the price of Huatai deviates from CSI 300, the $T + 0$ rule allows the institutional investors to take the cross-market arbitrage opportunities, and thus to attenuate, if not eliminate entirely, price deviations from the fundamental index value. However, when the price deviation emerges for Jiashi, the $T + 1$ rule impedes such cross-market arbitrage trading activities. As a result, speculation on Jiashi is more likely to occur due to trading restrictions caused by the $T + 1$ rule.

3.3. Data description

We have the transaction data (on the secondary market) of Huatai and Jiashi for the whole year from October 2014 to September 2015, consisting of 244

[12] http://www.twse.com.tw/en/page/products/trading_rules/day_trading.html.

[13] https://www.daytradetheworld.com/wiki/market_guides.

Table 1
Comparison of trading rules of Huatai and Jiashi

	Huatai	Jiashi
Primary market	Buy stocks on day T, create ETF shares on day T	Buy stocks on day T, create ETF shares on day $T + 1$
	Redeem ETF on day T, sell SSE stocks on day T and SZSE stocks on day $T + 2$	Redeem ETF on day T, sell stocks on day $T + 2$
Cross-market	Create ETF on day T, sell on day T	Create ETF on day T, sell on day $T + 2$
	Buy ETF on day T, redeem on day T	Buy ETF on day T, redeem on day $T + 2$
Secondary market	Buy ETF on day T, sell on day $T + 1$	Buy ETF on day T, sell on day $T + 1$

trading days in total. In addition, we obtain minute-level CSI 300 index data over the same time period. All data are from CSMAR, one of the most widely used stock market data vendors in China. The ETF transaction data include a time stamp, a unique trade number, the trade price and volume for each transaction. We first aggregate the transaction data to form the price series of the two ETFs in minute frequency. In detail, the price of an ETF at minute t equals to the volume-weighted average of the trade prices in the spell of this minute. If no transaction occurs in minute t, we shall define the aggregated price to be equal to that of the previous minute. Both Huatai and Jiashi are very liquid in our data sample so that in almost all of the trading minutes, there is at least one transaction for each ETF.[14]

In each trading day, the market opens at 09:30 hours and closes at 15:00 hours, with a 1 h and a half break in the middle of the day. While in most of the trading hours, trades are matched via a continuous double auction on an electronic limit order book, the Shenzhen Exchange, where Jiashi is traded, holds a call auction from 14:57 to 15:00 hours everyday right before the market close. To mitigate the possible impacts on the two ETF prices caused by different trading mechanisms, we remove the samples of the last three minutes of a trading day from our data. As a result, in each trading day, we have 237 observations for the two ETFs and the index. Table 2 reports the summary statistics of the trading activities of the two ETFs in the secondary market and the volatility of the index, for each month in the sample period.

Complementary to our focus on the sample around the recent stock market boom and bust, we also investigate a longer sample of the two ETFs, from

[14] We also consider another way to calculate the trade price when no trade occurs in a minute, by taking volume-weighted average of the trade prices in the immediate minutes before and after the minute in question. The results are essentially the same, as the fraction of minutes with no trade is quite low. We thank one anonymous referee for suggesting such an option.

Table 2
Summary statistics

	Huatai			Jiashi			
Month	Shares (10^9)	Volume (10^6)	Turnover rate (%)	Shares (10^9)	Volume (10^6)	Turnover rate (%)	CSI300 Intraday volatility (%)
2014/10	5.88	6.11	10.40	10.44	1.75	1.67	0.033
2014/11	5.26	8.63	16.41	10.05	2.11	2.10	0.044
2014/12	8.92	20.33	22.77	11.84	4.25	3.59	0.114
2015/01	8.33	13.56	16.27	12.14	3.20	2.64	0.089
2015/02	8.08	8.36	10.35	10.97	2.61	2.38	0.060
2015/03	7.66	14.05	18.34	10.50	3.35	3.19	0.056
2015/04	5.09	11.91	23.39	9.11	3.01	3.31	0.076
2015/05	4.99	13.56	27.17	7.70	2.53	3.29	0.079
2015/06	4.72	14.49	30.70	6.47	2.26	3.49	0.141
2015/07	9.06	14.37	15.87	6.62	1.69	2.55	0.164
2015/08	7.41	4.93	6.66	6.08	0.57	0.93	0.119
2015/09	6.77	2.01	2.98	5.66	0.39	0.70	0.100

p-value for *t*-test on mean difference.

January 2013 to September 2016.[15] One advantage with the longer sample is that we can assess the dynamics of the primary and secondary market more accurately. In particular, we calculate the monthly average of daily turnover rates in the secondary market for both ETFs, based on directly the trading data we have. In addition, we use the information on the creation and redemption of ETF shares disclosed by the two ETFs in their quarterly reports to calculate the primary market turnover rates.[16] Figure 1 reports the turnover rates of both ETF from 2013 to 2016.

Two messages emerge. First, the trading activities, as measured by the turnover rates, in the primary and secondary market are closely related to each other. Second, across the two ETFs, the turnover rates in both markets are of the same magnitude, where the quarterly average ratio of the turnover rate in the primary market to that of the secondary market is 0.6 over the entire sample period. This directly implies that the average trading volume in the

[15] Our data sample on the CSI300 index ends in September 2016. The trading activities of the two ETFs in the first half year after their establishments, especially for Jiashi, were considerably erratic, possibly due to an initial wave of fund inflows and ETF share creations. Consequently, we consider data from 2013 onwards only.

[16] For a given quarter, we sum the number of shares created and redeemed together to measure the trading volume in the primary market and divide the sum by the end-of-quarter shares of the ETF to get our main measure of the primary market turnover rate. We also consider a second measure by dividing the quarterly volume just defined with the average number of outstanding shares within the same quarter, and the dynamics of this alternative turnover rate remains largely the same in the sample period.

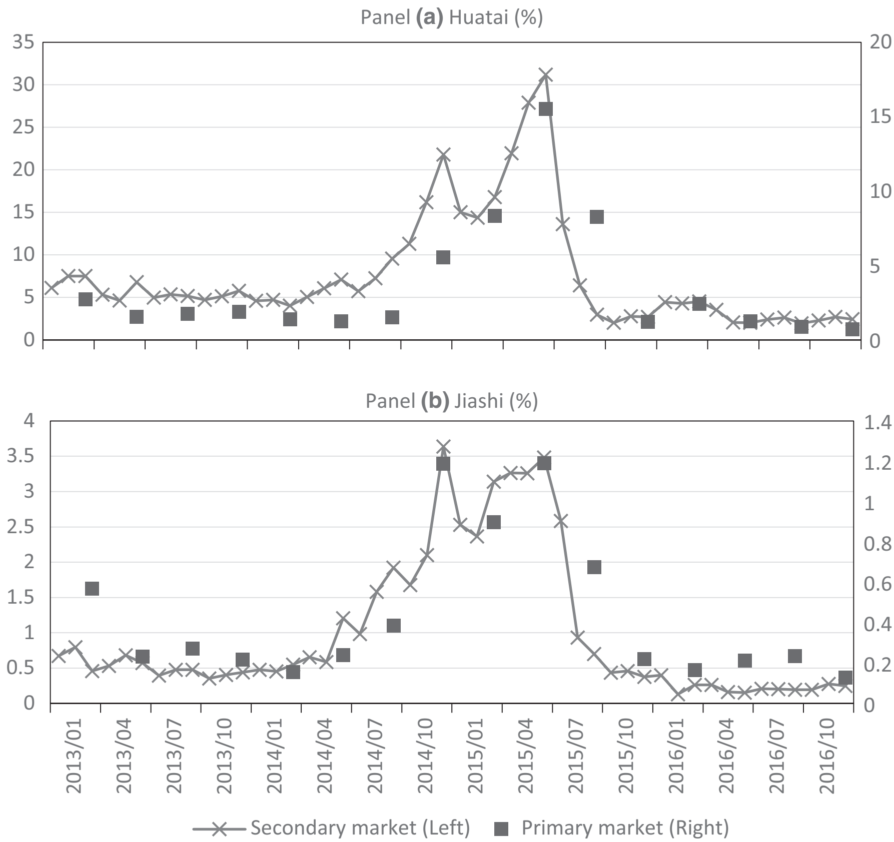

Figure 1 Average daily turnover rates by ETFs and markets

primary market is around 60 percent of the secondary market.[17] Taking together, the data suggest that there is a close connection between the primary and secondary market in ETF trading; thus, we may expect that different trading rules in the primary market will manifest in secondary market trading activities.

3.4. The 2015 stock market turbulence

Our data cover the period of the most recent boom and bust in China's stock market in 2015.

The first round of price boom was from 24 November to 31 December 2014, during which CSI 300 index increased by 38.1 percent. Starting from 13 March,

[17] Recall that the turnover rate in the secondary market equals to trading volume in shares divided by the number of outstanding shares.

the market experienced a persistent and strong 'bull' market, and CSI 300 index increased by 47.5 percent as of 12 June. Then came the market crash. From 15 June to 8 July, CSI 300 index dropped by almost 30 percent. Around 1 August, in order to stabilise the market, China Securities Regulatory Commission (CSRC) issued a series of stringent trading restrictions, including a short-sell ban, a requirement on the two stock exchanges to supervise accounts prone to high-frequency trading, and a cap on the position of CSI 300 futures that an account can hold. Trading reduced sharply under the new restrictions. In our data sample, the intraday volatility of CSI 300 index decreased after August significantly,[18] and the turnover rates of the two ETFs dropped considerably as well. The market turbulence is summarised in Table 2. During the week from 18 August to 26 August, coupled with shocks from the United States and other major financial markets, the CSI 300 dropped by almost 21 percent. Figure 2 shows CSI 300 index level and its intraday volatility over the 1-year period in our sample.

4. Empirical methodology

We specify in detail the empirical methodology we employ in this section. We present the empirical model first, followed by the hypotheses proposed, and lastly a brief summary of the estimation and testing methods.

4.1. Empirical model

Let $\mathrm{CSI300}_t$ be the price of the CSI 300 index and ETF^i_t, $i = H, J$, be the price of Huatai and Jiashi, respectively. Both ETFs track the CSI 300 index, with minimal differences in transaction cost, management fee and dividend rules.[19] As both the ETF prices and the index exhibit strong unit root property over the sample periods, therefore, similar to Hasbrouck (2003), we postulate that each of the ETF prices and the index should satisfy the following cointegration equation:

$$ETF^i_t = \beta^i_0 + \beta^i_1 CSI300_t + \epsilon^i_t \tag{1}$$

where ϵ^i_t represents temporary deviations of the ETF price from the CSI 300 index caused by all sorts of underlying driving forces, such as liquidity shocks and speculative trading.

As long as ϵ^i_t is not a unit root process or explosive, then by the Granger representation theorem in Engle and Granger (1987), for each i, the first

[18] Volatility is defined as the sample standard deviation of the log returns.

[19] To be specific, the fee structure of the two ETFs is identical and the transaction costs are very much the same as the trading mechanisms in Shanghai and Shenzhen Exchanges are almost the same. The dividend rules of the two are somehow different, where Huatai is employing a yearly dividend distribution rule and Jiashi a quarterly rule. However, as we are examining the intraday trading data, the difference in dividend rules is irrelevant.

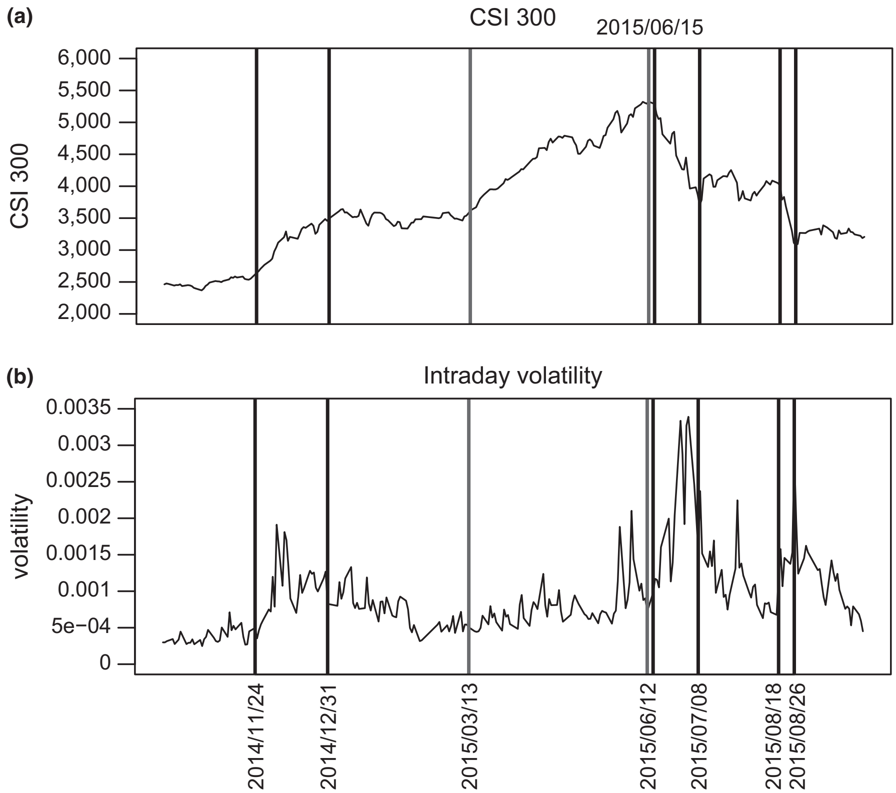

Figure 2 CSI 300 Index and intraday volatility

difference in the ETF price and the index admits an error correction representation as follows:[20]

$$\Delta ETF_t^i = \alpha^i + \sum_{j=1}^{l} \theta_j^i \Delta ETF_{t-j}^i + \sum_{k=0}^{l} \phi_k^i \Delta CSI300_{t-k} + \gamma^i \epsilon_{t-1}^i + u_t^i \tag{2}$$

where u_t^i is a white noise innovation with no serial correlation, and l denotes the common number of lags for ΔETF_i and $\Delta CSI300$.[21] From the Granger

[20] For practical purpose, we shall consider only finite lag order for Δ and Δ $CSI300^i_{t-l}$. For the same reason, we shall confine to the case where the residual term is merely u_t^i. In general, the residual term can be a moving average of u_t^i, as shown in Engle and Granger (1987).

[21] We remark that in order for the cointegration relationship of (1) to imply the error correction representation of (2), one does not need to assume ϵ_t^i. to be *stationary*. The only assumption required is that ϵ_t^i be neither explosive nor a unit root process. This allows for the possibility of potential *transitory* but *time-varying* behaviour in ϵ_t^i, which plays an important role in our empirical modelling.

representation theorem, price deviation ϵ_t^i is tied to innovation u_t^i through a moving average relationship, that is $\epsilon_t^i = K(\mathcal{L})u_t^i$, where $K(\cdot)$ denotes a polynomial, possibly infinite, and $\mathcal{L}$ denotes the lag operator. Because of this structural relationship, we can interpret u_t^i as summarising all possible shocks, be it liquidity or speculation, to the dynamics of the ETF price and index at time t.

Correspondingly, price deviation ϵ_t^i can be viewed as reflecting cumulative effects from underlying driving forces u_t^i. It is also clear from this relationship that whenever u_t^i displays time-varying properties, ϵ_t^i will also inhibit such time-varying features.

We shall argue that speculative trading will lead to time-varying features in the price deviation between ETF and index. As a result, in order to test for speculation, we can employ a structural break test to check the presence of time-varying behaviour in u_t^i, hence ϵ_t^i. To be more specific, we think of u_t^i as having two components:

$$u_t^i = v_t^i + s_t^i, \tag{3}$$

where v_t^i is white noise with zero mean and constant variance, and s_t^i is potentially time-varying, either deterministic or stochastic.[22] We interpret v_t^i as capturing the *normal* market force such as liquidity shocks, which leads to transient deviations between the ETF price and the index. Under such shocks, arbitrage activities are expected to quickly eliminate any price deviation. In contrast, s_t^i intends to capture the effect of speculative trading. Under speculation, price deviations are not immediately eliminated by arbitrage, and on the contrary, speculators are ready to exploit price deviations to make capital gains over a *persistent*, but *finite*, time period. In the process, price deviations are typically amplified, either upwards or downwards, resulting in speculative bubbles or implosions.[23] Such price deviation dynamics manifest themselves in shifting levels of s_t^i. For instance, consider the following form of the dynamics for s_t^i:

$$s_i^t = \begin{cases} = 0 & \text{for } t < t_0 \text{ and } t > t_1, \\ \lesseqgtr 0 & \text{for } t_0 \leq t \leq t_1, \end{cases}$$

[22] To be consistent with zero autocorrelation for $u_t{}^i$, $s_t{}^i$ is assumed to be serially uncorrelated when the term is stochastic.

[23] For a security such as a small- or medium-cap stock, locally persistent price deviation from its fundamental value may also be caused by a lack of liquidity. However, in our investigation of the ETF prices and the CSI index, liquidity is not likely to be a major issue in most of our sample periods, as the two ETFs we choose are very liquid, except for the extreme market condition experienced in the immediate aftermath of the stock market crash in 2015. We elaborate on this point further in the next section.

for some t_0 and t_1. When $u_t^i > 0$ over $[t_0, t_1]$, there will be *temporary* yet *locally persistent* upward deviation of the ETF price relative to the index. Likewise, when $s_t^i < 0$ over $[t_0, t_1]$, the deviation is downward.[24]

It is worth to stress that, as originally articulated by Keynes (1936), the essence of speculation has two dimensions, one for quantity and the other for price. There must be certain price deviations to be exploited and re-enforced by speculators, and the dynamics must also be accomplished by actual speculative trading carried out by speculators. In general, it is always a daunting task to disentangle the speculative component in either quantity or price from the remaining components determined by ordinary market forces. However, given the special feature of our data on index ETFs, we can directly observe the *fundamental value* and the associated *price deviation*.[25] This provides a rare opportunity of reducing the daunting task to one of testing for time-varying parameters. In contrast, were we to work along the quantity dimension, we would still face the intricate problem of identifying the speculative component in the ETF trading data.

To sum up, the empirical model (1)–(3) provides a parsimonious reduced form description of the ETF dynamics with speculation possibility. As shown below, the model is also convenient to estimate and test for the presence of speculation.

4.2. *Hypotheses on trading rules*

The recent literature on speculation, for example Scheinkman and Xiong (2003), Xiong (2013) and Scheinkman (2013), emphasises the interaction of trading restrictions and investor belief heterogeneity in causing speculative trading. The basic logic is intuitive. When pessimistic investors are constrained by trading restrictions such as short-selling ban, then optimistic investors dominate the market and the security price tends to be above its fundamental value. In a dynamic setting, such price deviation gives rise to an option of holding the security for a while and then trades it in the future for a pure capital gain due to market price variation, which is unrelated to changes in the fundamental value. This is just the classic characterisation of speculation, originally laid out in Keynes (1936, ch. 12). Essentially, belief heterogeneity and its dynamics create the room for price deviations, either upwards or

[24] Most of the theoretic literature focuses on the upward deviation, that is speculative bubbles. However, as no bubble persists forever in real markets, bubbles must follow by crashes, and in such case, downward deviation, where price is below fundamental value, is equally likely in a selling wave.

[25] One side benefit of our ETF data relies on the fact that the fundamental value, that is the index, is common to both ETFs. This helps us control for any common factors, such as market-wide investor sentiments, that may influence both ETFs simultaneously. We thank one anonymous referee for raising this question to us.

downwards, relative to the fundamental. And by preventing effective arbitrage, trading restrictions amplify and induce persistence in price deviations.

There are numerous trading restrictions in Chinese stock market, and chief among them is the $T + 1$ rule. The original contemplation of the $T + 1$ rule is for restricting excessive speculation, as by putting a break on intraday speculative selling orders, speculators will become more measured as well in placing buying orders earlier. However, the $T + 1$ rule also limits intraday arbitrage trading, and in particular, it prevents more efficient price deviation correction. Furthermore, the limits to arbitrage may effectively cause more speculation in the first place. Finally, the pro-speculation effect of $T + 1$ rule should be more likely to observe when the market liquidity is in normal condition. As liquidity service is one aspect of arbitrage activities, drying up of market liquidity indicates the absence of enough arbitrage. In this case, the $T + 1$ restriction becomes not binding as there is no arbitrage trading to be restricted.

Accordingly, we propose three hypotheses to be tested based on the empirical model describe above. First, as in any error correction model, γ^i measures the speed at which a given deviation ϵ_t^i is corrected. A more negative value of γ means that the impact of the temporary deviation to the long-run balance expressed in the cointegration equation (1) will be absorbed more quickly. Consequently, we expect γ^H for Huatai ETF (under $T + 0$) and γ^J for Jiashi ETF (under $T + 1$) to be both negative, and moreover $\gamma^H < \gamma^J$.

Hypothesis 1: On average, the error correction coefficient in (2) is more negative under the $T + 0$ rule than the $T + 1$ rule, that is $\gamma^H < \gamma^J < 0$.

Second, when the market liquidity is normal, we expect Huatai ETF to display less speculation. In particular, we focus exclusively on the speculative *price deviation*. Speculation has both implications on price and quantity. Although many empirical studies use quantity-based measures,[26] such as volume, turnover and volatility, they are indirect indicators of speculation per se, and such identification relies on theoretic relations between the observed quantity and speculation. This makes it difficult to differentiate speculation from other trading behaviour, such as liquidity trading.[27] In contrast, as speculation is directly linked to *persistent* albeit *finite* price deviation from the fundamental value, therefore, price deviation provides a more accurate indicator for speculation. Unlike typical empiric studies in asset pricing where the measure of fundamental value is among the biggest challenges, in our index ETF setting, the fundamental value of both ETFs is unambiguously given by the CSI 300 index.

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[26] See Mei *et al.* (2009) for an example.

[27] See Campbell *et al.* (1993) for a seminal reference and Vayanos and Wang (2013) for a recent extensive survey of both theory and empirical evidence.

Our empirical model is designed specifically for measuring such price deviations ϵ_t^i through the cointegration equation (1). More importantly, our model directly considers the possibility of a speculative component s_t^i in the price deviation, through the residual term in the error correction equation (2) associated with the cointegration relationship. As a result, a test of speculation is transformed into a test of the presence of nonzero s_t^i. This leads to the second hypothesis:

Hypothesis 2: Under normal market liquidity condition, speculation is more likely under the $T + 1$ rule than the $T + 0$ rule, that is s_t^J is more likely to be nonzero than s_t^H.

Hypothesis 2 is the main hypothesis in this article. As it mainly focuses on the case in which the relevant market liquidity is abundant, we complement this hypothesis with the following one, which is concerned with the case of liquidity shortage.

Hypothesis 3: When market liquidity is in a shortage, speculation is equally likely under the $T + 1$ rule and the $T + 0$ rule, that is s_t^J and u_t^H are equally likely to be nonzero.

4.3. Estimation and testing

We estimate the cointegration relationship of (1) and (2) through the standard two-step approach in Engle and Granger (1987). In particular, we first run OLS regression on the cointegration equation (1) to obtain the price deviations ϵ_t^i as the regression residuals, and then use the estimated deviations for a second OLS regression on the error correction equation (2). From the second regression, we obtain estimate of γ^i and innovation u_t^i To test for the presence of speculation, we use the classical cumulative sum (CUSUM) method (Brown *et al.*, 1975; Kramer *et al.*, 1988) to test mean shifting in the innovation process $\{u_t^i\}$. When there is speculative price deviation, CUSUM test will reject the null hypothesis of zero speculative component s_t^i. We conduct the estimation and testing exercises on a day-by-day base for 244 trading days in our sample. In each trading day, we perform the same estimation and testing procedure based on the minute-level trading data, as detailed in Section 3.3. All exercises are implemented in RStudio, and in particular, we use the strucchange package to perform the CUSUM test.[28]

We leave one remark on the procedure of CUSUM test we choose. By testing mean shifting inu_t^i, we are running CUSUM test on the error correction equation (2). An alternative procedure is to run CUSUM test on the cointegration equation (1). As price deviation ϵ_t^i is a moving average of

[28] The package is developed by Achim Zeileis, Friedrich Leisch, Kurt Hornik and Christian Kleiber.

innovation u_t^i, level shifts in u_t^i will also induce shifts in ϵ_t^i; thus, a CUSUM test can be performed following, for example, the method of Xiao and Phillips (2002). A drawback with this approach is that ϵ_t^i typically has serial correlation, and some correction of this correlation is required for a CUSUM test to perform well (Deng and Perron, 2008). However, as the nature of the serial correlation is unknown, a test based on ϵ_t^i necessarily entails some efficiency loss.

5. Empirical results

In this section, we report the empirical results. First, we discuss results based on the two-step cointegration regressions. Second, we present the main results from the CUSUM test.

In the end, we present some robustness tests.

5.1. Cointegration analysis

As a preliminary step, we conduct standard ADF test to make sure both ETF prices and index series are unit root processes in our data sample. We use minute-level observations to perform ADF test for each trading day. Over the total 244 trading days, ADF test cannot reject the unit root null hypothesis for 230 trading days at the 5 percent significance level, while for the remaining 14 days, the p-values of the unit root null are in borderline and not exceeding 10 percent. In summary, all the data series can be identified as $I(1)$.

To estimate the cointegration system, the following two-step procedures are used. For the first step regression of the cointegration equation (1) and over the 244 trading days, the average R^2 is about 0.95 for Huatai and 0.84 for Jiashi, and the average autocorrelation of lag 5 of the estimated residuals ϵ_t^i is 0.016 for Huatai and 0.035 for Jiashi. The regression results indicate that, on average, the variation and persistence of intraday price deviation of Jiashi are larger than those of Huatai. In addition, we perform ADF test on ϵ_t^H and ϵ_t^J for ϵ each trading day, and the unit root null is rejected at 5 percent level for all 244 trading days. This confirms the cointegration relationship between ETF^i and $CSI300$ for $i = H, J$.

In the second step, we use first step residuals $\hat{\epsilon}_t^i$ in conjunction with ΔETF_t and $\Delta CSI300_t$ to estimate the error correction equation (2) by OLS for each trading day. To determine the lag structure in the error correction equation, we rely on AIC information criterion. Specifically, we choose the number of lags l using AIC for each trading day and for $i = H, J$ separately. In our sample of 244 trading days, AIC criterion favours either $l = 0$ or 1. With a relatively small number of observations for each trading day, which is 237, the model specification does not prefer one with many lags.[29] Figure 3 shows the

[29] In running AIC test, we set the maximum number of lags to be 2. Taking into the fact that variables in the error correction equation are in first difference except for the error term, the number of lags up to 2 already provides a rich dynamic structure.

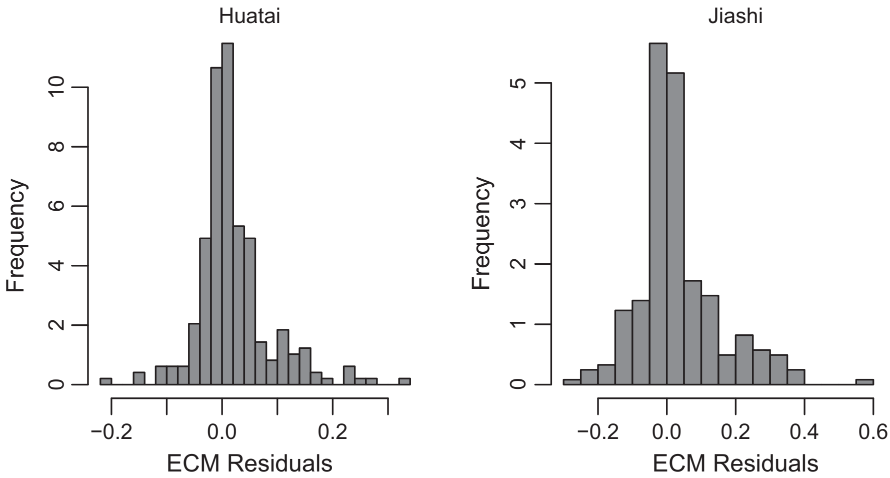

Figure 3 Histogram of first-order autocorrelation for u_t^H and u_t^J

histogram of the first-order autocorrelation of the estimated residuals u_t^i over the 244 trading days, for both Huatai and Jiashi. It is evident that for most of the trading days, the absolute value of the autocorrelation is not greater than 0.2, and the maximum value is 0.6 which happens only once in the sample. This suggests that with a lag structure of $l \leq 1$, the error correction equation can capture the dynamics of the ETF price and index well.

For both ETFs, the error correction coefficient estimates γ^i are significant at 5 percent level for all but 6 days in our sample. For easiness of exposition, we report in Table 3 the monthly average of γ^i for $i = J, H$. Across the 12 months, the average γ^H is significantly more negative than γ^J. Going through month by month, we see that for the 3 months in which γ^H is greater than γ^J, the difference is significant in only one month (November 2014) and is at 10 percent but not 5 percent. These results confirm Hypothesis 1 that the $T + 0$ rule features in faster price deviation correction than the $T + 1$ rule. This is the first evidence that the $T + 0$ rule may actually work better at containing speculation by reducing limits to arbitrage.

5.2. Speculation test

As discussed in the previous section, we use the CUSUM test to detect the presence of speculative price deviation in each trading day for the two ETFs. This amounts to test level shifts in the regression residuals from the error correction equation estimation. To get some flavour of the test, we first plot in Figure 4 the error correction residual series for both ETFs on 29 July 2015.[30]

[30] The choice of this date is only for an illustration.

Table 3
Error correction coefficient

Month	Huatai	Jiashi	p-value (%)
2014/10	−0.1287	−0.1704	14.5
2014/11	−0.0946	−0.1292	7.87
2014/12	−0.1746	−0.1619	61.97
2015/01	−0.2438	−0.2167	36.10
2015/02	−0.2026	−0.2320	38.03
2015/03	−0.1500	−0.1331	30.54
2015/04	−0.1671	−0.1152	0.44
2015/05	−0.2181	−0.1360	0.01
2015/06	−0.2367	−0.1547	0.25
2015/07	−0.2740	−0.1420	0.02
2015/08	−0.2818	−0.1514	0.00
2015/09	−0.2989	−0.1644	0.03
Average	−0.2069	−0.1567	0.00

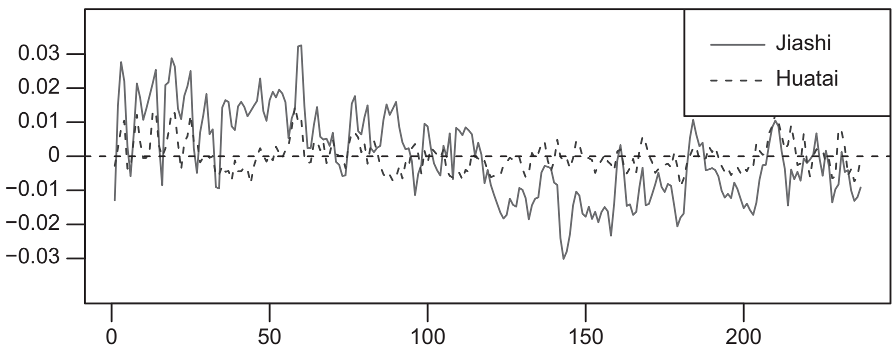

Figure 4 Cointegration residuals of Huatai and Jiashi on 2015/7/29

The figure clearly shows that Jiashi is subject to residuals in larger magnitude than Huatai, which also suggests that the price deviations in Jiashi are greater than Huatai.

The greater magnitude and variation in residuals for Jiashi are what drive the CUSUM test to reject the null hypothesis of no mean shift. The CUSUM test is based on the partial sum of residuals $S_t^i = \sum_{1 \le \tau \le t} u_\tau^i$.[31] Under the null hypothesis with no mean shift, the partial sum process $\{S_t^i\}$ converges to a

[31] To be clear, the CUSUM we employ is based on the recursive partial sum, where ~ is the *recursive residual*. The recursive residual is essentially the recursive prediction error, obtained by taking the difference between time t dependent variable and its predicted value using OLS regression coefficients on the first $t-1$ samples. See the introduction document to the strucchange package and Krämer *et al*. (1988) for details.

Brownian motion; thus, a confidence region can be constructed under the null to bound the empirical process $\{S_t^i\}$. When there are level shifts in u_t^i, the partial sum S_t^i will contain a trend component, which in turn will drive the empirical process to go out of the bounds. If such an event occurs, then the CUSUM test will reject the null hypothesis. Figure 5 shows the CUSUM test results for Huatai and Jiashi on 29 July 2015.[32] Roughly all the way in the second trading hour,[33] the partial sum S_t^i is above the upper bound of the 95 percent confidence region under the null hypothesis for Jiashi, whereas for Huatai, the partial sum is always within the confidence region. This leads to the CUSUM test to reject the null of no level shifting for price deviation innovation process $\{u_t^J\}$, and hence provides evidence that Jiashi is subject to speculation on the particular trading day.

The CUSUM test results for the baseline sample are summarised in Table 4. We report the monthly number of trading days which do not pass the CUSUM test at a significance level of 5 percent, and classify these days as subject to speculation.[34] The first two columns report the number of trading days subject to speculation for Huatai and Jiashi, respectively. It is clear that Jiashi is more susceptible to speculation risk overall, with 89 trading days identified with speculation, whereas only 57 days are identified with speculation for Huatai. However, the overall number on speculation may underestimate the differential effect of the $T + 1$ and $T + 0$ rules on speculation, as it ignores the fact that some common factor, which by definition excludes the distinct trading rules for the two ETFs, is driving the speculation results. To overcome this drawback, columns 3–5 report the numbers of trading days, respectively, for the cases in which only Huatai is subject to speculation, only Jiashi is subject to speculation, and both Huatai and Jiashi are subject to speculation simultaneously. Such a decomposition shows that speculation in Jiashi alone is much more likely than that in Huatai alone, which shows clearer and stronger evidence that the $T + 1$ rule is more conductive to speculation.

A closer look at Table 4 shows that there is a clear pattern of the dominant role in speculation by Jiashi in the first ten months in our sample. The ratio of overall number of days with speculation is close to 1:2 for Huatai over Jiashi, and the ratio of the stand-alone days is almost 1:4 for the two ETFs. We

[32] The upper and lower bounds are rescaled to reflect the fact the variance of the empirical process $\{S_t^i\}$ is proportional to t, as the limiting process is a Brownian motion. The partial sum S_t^i itself is also scaled accordingly.

[33] There are 4 hours in each trading day, so the relative time of 0.25–0.5 indicates the second trading hour.

[34] For a robustness check, we also report results on speculation test using 1 percent and 10 percent as the significance level in the next subsection. It is worth to stress that the focus is not on the absolute number of trading days identified as subject to speculation, but on the relative days of speculation for Huatai and Jiashi. Hypothesis 2 is only concerned with contrasting the $T + 1$ and $T + 0$ rule. Therefore, the level of significance in the CUSUM test per se is irrelevant.

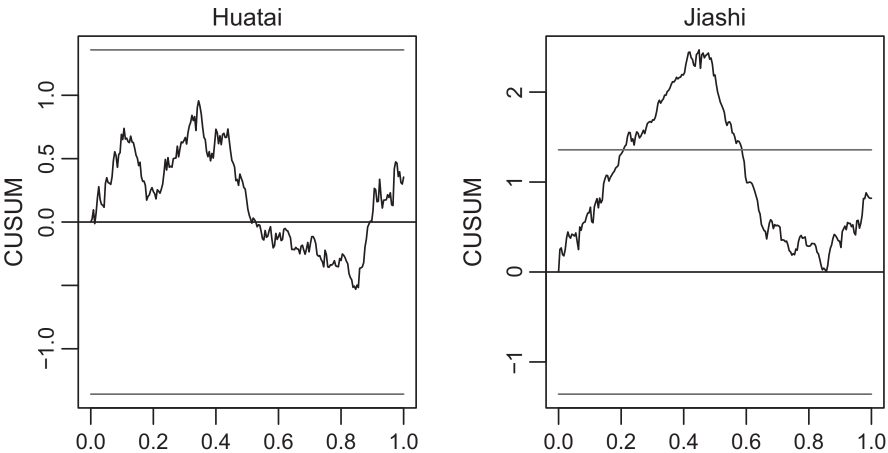

Figure 5 CUSUM tests for Huatai and Jiashi on 29 July 2015. *Notes*: the horizontal axis in each plot is the time period with a normalised total length of 1; two horizontal bars around ±1.4 are the (rescaled) bounds at 5 percent level under the null hypothesis for the (rescaled) partial sum process $\{S_t^i\}$; the remaining line is the (rescaled) partial sum process.

Table 4
Days with speculation in each month

	Overall		Decomposition		
Month	Huatai	Jiashi	Huatai alone	Jiashi alone	Both
2014/10	2	3	0	1	2
2014/11	4	6	1	3	3
2014/12	3	7	3	7	0
2015/01	6	8	1	3	5
2015/02	3	8	1	6	2
2015/03	3	5	0	2	3
2015/04	4	5	3	4	1
2015/05	3	8	1	6	2
2015/06	7	11	2	6	5
2015/07	4	13	1	10	3
Subtotal	39	74	13	48	26
15/08	10	9	6	5	4
15/09	8	6	4	2	4
Total	57	89	23	55	34

interpret this result as strongly favouring Hypothesis 2. From Table 2, it is evident that for both ETFs, the first 10 months in the sample show much more active trading than the last 2 months. For Jiashi, the average trading volume in the first months is more than five times of the average in the last 2 months, and the average turnover rate is more than 3 times of the last 2 months. For Huatai, the respective ratio is more than 3 and close to 4 as well. These numbers suggest that the market liquidity of the two ETFs is much higher in the first 10 months than in the last 2 months. As liquidity is not an issue over the first subperiod, the distinction between the $T + 1$ rule and $T + 0$ rule is relevant for the trading performance of the two ETFs. In particular, as the $T + 1$ rule for Jiashi becomes a more binding restriction on the effectiveness of arbitrage, Jiashi tends to be considerably more speculative than Huatai, where the latter enjoys a better trading environment provided by the $T + 0$ rule.

In contrast, for the subperiod of the last two month in our sample, Huatai does not show any advantage in terms of containing speculation relative to Jiashi. If anything, the CUSUM test identifies slightly more trading days with speculation for Huatai. We view such a result to be consistence with the importance of market liquidity as a conditioning variable for the speculative effect of the trading rules. When the market liquidity is in a shortage, arbitrage trading drops and the $T + 1$ rule ceases to be a binding restriction; thus, the $T + 0$ rule is no longer effective in reducing speculation.

It is worth to point out that the dramatic drop in liquidity is not confined to the ETFs in our sample, but is genuinely a market-wide phenomenon after the market crash in 2015. On the one hand, more than 1,000 stocks suspended trading starting from late July 2015, either because of hitting the limit on daily price decrease or because the companies decided to suspend out of their own consideration.[35] On the other hand, CSRC imposed numerous trading restrictions related to the market indices, such as stringent rules in stock index future trading, which put further constraints on market trading activities. Therefore, the dry-up in the ETF liquidity is largely due to factors exogenous to the ETF market. In fact, it is evident from Table 4 that the number of trading days with speculation jumped for Huatai from July to August when market liquidity dried up. This corroborates our analysis that trading restriction is conductive to speculation in general.

To summarise, the empirical results on speculation we present in this subsection confirm Hypothesis 2 and Hypothesis 3, that ETF trading under the $T + 0$ rule is less prone to speculation when the market liquidity is not in a shortage, and such containing function may become ineffective when the market liquidity dried up.

5.3. *Robustness check*

In this subsection, we demonstrate that our results are robust to alternative estimation specification, continue to hold during market turbulent periods and remain largely the same under different empirical model configuration.

[35] Chinese stock market regulation allows a company to apply for suspending stock trading because of 'big' issues undergoing decision process. This option is widely used in the stock market crash to prevent excessive stock price declines.

5.3.1. Lag structure and CUSUM test specification

The first robustness check we perform is concerned with the estimation specification, both in the error correction regression and the CUSUM test. To assess how much our results depend on the way we choose the lag structure in the error correction equation, that is determining the lag structure according to the AIC criterion, we redo all the estimation and testing procedure by setting $l = 0$. To ease the potential interference from the market crash and its aftermath, we focus on the 7 months in the first part of our sample, from November 2014 to May 2015. The result is displayed in the second row of Table 5, which is entirely in line with the original result. To confirm that our particular choice of a significance level α at 5 percent for the CUSUM test is irrelevant for the comparison of the trading rules, we redo the CUSUM test with α = 1 percent and 10 percent.

The result is shown in Table 5 as well, which is qualitative the same as the original one.

5.3.2. Market boom and bust

One concern about our claim that the $T + 0$ rule may be actually better at containing speculation is that the mechanism applies primarily to the tranquil phase, and when the market is in boom or bust, the differential impacts of the trading rules will be washed out by market frenzy or panic. This argument becomes even more relevant when coming to the policy implications of our results, as the speculation containing effect of the $T + 0$ rule is most useful when the market is in turbulence. To address this concern, we conduct the benchmark estimation and CUSUM test for the four turbulence subperiods discussed in Section 3.4. The results are in Table 6, where the first two rows show the results for booms and the last two rows for busts. Qualitatively, the results are identical to the original results, where monthly results are based on calendar date. The only case in which the $T + 0$ rule shows no advantage than

Table 5
Days of speculation over November 2014–May 2015

	$l = 0$		l by AIC	
α (%)	Huatai	Jiashi	Huatai	Jiashi
1	7	14	7	13
5	19	45	23	39
10	37	51	35	47

α denotes the significance level of the CUSUM test; $l = 0$ indicates zeros lag in the error correction regression; l by AIC means lag in the error correction regression determined by AIC criterion.

Table 6
Estimation results for the four turbulence periods

	Error correction coefficient		Days with speculation	
Period	Huatai	Jiashi	Huatai	Jiashi
Boom				
2014/11/24 to 12/31	−0.1590	−0.1549	3	8
2015/3/13 to 6/12 Bust	−0.1829	−0.1310	14	20
2015/6/15 to 7/8	−0.2633	−0.1479	4	12
2015/8/18 to 8/26	−0.2617	−0.1088	4	3

the $T + 1$ rule is for the last bust period in August, but as we stress in the previous subsection, when liquidity dries up, different trading rules are likely to deliver the same impact on speculation.

5.3.3. *Different model configuration*

In the benchmark empirical model, we choose to focus on the *level* of the ETF prices and index, and proceed to construct a testing framework based on their cointegration relationship. Another commonly adopted configuration is to use the *logarithm* of prices. With such a transformation of variable, the error correction equation becomes a statement in terms of security returns. This is intuitively attractive as investors may be arguably more concerned with returns than price levels. In Table 7, we report results from replacing all price and index *levels* with their logarithms. Again, it is clear that the qualitative patterns are very much similar to those in Tables 3 and 4.

5.3.4. *Speculation in the longer sample*

To further test the robustness of the theoretic prediction on the tendency of speculation under the $T + 1$ rule, we use the longer sample from 2013 to 2016 and repeat the CUSUM test on the error correction residuals on each trading day. To save space, we only report the number of days with speculation by quarter, yet with the same decomposition as in Table 4. The results are shown in the following Table 8.

Overall, the quarterly results over the 4 years are clearly consistent with the monthly results around the recent market boom and bust: Huatai ETF features less speculative behaviour relative to Jiashi ETF, and in particular, speculations associated with Huatai alone are significantly less than Jiashi. Furthermore, there is a clear difference between the likelihoods of speculative trading before and after Q3 of 2015, the beginning of the recent market turmoil. For the earlier part of the sample, speculations in Huatai alone account for less than

Table 7
Estimation results using log return

	Error correction coefficient		Days with speculation	
Month	Huatai	Jiashi	Huatai	Jiashi
2014/10	−2.3143	−3.0650	2	3
2014/11	−1.8746	−2.4907	4	6
2014/12	−4.0066	−3.6143	4	5
2015/01	−4.8442	−4.3136	5	8
2015/02	−3.0113	−3.4377	3	7
2015/03	−3.3016	−2.8987	3	5
2015/04	−3.5179	−2.3440	4	5
2015/05	−4.3627	−2.6882	3	8
2015/06	−4.9726	−3.2524	6	10
2015/07	−6.2789	−3.2213	4	13
2015/08	−5.8593	−3.1751	9	9
2015/09	−5.9469	−3.2604	8	6

Table 8
Days with speculation by quarter over January 2013–September 2016

	Overall		Decomposition		
Quarter	Huatai	Jiashi	Huatai alone	Jiashi alone	Both
2013Q1	10	21	3	14	7
2013Q2	15	23	5	13	10
2013Q3	12	22	7	17	5
2013Q4	5	15	2	12	3
2014Q1	13	19	8	14	5
2014Q2	12	21	5	14	7
2014Q3	10	15	5	10	5
2014Q4	9	16	4	11	5
2015Q1	12	21	2	11	10
2015Q2	14	24	6	16	8
Subtotal	112	197	47	132	65
2015Q3	22	28	11	17	11
2015Q4	17	21	10	14	7
2016Q1	20	26	8	14	12
2016Q2	17	18	10	11	7
2016Q3	18	30	8	20	10
Total	206	320	94	208	112

half of overall speculations, suggesting that the market-wide speculative force is at play more often; while in the recent period, speculations in Huatai alone become as likely as those common to both ETFs. This pattern is in accordance with the intuition we explain above that the drop in the market liquidity plays a role in spurring more speculative trading.

6. Conclusion

In this article, we measure and compare the price deviation of two Chinese ETFs, Huatai and Jiashi. They both mirror CSI 300 and are only different in the $T + 0/T + 1$ trading rules. Based on a simple cointegration framework of the ETF-index pair, we build an error correction model to distinguish the speculative component in the price deviation and statistically detect its existence by CUSUM test. Using the high-frequency trading data of the two ETFs from October 2014 to September 2015, we find that the price deviation of the two ETFs is indeed different in the sense that (i) Huatai's price deviation is corrected faster and (ii) Jiashi's price deviation is more persistent to induce speculative trading. As the two ETFs mirror the same index and open to the same group of investors, we can attribute this difference to the different trading rules.

Based on our empiric study, we have two conclusions. First, under $T + 0$ rule, the price deviation is corrected faster. Second, the $T + 0$ rule actually prevents speculative trading in the period when the market liquidity is sufficient. These findings are different from early studies on the $T + 1/T + 0$ rules, but consistent with the recent theory of speculative bubbles. On the other hand, our empirical results indicate that the benefit of $T + 0$ rule is not unconditioned. It relies on at least two prerequisites: first, institutional investors account a significant portion of the market, and second, the market is sufficiently liquid. As a consequence, to answer whether it is good to adopt $T + 0$ rule on whole financial market in China requires more careful evaluation on the market condition.

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