Does the T+1 Rule Really Reduce Speculation? 
Evidence from Chinese Stock Index ETF

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Abstract
Stock trading in China is subject to the T+1 rule, which requires investors to hold the asset for at least one day before selling. This rule was initially imposed in the mid 1990's, replacing the previous T+0 rule, to prevent excessive speculative trading. Given the considerable changes of 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.

Keywords: Trading rules; T+1; T+0; Speculation; CSI 300 ETF

JEL codes: 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 adopts the so called “T+1” trading rule. In both Shanghai Stock Exchange and Shenzhen Stock Exchange, investors can not sell shares of stocks or funds that are bought on the same day. Historically, the T+1 rule was imposed in the mid 1990’s 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 1990s, with 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, e.g., 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.\footnote{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.}

Reflecting the opposite views, we attempt to provide some empirical evidence in this paper on the potentially distinct effects of the T+1 vs. 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, which is necessarily a multi-dimensional object cumbersome to measure accurately, favored by advocates of the T+0 rule; while 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,\footnote{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.} 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 that before 2001, thus it is of little use to compare the market trading behavior 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 behavior and price deviation from fundamental value. Empirically, however, it is typically difficult to distinguish buying-for-selling trading from other trading behavior, and to measure fundamental value properly.

Our research design addresses both challenges. Our first contribution is the utilization 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, over the period of October 2014 to September 2015, which covers the 2015 Chinese stock market crash. The two ETFs both track the CSI 300 stock index, 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. The unique difference in the trading rules enables us to identify potential 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 modeling and measure of speculation. Most empirical works use volatility and its variants to measure 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

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3The original articulation of speculation is due to Keynes (1936, ch. 12), and subsequently elaborated by Harrison and Kreps (1978) and Morris (1996).

4Huatai 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.

5Chinese 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.

6CSI 300 index covers 300 stocks traded in both Shanghai Stock Exchange and Shenzhen Stock Exchange, and the selected stocks have both large market capitalization and high liquidity. CSI 300 is by far the most representative stock index for China’s stock market.

7More 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.
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 since the index is directly observable in real time, it can be readily used as the measure of fundamental value for the ETFs. In this paper, 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 cointegrate, 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 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 behavior. 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%, 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 cautious 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 scrutinize more widely the relevant factors across Chinese stock market before making decision on lifting the T+1 rule.

The rest of the paper is organized 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 summarizes 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) analyze the daily price amplitudes for A shares from 1992 to 1996 and for B shares from 1996 to 2008, and concludes that the T+1 rule reduces stock volatility. Wu and Qin (2015) takes the 2001 adoption of the T+1 rule for B shares as a quasi-natural experiment, and uses 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.

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, Bian and Su (2010) takes 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.

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8For example, in the DID setup 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.
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.\(^9\) In addition, Yu and Xiong (2011) also notes the different trading rules for stocks and warrants in China, but does not test formally the implications of the trading rules.

Different from the above empirical works, Guo, Li, and Tu (2012) builds a theoretic model with a single manipulator, illustrating that the T+1 rule could effectively limit manipulation behavior 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 setup is likely to be at odds with the ETF market where institutional investors dominate. Using an agent-based model, Cheng, Liu, and Qiu (2011) suggests 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, Daigler, and Gleason (2008) and Marshall, Nguyen, and Visaltanachoti (2013) document arbitrage opportunities caused by price disparities among S&P500 index, ETFs and futures.

### 3 Institutional Details and Data Description

#### 3.1 Trading Rules of the Two ETFs

To understand the difference of 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 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

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\(^9\) One potentially difficulty with this approach is the validity of the BS option pricing formula to Chinese warrant market. Chang, Luo, Shi, and Zhang (2013) shows 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, Su, and Wang (2015) by examining different option pricing theories.
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.

3.2 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 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 includes 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-weight 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 are at least one transaction for each ETF.

In each trading day, the market opens at 9:30am and closes at 15:00pm, with an one hour 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 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.

3.3 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 November 24th to December 31st 2014, during which CSI 300 index increased by 38.1%. Starting from March 13rd, the market experienced a persistent and strong “bull” market, CSI 300 index increased by 47.5% as of June 12th. Then came the market crash. From June 15th to July 8th, CSI 300 index dropped by almost 30%. Around August 1st, in order to stabilize 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 intra-day volatility of CSI 300 index decreased after August significantly,\textsuperscript{10} and the turnover rates of the two ETFs dropped considerably as well. The market turbulence is summarized in Table 2. During the week from August 18th to 26th, coupled with shocks from the US and other major financial markets, the CSI 300 dropped by almost 21%. Figure 1 shows CIS 300 index level and its intraday volatility over the one 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 $CSI300_t$ 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 CIS 300 index, with minimal differences in

\textsuperscript{10}Volatility is defined as the sample standard deviation of the log returns.
transaction cost, management fee and dividend rules.\(^\text{11}\) Since 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 \(\epsilon^i_t\) 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 \(\epsilon^i_t\) is not a unit root process or explosive, then by the Granger representation theorem in Engle and Granger (1987), for each \(i\), the first difference of the ETF price and the index admits an error correction representation as follows:\(^\text{12}\)

\[
\Delta ETF^i_t = \alpha^i + \sum_{j=1}^{\ell} \theta^i_j \Delta ETF^i_{t-j} + \sum_{k=0}^{\ell} \phi^i_k \Delta CSI300_{t-k} + \gamma^i \epsilon^i_{t-1} + u^i_t, \tag{2}
\]

where \(u^i_t\) is a white noise innovation with no serial correlation, and \(\ell\) denotes the common number of lags for \(\Delta ETF^i\) and \(\Delta CSI300\).\(^\text{13}\) From the Granger representation theorem, price deviation \(\epsilon^i_t\) is tied to innovation \(u^i_t\) through a moving average relationship, i.e., \(\epsilon^i_t = K(\mathcal{L}) u^i_t\), where \(K(\cdot)\) denotes a polynomial, possibly infinite, and \(\mathcal{L}\) denotes the lag operator. Because of this structural relation, we can interpret \(u^i_t\) as summarizing all shocks, be it liquidity or speculation, to the dynamics of ETF price and index at time \(t\). Correspondingly, price deviation \(\epsilon^i_t\) can be viewed as reflecting cumulative effects from underlying driving forces \(u^i_t\). It is also clear from this relationship that whenever \(u^i_t\) displays time-varying properties, \(\epsilon^i_t\) 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 structure break test to check the presence of time-varying behavior in \(u^i_t\), hence \(\epsilon^i_t\).

\(^{11}\)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, since we are examining the intraday trading data, the difference in dividend rules is irrelevant.

\(^{12}\)For practical purpose, we shall consider only finite lag order for \(\Delta ETF^i_{t-k}\) and \(\Delta CSI300^i_{t-l}\). For the same reason, we shall confine to the case where the residual term is merely \(u^i_t\). In general, the residual term can be a moving average of \(u^i_t\), as showed in Engle and Granger (1987).

\(^{13}\)We remark that in order for the cointegration relationship of (1) to imply the error correction representation of (2), one do not need to assume \(\epsilon^i_t\) to be stationary. The only assumption required is that \(\epsilon^i_t\) be neither explosive nor a unit root process. This allows for the possibility of potential transitory but time-varying behavior in \(\epsilon^i_t\), which plays an important role in our empirical modeling.
To be more specific, we can decompose $u_t^i$ into two parts:

$$u_t^i = v_t^i + s_t^i,$$

where $v_t^i$ is white noise with identical mean and variance, and $s_t^i$ is potentially time-varying, either deterministic or stochastic.\(^\text{14}\) 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 some time period. In the process, price deviations are typically amplified, either upwards or downwards, resulting in speculative bubbles or implosions.\(^\text{15}\) Such price deviation dynamics manifest themselves in shifting levels of $s_t^i$. For instance, consider the following form of the dynamics for $s_t^i$:

$$s_t^i \begin{cases} 
 0 & \text{for } t < t_0 \text{ and } t > t_1, \\
 \geq 0 & \text{for } t_0 \leq t \leq t_1,
\end{cases}$$

for some $t_0$ and $t_1$. When $s_t^i > 0$ 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.\(^\text{16}\)

The empirical model (1)–(3) provides a parsimonious reduced form description of the ETF dynamics with speculation possibility. As showed 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, e.g., Scheinkman and Xiong (2003), Xiong (2013), and Scheinkman (2013), emphasize the interaction of trading restrictions and investor belief heterogeneity in causing speculative trading. The basic logic is intuitive. When pessimistic

\(^{14}\)To be consistent with zero autocorrelation for $u_t^i$, $s_t^i$ is assumed to be serially uncorrelated when the term is stochastic.

\(^{15}\)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.

\(^{16}\)Most of the theoretic literature focuses on the upward deviation, i.e., speculative bubbles. However, since 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.
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 trade 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 characterization of speculation, originally laid out in Keynes (1936, ch. 12). Essentially, belief heterogeneity and its dynamics create the room for price deviations, either upward or downward, relative to 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, since 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, market liquidity dry up indicates 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, $\gamma^i$ measures the speed at which a given deviation $\epsilon^i_t$ is corrected. A more negative value means 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 $\gamma^H$ for Huatai ETF (under T+0) and $\gamma^J$ 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, i.e., $\gamma^H < \gamma^J < 0$.

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, such as volume, turnover and volatility based on quantity, they are indirect indicators of speculation per se, and identification relies on theoretic relations between observed quantity and speculation. This makes it difficult to differentiate speculation from

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17See Mei, Scheinkman, and Xiong (2009) for an example.
other trading behavior, such as liquidity trading. In contrast, since speculation is directly links 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 are unambiguously given by the CSI 300 index.

Our empirical model is designed specifically for measuring such price deviations \( \epsilon_i^t \) through the cointegration equation (1). More importantly, our model directly consider the possibility of a speculative component \( s_i^t \) 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 non-zero \( s_i^t \). 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, i.e., \( s_J^t \) is more likely to be nonzero than \( s_H^t \).

Hypothesis 2 is the main hypothesis in this paper. Since 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, i.e., \( s_J^t \) and \( s_H^t \) 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 \( \hat{\epsilon}_i^t \) 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 \( \hat{\gamma}^i \) and innovation \( \hat{u}_i^t \). To test for the presence of speculation, we use the classical cumulative sum (CUSUM) method (Brown, Durbin, and Evans, 1975; Krämer, Ploberger, and Alt, 1988) to test mean shifting in the innovation process \( \{\hat{u}_i^t\} \). When there is speculative price deviation, CUSUM test will reject the null hypothesis of zero speculative component \( s_i^t \). 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,

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as detailed in Section 3.2. All exercises are implemented in RStudio, and in particular, we use the `strucchange` package to perform the CUSUM test.\textsuperscript{19}

We leave one remark on the procedure of CUSUM test we choose. By testing mean shifting in $\hat{u}_t$, we are running CUSUM test on the error correction equation (2). An alternative procedure is to run CUSUM test on the cointegration equation (1). Since price deviation $\epsilon_t$ is a moving average of innovation $u_t$, level shifts in $u_t$ will also induce shifts in $\epsilon_t$, thus a CUSUM test can be performed following for example the method of Xiao and Phillips (2002). A drawback with this approach is that $\epsilon_t$ typically has serial correlation, and some correction of this correlation is required for a CUSUM test to perform well (Deng and Perron, 2008). However, since the nature of the serial correlation is unknown, a test based on $\epsilon_t$ 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 can not reject the unit root null hypothesis for 230 trading days at the 5% significance level, while for the remaining 14 days, the $p$-values of the unit root null are in borderline and not exceeding 10%. In summary, all the data series can be identified as $I(1)$.

To estimate the cointegration system following the two-step procedure. 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 $\hat{\epsilon}_t$ is 0.016 for Huatai and 0.035 for Jiashi. The regression results indicates that on average, the variation and persistence of intraday price deviation for Jiashi is larger than that of Huatai. In addition, we perform ADF test on $\hat{\epsilon}_t^H$ and $\hat{\epsilon}_t^J$ for each trading day, and the unit root null is rejected at 5% 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 $\{\hat{\epsilon}_t\}$ in conjunction with $\Delta ETF_t$ and $\Delta CSI300_t$ to estimate the error correction equation (2) by OLS for each trading day. To

\textsuperscript{19}The package is developed by Achim Zeileis, Friedrich Leisch, Kurt Hornik and Christian Kleiber.
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 favors 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.\(^{20}\) Figure 2 plot the histogram of the first-order autocorrelation of the estimated residuals \( \hat{u}_t^i \) 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.

[ Insert Figure 2 here ]

For both ETFs, the error correction coefficient estimates \( \gamma^i \) are significant at 5% level for all but 6 days in our sample. For easiness of exposition, we report in Table 3 the monthly average of \( \hat{\gamma}^i \) for \( i = J, H \). Across the 12 months, the average \( \gamma^H \) is significantly more negative than \( \gamma^J \). Going through month by month, we see that for the 3 months in which \( \gamma^H \) is greater than \( \gamma^J \), the difference is significant in only one month (November 2014), and is at 10% but not 5%. 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.

[ Insert Table 3 here ]

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 flavor of the test, we first plot in Figure 3 the error correction residual series for both ETFs on July 29th, 2015.\(^{21}\) The Figure clearly shows that Jiashi is subject to residuals in larger magnitude than Huatai, which also suggests that the price deviations in Jiashi is greater than Huatai.

[ Insert Figure 3 here ]

\(^{20}\)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 is in first difference except for the error term, lags up to 2 already provides a rich dynamic structure.

\(^{21}\)The choice of this date is only for an illustration.
The greater magnitude and variation in residuals for Jiashi is what drives the CUSUM test to reject the null hypothesis of no mean shift. The CUSUM test is based on the partial sum of residuals $S_t^i \equiv \sum_{1 \leq \tau \leq t} \tilde{u}_t^{i}$. Under the null hypothesis with no mean shift, the partial sum process $\{S_t^i\}$ converges to the a 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 4 shows the CUSUM test results for Huatai and Jiashi on July 29th, 2015. Roughly all the way in the second trading hour, the partial sum $S_t^i$ is above the upper bound of the 95% 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 $\{\hat{u}_t^J\}$, hence provides evidence that Jiashi is subject to speculation on the particular trading day.

[ Insert Figure 4 here ]

The CUSUM test results for the entire sample is summarized in Table 4. We report the monthly number of trading days which do not pass the CUSUM test at a significance level of 5%, and classify these days as subject to speculation. 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, since it ignores the fact that some common factor, which by definition

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22To be clear, the CUSUM we employ is based on the recursive partial sum $\tilde{S}_t^i \equiv \sum_{1 \leq \tau \leq t} \tilde{u}_t^i$, where $\tilde{u}_t^i$ 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, Ploberger, and Alt (1988) for details.

23The upper and lower bound 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.

24There are 4 hours in each trading day, so the relative time of 0.25 to 0.5 indicates the second trading hour.

25For a robustness check, we also report results on speculation test using 1% and 10% 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.
excludes the distinct trading rules for the two ETFs, is driving the speculation results. To overcome this drawback, column 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.

[ Insert Table 4 here ]

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 interpret this result as strongly favoring Hypothesis 2. From Table 2, it is evident that for both ETFs, the first ten months in the sample show much more active trading than the last two months. For Jiashi, the average trading volume in the first months is more than 5 times of the average in the last two months, and the average turnover rate is more than 3 times of the last two months. For Huatai, the respective ratio is more than 3 and close to 4 as well. These number suggests that the market liquidity of the two ETFs is much higher in the first 10 months than in the last two months. Since liquidity is not an issue over the first sub-period, 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 1000 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. On the other hand, CSRC imposed numerous trading restrictions related to the market indices, such as stringent rules in stock index future

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26Chinese stock market regulation allows a company to apply for suspending stock trading because of
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 summarize, the empirical results on speculation we present in this subsection confirm Hypothesis 2 and 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.

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, i.e., determining the lag structure according to the AIC criterion, we redo all the estimation and testing procedure by setting \( \ell = 0 \). 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 \( \alpha \) at 5% for the CUSUM test is irrelevant for the comparison of the trading rules, we redo the CUSUM test with \( \alpha = 1\% \) and 10%. The result is shown in Table 5 as well, which is qualitative the same as the original one.

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, since the speculation containing effect of the T+0 rule is most useful when the market is in turbulence. To address this concern,

“big” issues undergoing decision process. This option is widely used in the stock market crash to prevent excessive stock price declines.
we conduct the benchmark estimation and CUSUM test for the four turbulence subperiods discussed in Section 3.3. 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 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.

[Insert Table 6 here ]

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 is very much similar to those in Table 3 and Table 4.

[ Insert Table 7 here ]

6 Conclusion

In this paper, 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 are indeed different in the sense that 1) Huatai’s price deviation is corrected faster, 2) 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.

References


### A Tables

Table 1: Comparison of trading rules of Huatai and Jiashi

<table>
<thead>
<tr>
<th></th>
<th>Huatai</th>
<th>Jiashi</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Primary market</strong></td>
<td>Buy stocks on day T, create ETF shares on day T</td>
<td>Buy stocks on day T, create ETF shares on day T+1</td>
</tr>
<tr>
<td></td>
<td>Redeem ETF on day T, sell SSE stocks on day T and SZSE stocks on day T+2</td>
<td>Redeem ETF on day T, sell stocks on day T+2</td>
</tr>
<tr>
<td><strong>Cross market</strong></td>
<td>Create ETF on day T, sell on day T</td>
<td>Create ETF on day T, sell on day T+2</td>
</tr>
<tr>
<td></td>
<td>Buy ETF on day T, redeem on day T</td>
<td>Buy ETF on day T, redeem on day T+2</td>
</tr>
<tr>
<td><strong>Secondary market</strong></td>
<td>Buy ETF on day T, sell on day T+1</td>
<td>Buy ETF on day T, sell on day T+1</td>
</tr>
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### Table 2: Summary statistics

<table>
<thead>
<tr>
<th>Month</th>
<th>Huatai Shares $(10^9)$</th>
<th>Huatai Volume $(10^6)$</th>
<th>Huatai Turnover rate</th>
<th>Jiashi Shares $(10^9)$</th>
<th>Jiashi Volume $(10^6)$</th>
<th>Jiashi Turnover rate</th>
<th>CSI 300 Intra-day volatility</th>
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<td>2014/10</td>
<td>5.88</td>
<td>6.11</td>
<td>10.40%</td>
<td>10.44</td>
<td>1.75</td>
<td>1.67%</td>
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<td>8.63</td>
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<td>2.11</td>
<td>2.10%</td>
<td>0.044%</td>
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### Table 3: Error correction coefficient

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<th>Jiashi</th>
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<td>−0.2438</td>
<td>−0.2167</td>
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</tr>
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<td>−0.2026</td>
<td>−0.2320</td>
<td>38.03%</td>
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<td>−0.1331</td>
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<td>2015/04</td>
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<td>2015/09</td>
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<tr>
<td>Average</td>
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<td>−0.1567</td>
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*Notes: p-value for t-test on mean difference*
Table 4: Days with speculation in each month

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<th>Month</th>
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<td>Jiashi</td>
<td>Huatai alone</td>
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<tr>
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<td>4</td>
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<td>23</td>
<td>55</td>
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Table 5: Days of speculation over Nov. 2014–May 2015

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<th>α</th>
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<th>ℓ by AIC</th>
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<td>Jiashi</td>
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<tr>
<td>1%</td>
<td>7</td>
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<td>5%</td>
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<td>45</td>
</tr>
<tr>
<td>10%</td>
<td>37</td>
<td>51</td>
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</table>

*Notes: 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*. 

24
<table>
<thead>
<tr>
<th>Period</th>
<th>Error correction coefficient</th>
<th>Days with speculation</th>
</tr>
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B Figures

Figure 1: CSI 300 Index and intraday volatility

![CSI 300 Index and Intraday Volatility Graph]

- **CSI 300 Index**
  - Volatility Scale: 0 to 0.0035
Figure 2: Histogram of first-order autocorrelation for $\hat{u}_t^H$ and $\hat{u}_t^J$

![Histogram of first-order autocorrelation](image)

Figure 3: Cointegration residuals of Huatai and Jiashi on 2015/7/29

![Cointegration residuals](image)
Figure 4: CUSUM tests for Huatai and Jiashi on 2015/7/29

Notes: the horizontal axis in each plot is the time period with a normalized total length of 1; two horizontal bars around ±1.4 are the (rescaled) bounds at 5% level under the null hypothesis for the (rescaled) partial sum process \( \{S_i\} \); the remaining line is the (rescaled) partial sum process