We firstly report an interesting puzzle that the average overnight return on market portfolio is significantly negative in China’s stock market, which is the second largest capital market in the world. This market anomaly violates traditional assets pricing theory. More interesting, this puzzle seems unique in China’s stock market, while the average overnight returns on various stock indices from other countries’ or regions’ markets are all positive. Theoretical analysis implies that a unique arrangement in China’s stock market potentially explains the puzzle, i.e. T+1 trading rule. T+1 trading rule prohibits agents to sell the shares that they bought on the same day. This arrangement periodically produces discounts on logarithmic daily opening prices (T+1 discount), but not on closing prices. Empirical evidence reveals that T+1 discount indeed explains overnight return puzzle and significantly contributes to overnight return’s expectation. The average T+1 discount on Shanghai Stock Exchange Composite Index is around 15 basis points, which is almost two times of the average return driven by fundamental value movements. Besides, T+1 discount’s contribution to overnight risks is about 13.19%, which is much less than the contribution of fundamental value movements.

**Keywords**: Overnight Return Puzzle, Trading Mechanism, T+1 Trading Rule, T+1 Discount.  
**JEL**: G10, G12
I. Introduction

Traditional assets pricing theory concludes that wealth portfolio (market portfolio) should generate positive expected return, which is greater than risk-free rate. This conclusion is widely verified by using closing prices based 24-hour returns. However, we firstly report an interesting puzzle that the average overnight return on market portfolio is significantly negative in China’s stock market. More interesting, this puzzle seems unique in China’s stock market, while the market portfolios of other countries’/regions’ stock market all generate positive average overnight returns. It is of interest to understand the cause of this unique market anomaly in the second largest capital market in the world. We attempt to explain the puzzle by a unique financial arrangement in China stock market, i.e. T+1 trading rule.

Financial assets’ overnight returns have received considerable attention from academia. Different from commonly used closing prices based returns, overnight returns are constructed by opening prices and lagged closing prices. Some literature utilizes it to study the information diffusion and financial contagion among different markets; see Lin et al. (1994), Becker et al. (1990), Karolyi and Stulz (1996a), Wang and Firth (2004). Existing findings support that the average overnight returns in stock markets are mostly positive; see Kelly and Clark (2011), Kang and Babbs (2010), Berkman et al. (2012), Karolyi and Stulz (1996b), Lockwood and Mcinish (1990), Masulis and Ng (1995), Liu and Tse (2017), Chan et al. (1996), Riedel and Wagner (2015), Gutierrez et al. (2009). These findings are consistent with financial theory. Risk averse agents require a compensation for holding risky assets, then the expected returns on risky assets are expected to be

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positive and larger than risk-free rate. This argument holds at least for market portfolio. Surprisingly, a few literature reports opposite findings in China’s stock market. Based on different market indices and sample periods, it is reported that the average overnight return on market portfolio in China’s stock market tends to be negative; see Chen et al. (2016), Liu et al. (2015). Existing literature presents this finding, but does not claim that it is a market anomaly or puzzle. And, the cause of this phenomenon is still unclear yet. Some of previous studies simply attribute it to the downward trend in their sample. However, in this paper, it will be shown that overnight return puzzle constantly exists in China’s stock market, even in bullish period.

As a unique arrangement in China stock market, T+1 trading rule is helpful to explain the overnight return puzzle. T+1 trading prohibits buyers to sell the shares that they bought on the same day. As a temporary trading rule, regulators believe that this arrangement can efficiently reduce prices’ volatility. Previous studies on T+1 trading rule’s impacts mainly focus on volatility and liquidity; see Wu and Qin (2015), Guo et al. (2012). Less literature pays attention to its impact on assets’ prices. Bian and Su (2010) find that T+1 trading rule reduces market liquidity, and then causes an illiquidity discount on assets’ prices.

Distinct from previous studies, we point out that T+1 trading rule has asymmetric effects on buyers and sellers. The asymmetric effects periodically produce discounts on logarithmic daily opening prices, but not on closing prices. It is called T+1 discount in this paper. The periodic pattern of T+1 discount potentially explains overnight return puzzle in China’s stock. Empirical results show that the magnitude of average T+1 discount is about 15 basis points, which is almost two times of the average return driven by fundamental value movements. Besides, T+1 discount’s contribution to overnight risks is about 13.19%, which is much less than the contribution of fundamental value movements.

The rest of the paper proceeds as follows. In next section, the overnight
return puzzle in China’s stock market is elaborated. Section III develops a theoretical model to incorporate T+1 discount into assets’ opening prices. Then, the T+1 discount’s significance and magnitude are examined empirically. Section IV provides some additional evidence to support our conclusion. Section V addresses T+1 discount’s contribution to overnight risk. Finally, section VI concludes.

II. Overnight Return Puzzle in China’s Stock Market

For measuring the movements of financial assets’ prices during overnight and daytime periods, its close-to-close 24-hours returns are decomposed into overnight returns and daytime returns, namely

\[ R_t = R_o^t + R_d^t, \]

where \( R_t = P_c^t - P_{t-1}^c; R_o^t = P_o^t - P_{t-1}^o; R_d^t = P_c^t - P_o^t; P_o^t \) and \( P_c^t \) denote the logarithmic opening and closing prices for trading day \( t \), respectively. Intuitively, in an efficient market, overnight return fully reflects the information, about macro-economy and enterprise operation, released during the non-trading period between the closing bell yesterday and opening bell today. Besides, daytime return reflects the information released during the trading period between opening bell and closing bell. This decomposition can be easily applied for individual stocks, portfolios or stock price indices. In particular, aggregative stock market indices, e.g. S&P500 Index, DOWJONES Index and NASDAQ Index, are widely used as proxies of market portfolio or wealth portfolio. Following the traditional financial theory, it is natural to expect that the expectation of overnight return and daytime return are both positive and greater than risk-free rate, if they are calculated based on an aggregative stock market index. This conjecture is simply in the light of the commonly used financial assumption that risk averse agents require a premium for holding risky assets; see Lucas (1978), Sharpe (1964), Mer-
ton (1973).

Our main sample set is the daily data of Shanghai Stock Exchange Composite Index (henceforth SSE Index), including opening prices, closing prices, lowest prices and highest prices. Sample period is from January 4th, 2000 to July 3rd, 2017. All the data are collected from Tinysoft financial database. Shanghai Stock Exchange is one of the two separated stock exchanges in China, and the other one is Shenzhen Stock Exchange. SSE Index measures the total market value of all listed shares in Shanghai Stock Exchange, which is constructed as

\[
\text{Current Total Capitalization of Shares Outstanding} \times 100 \\
\text{Total Capitalization of Shares Outstanding, on Dec. 19th, 1990}
\]

where the total capitalization is measured in domestic currency (CNY). Referring to Eq. (1), the 24-hours return \( R_t \), overnight return \( R^o_t \) and daytime return \( R^d_t \) on SSE Index are calculated for each of the trading days. The summary statistics of \( R^o_t \) and \( R^d_t \) are reported in Panel A of Table 1.

Surprisingly, panel A of Table 1 shows that the average overnight return on SSE Index is about -0.058% and significant at 1% level. This finding violates our previous conjecture that overnight return on an aggregative market index should have a positive expected value. Besides, its magnitude is also economically significant. Actually, it indicates that the overnight returns produce an average annualized loss of 0.058%×240=13.920%, which is calculated by using an approximate number of trading days every year, 240 days. Traditional efficient market hypothesis hardly explains such a huge loss during overnight periods.

Various robustness checks in China’s stock market are presented in Panel B of Table 1, based on different market regimes (bear or bull), sample periods, stock exchanges, types of shares, and capitalization. Firstly, the market regimes are identified by a two-regime Markov regime switching model for SSE Index with

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2 For further details of SSE Index’s construction, see http://www.sse.com.cn/market/sseindex/overview/.
Table 1—Overnight Returns and Daytime Returns in China’s Stock Market

<table>
<thead>
<tr>
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<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Overnight Return</td>
</tr>
<tr>
<td></td>
<td># of Obs.</td>
</tr>
<tr>
<td>SSE Index</td>
<td>4228</td>
</tr>
<tr>
<td></td>
<td>(-5.52)</td>
</tr>
</tbody>
</table>

| Panel B: Robustness Checks of Overnight Return in China’s Stock Market. |
|------------------|------------------|
|                  | Overnight Return | Daytime Return |
|                  | # of Obs. | Mean (%) | # of Obs. | Mean (%) |
| SSE Index (Bear Market) | 1050     | -0.116*** | 1051     | 0.123*  |
|                  | (-3.07)  |           | (1.63)   |           |
| SSE Index (Bull Market) | 3178     | -0.039*** | 3179     | 0.063***|
|                  | (-6.90)  |           | (3.58)   |           |
| SSE Index (Expanded Sample) | 5454     | -0.030*** | 5455     | 0.059***|
|                  | (-2.65)  |           | (2.74)   |           |
| Shenceng Index    | 3969     | -0.044*** | 3970     | 0.072***|
|                  | (-2.63)  |           | (2.83)   |           |
| B-share Index     | 3498     | -0.041*** | 3499     | 0.060** |
|                  | (-2.71)  |           | (2.02)   |           |
| CSI300 Index      | 2740     | -0.078*** | 2741     | 0.125***|
|                  | (-4.07)  |           | (4.06)   |           |
| SSE50 Index       | 3129     | -0.063*** | 3130     | 0.090** |
|                  | (-4.33)  |           | (3.04)   |           |
| M&S CAP Index     | 2278     | -0.098*** | 2279     | 0.166***|
|                  | (-4.95)  |           | (4.34)   |           |

Note: This table reports the average overnight return and daytime return in China’s stock market. Overnight returns are calculated as $R_0^t = P_0^t - P_{t-1}^t$. Daytime returns are calculated as $R_d^t = P_c^t - P_0^t$. $P_0^t$ and $P_c^t$ denote the logarithmic opening and closing prices for trading day $t$, respectively. Panel A shows the average overnight return and daytime return on Shanghai Stock Exchange Composite Index, from *January 4th, 2000* to *July 3rd, 2017*. Panel B presents the average overnight returns and daytime returns on various stock indices during different periods, in China’s stock market, i.e. SSE Index during bearish periods, SSE Index during bullish periods, SSE Index during expanded sample period (*January 4th, 1995* to *July 3rd, 2017*), Shenceng Index (*January 4th, 2000* to *July 3rd, 2017*), B-share Index (*January 4th, 2002* to *July 3rd, 2017*), CSI300 Index (*January 4th, 2005* to *July 7th, 2017*), SSE50 Index (*January 12th, 2004* to *July 7th, 2017*), M&S CAP Index (*January 14th, 2006* to *July 3rd, 2017*). Market regimes (bear or bull) are identified by a two-regime Markov regime switching model for SSE Index with regime-based expected close-to-close 24-hours return and conditional volatility. Kalman filtering probability serves for identifying market regimes. The market is recognized as bearish if Kalman filtering probability of regime one is larger than $\frac{1}{2}$, otherwise it is recognized as bullish. All the data are collected from Tinysoft financial database; see http://www.tinysoft.com.cn/TSDN/HomePage.tsl. *, ** and *** denote 10%, 5% and 1% significance respectively. The t-statistics of coefficients’ estimators are presented in the brackets.
T+1 RULE AND OVERNIGHT RETURN PUZZLE IN CHINA’S STOCK MARKET

is larger than $\frac{1}{2}$, otherwise it is recognized as bullish. The summary statistics show that the average overnight returns are both significantly negative for the two regimes (-0.116% and -0.039% respectively), which implies that the news released during overnight periods cannot generate a positive expected overnight return even during bullish periods. Secondly, an expanded sample of SSE Index, from January 4th, 1995 to July 3th, 2017, is examined similarly. It still turns out that the average overnight return is significantly negative (-0.030%). Thirdly, to exclude the effects of different stock exchanges, Shencheng Index’s average overnight return is reported as well. Shencheng Index measures the total capitalization of top 500 most liquid stocks listed in Shenzhen Stock Exchange, which is another stock exchange in China. The result shows that the mean of overnight returns on Shencheng Index is also significantly negative (around -0.044%). Fourthly, for ruling out the disturbance caused by different types of shares, the summary statistics of overnight returns on B-share Index are presented next. B-share index reflects the total capitalization of all domestically listed foreign shares traded in Shanghai Stock Exchange. It results in an average overnight return around -0.041%, which is significant at 1% level. Finally, the average overnight returns on CSI300 Index, SSE50 Index and M&S CAP Index are presented at last. Specifically, CSI300 Index measures the total market value of top 300 most liquid stocks traded in Shanghai Stock Exchange or Shenzhen Stock Exchange; SSE50 Index measures the total market value of top 50 most liquid stocks listed in Shanghai Stock Exchange; M&S CAP Index reflects the total market value of top 100 most liquid stocks with medium or small capitalization, which are traded in Shenzhen Stock Exchange. Note that, as comparisons of M&S CAP Index, most of the componential stocks of CSI300 and SSE50 are big-cap. The results show that the average overnight returns on CSI300, SSE50 and M&S CAP Indices are consistently negative and significant at 1% level. For the details of these indices, see the footnotes of Table 1. All of the above findings
convince us that the phenomenon of negative expected overnight return widely exists in China’s stock market. It is robust to various market regimes, sample periods, stock exchanges, types of shares and capitalization. This counter intuitive phenomenon is named “overnight return puzzle” in this paper.

In comparison with China’s stock market, a number of stock indices from other countries’ and regions’ stock markets are investigated as well. Three stock indices from developed markets and three others from emerging markets are selected as our comparisons, i.e. Hang Seng Index (from Hong Kong), S&P500 Index (from United States), Nikkei Stock Index (from Japan) and TSEC Index (from Taiwan), IPC Index (from Mexico), KOSPI Index (from South Korea). Table 2 reports the summary statistics of their overnight returns and daytime returns. For the details of the data, see the footnotes of Table 2. The signs and significance of average daytime returns are capricious, but it is not the focus of this paper. Our interest is the average overnight return. All of the signs of average overnight returns are consistently positive, and most of them are very significant (except S&P500 Index). This finding is consistent with our previous conjecture that average overnight return of an aggregative market index should be positive. Existing literature also reports similar findings from various stock markets, except China’s stock market; see Kelly and Clark (2011), Kang and Babbs (2010), Berkman et al. (2012), Karolyi and Stulz (1996b), Lockwood and Mcinish (1990), Masulis and Ng (1995), Liu and Tse (2017), Chan et al. (1996). That is to say, overnight return puzzle seems a unique phenomenon in China’s stock market. It does not exist in any other developed or emerging markets.

There are two plausible explanations for overnight return puzzle in China’s stock market: investors’ overreaction and speculators’ manipulation. Firstly, investors may overreact to the bad news which is released during overnight periods, and then the opening prices drop sharply. However, it is hard to explain why investors only overreact to bad news, but not to good news. If investors’
Table 2—Overnight Returns and Daytime Returns In Other Countries’/Regions’ Stock Markets

<table>
<thead>
<tr>
<th></th>
<th>Overnight Return</th>
<th></th>
<th>Daytime Return</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of Obs.</td>
<td>Mean (%)</td>
<td># of Obs.</td>
<td>Mean (%)</td>
</tr>
<tr>
<td>Hang Seng Index (Hong Kong)</td>
<td>4315</td>
<td>0.051***</td>
<td>4316</td>
<td>-0.041**</td>
</tr>
<tr>
<td>S&amp;P500 Index (United States)</td>
<td>4401</td>
<td>0.000</td>
<td>4402</td>
<td>0.011</td>
</tr>
<tr>
<td>Nikkei Stock Index (Japan)</td>
<td>4208</td>
<td>0.036***</td>
<td>4290</td>
<td>-0.040**</td>
</tr>
<tr>
<td>TSEC Index (Taiwan)</td>
<td>4244</td>
<td>0.110***</td>
<td>4309</td>
<td>-0.106***</td>
</tr>
<tr>
<td>IPC Index (Mexico)</td>
<td>4319</td>
<td>0.003**</td>
<td>4385</td>
<td>0.041**</td>
</tr>
<tr>
<td>KOSPI Index (South Korea)</td>
<td>4233</td>
<td>0.059***</td>
<td>4318</td>
<td>-0.042**</td>
</tr>
</tbody>
</table>

Note: This table reports the average overnight returns and daytime returns on six market indices from other countries’ and regions’ stock markets, i.e. Hang Seng Index (Hong Kong, from January 3rd, 2000 to July 3rd, 2017), S&P500 Index (United States, from January 3rd, 2000 to June 30th, 2017), Nikkei Stock Index (Japan, from January 4th, 2000 to June 29th, 2017), TSEC Index (Taiwan, from January 4th, 2000 to July 3rd, 2017), IPC Index (Mexico, from January 3rd, 2000 to July 3rd, 2017), and KOSPI Index (South Korea, from January 4th, 2000 to July 3rd, 2017). All the data is downloaded from Yahoo Finance; see https://finance.yahoo.com/world-indices. Overnight returns are calculated as \( R_{t}^{o} = \ln(P_{t}) - \ln(P_{t-1}) \). Daytime returns are calculated as \( R_{t}^{d} = \ln(P_{t}) - \ln(P_{t-1}) \). \( P_{t}^{o} \) and \( P_{t}^{d} \) denote the logarithmic opening and closing prices for trading day \( t \), respectively. *, ** and *** denote 10%, 5% and 1% significance respectively. The t-statistics of coefficients’ estimators are presented in the brackets.

Overreaction responses to good news and bad news symmetrically, the average overnight return should not deviate from the rational mean of returns driven by fundamental value movements, which is expected to be positive. In addition, investors’ overreaction is a worldwide phenomenon, not exclusive to China’s stock market. Why overnight return puzzle does not exist in any other countries’ markets? Secondly, speculators may manipulate the assets’ prices deviating from equilibrium at the end of a trading day. To be specific, if speculators have motivation to present “good” closing prices to the public, they will drive up the assets’ prices at the closing bell, then the price bubbles are generated, which could be called “closing bubbles”. It is another possible explanation of overnight return puzzle: the negative average overnight return is caused by the bursting of the closing bubbles. However, this explanation neglects that specu-
lators also have motivation to drive down the assets’ prices for showing “bad”
closing prices to the public. Besides, it is apparently that the intention of spec-
ulators to drive up the closing prices is boosting the market in the following
period. If the bubbles burst, it means speculators’ strategy fails. It is hard to
believe these speculators keep on employing this failing strategy for more than
20 years. In addition, as another worldwide phenomenon, price manipulation
cannot explain why overnight return puzzle is unique in China’s stock market.
Moreover, if closing bubbles indeed explain overnight return puzzle, overnight
returns should be negatively correlated with the sizes of the closing bubbles.
This relationship can be examined with the following regression,

\[ R^o_t = \alpha + \beta B^c_{t-1} + \epsilon_t, \]  

where \( B^c_{t-1} \) is a proxy of closing bubble for trading day \( t - 1 \). Table 3 shows the
estimation with three proxies of closing bubbles, i.e. \( P^c_{t-1} - \frac{p^l_{t-1} + p^h_{t-1}}{2}, P^c_{t-1} - p^l_{t-1} \)
and \( R^d_{t-1} = P^c_t - P^o_t \), where \( P^c_{t-1}, P^l_{t-1} \) and \( P^h_{t-1} \) refer to logarithmic closing price,
lowest price and highest price, respectively. In contrary to closing

<table>
<thead>
<tr>
<th>Table 3—Analysis of Overnight Returns and Closing Bubbles</th>
</tr>
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<tbody>
<tr>
<td>( B^c_{t-1} )</td>
</tr>
<tr>
<td>Coef.</td>
</tr>
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<td></td>
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Note: This table reports the OLS estimation of the following equation,

\[ R^o_t = \alpha + \beta B^c_{t-1} + \epsilon_t. \]

Overnight returns are calculated as \( R^o_t = P^c_t - P^c_{t-1} \). \( P^c_t \) and \( P^c_{t-1} \) denote the logarithmic opening and closing
prices of Shanghai Stock Exchange Composite Index, respectively. The closing bubbles \( B^c_{t-1} \) are proxied by \( P^c_{t-1} - \frac{p^l_{t-1} + p^h_{t-1}}{2}, P^c_{t-1} - p^l_{t-1} \) and \( R^d_{t-1} = P^c_t - P^o_t \), where \( P^c_{t-1}, P^l_{t-1} \) and \( P^h_{t-1} \) refer to logarithmic closing price,
lowest price and highest price, respectively. Sample period is from January 4th, 2000 to July 3rd, 2017. The
data are collected from Tinysoft financial database; see http://www.tinysoft.com.cn/TSDN/HomePage.tsl.
* *, ** and *** denote 10%, 5% and 1% significance respectively. The t-statistics of coefficients’ estimators are
presented in the brackets.
bubbles hypothesis, Table 3 shows that the estimators of $\beta$ are constantly positive and significant at 1% level. It implies that there is a strong positive relation between overnight returns and closing bubbles. The above analysis leads us to question that overnight return puzzle stems from closing bubbles. Actually, as a unique phenomenon in China’s stock market, overnight return puzzle needs to be explained by a unique characteristic of China’s stock market. It will be shown that this puzzle can be explained by a unique arrangement in China’s stock market, T+1 trading rule.

III. T+1 Trading Rule Explains Overnight Return Puzzle

China’s stock market currently adopts a unique trading restriction “T+1”, which prohibits buyers to sell the shares that they bought on the same day. In another word, if an investor buys $N$ shares of an asset on day $t$, he can only sell them on day $t + 1$ or later. Unlike China’s stock market, all other countries’ stock markets adopt “T+0” that allows buyers to sell their shares at any time, including the day they bought them. As a temporary arrangement in this typical emerging market, regulators believe T+1 trading rule can efficiently reduce prices’ volatility and the shortfall caused by pessimistic sentiment of investors or speculators’ manipulation.

To bridge T+1 trading rule with China’s stock market’s overnight return puzzle, T+1 trading rule’s effects on buyers and sellers are analyzed respectively. Suppose that the sellers sold $N$ shares to the buyers in the morning of a trading day. For the sellers, T+1 trading rule’s effect is relatively weaker, because they are still allowed to buy them back at a later time of the day, when they find a good investment opportunity. This suggests that sellers’ sell-and-buy intro-day reversing trading is still possible in T+1 environment. On the contrary, for the buyers, T+1 trading rule imposes a significant constraint on their behavior. Properly speaking, these buyers are prohibited to sell the shares they bought on the
same day, even if the asset prices exhibit an extreme intro-day movement which exceeds their anticipation. It means that T+1 trading rule restrains the buyers to do buy-and-sell intro-day reversing trading. It will be shown that China’s stock market’s overnight return puzzle can be explained by the asymmetric effects.

The asymmetric effects of T+1 trading rule produce discounts on opening prices. Different from US stock market, China’s stock market is purely driven by electronic order book, instead of market markers. Thus, the opening prices are entirely determined by the supply and demand, namely those limited orders in the order book. In T+0 environment, at the opening bell of a trading day, suppose an asset’s supply and demand are denoted as \( S^{T_0} \) and \( D^{T_0} \). It is assumed that \( S^{T_0}(\ast) \) and \( D^{T_0}(\ast) \) only depend on logarithmic opening price \( P^o \). Conventionally, \( S^{T_0}(\ast) \) is assumed to be a monotone increasing function of \( P^o \), and \( D^{T_0}(\ast) \) is assumed to be a monotone decreasing function of \( P^o \). Market clearing condition determines an equilibrium logarithmic opening price \( P^{o,T_0} \), which matches the supply and demand, i.e. \( S^{T_0}(P^{o,T_0}) = D^{T_0}(P^{o,T_0}) \). Now we turn to T+1 environment. As aforementioned, the introducing of T+1 trading rule does not affect the behavior of sellers who are the supply-side of the asset. Thus, the supply of the asset will preserve in T+1 environment. It means \( S^{T_1}(P^o) = S^{T_0}(P^o) \), for \( \forall P^o \). On the other hand, T+1 trading rule prohibits the buyers, who are the demand-side of the asset, to do buy-and-sell reversing trading. Consequently, these buyers will exposure to the risk of extreme intro-day fluctuation. The most risk averse buyers tend to postpone their trading, then the demand of the asset decreases. This implies \( D^{T_1}(P^o) < D^{T_0}(P^o) \), for \( \forall P^o \). Hence,

\[
S^{T_1}(P^{o,T_0}) = S^{T_0}(P^{o,T_0}) = D^{T_0}(P^{o,T_0}) = D^{T_1}(P^{o,T_0}).
\]

Eq. (4) reveals that the equilibrium logarithmic opening price in T+0 environment, \( P^{o,T_0} \), generates a gap between supply and demand in T+1 environment.
For clearing the market, the sellers need to lower their quote to promote the demand. That is to say, the equilibrium price in T+1 environment, $P_{o,T1}$, should be lower than T+0 environment. The spread between $P_{o,T1}$ and $P_{o,T0}$ is defined as "T+1 discount". Fig. (1) shows the supply/demand curve and equilibrium logarithmic opening prices in both T+0 and T+1 environments. The rest of this paper will focus on testing T+1 discount’s significance and estimating its magnitude.

**Figure 1. Supply and Demand in T+0 and T+1 Environments**

*Note: This figure shows the supply/demand curve and equilibrium logarithmic opening prices in both T+0 and T+1 environments. $S^{T0}$ and $S^{T1}$ are the supply curves in T+0 and T+1 environments, respectively. $D^{T0}$ is the demand curve in T+0 environment; $D^{T1}$ is the demand curve in T+1 environment. $P_{o,T0}$ is the equilibrium logarithmic opening price in T+0 environment; $P_{o,T1}$ is the equilibrium logarithmic opening price in T+1 environment.*

Because T+1 discount is produced by prohibiting buyers’ buy-and-sell reversal trading, a direct way to assess it is quantifying the strength of buyers’ in-
centive of buy-and-sell reversal trading. Generally, it is classified into two types: incentive for taking profit and incentive for stopping loss. Firstly, suppose buyers bought \( N \) shares of an asset at the logarithmic opening price \( p_{o} \), and the asset’s logarithmic prices rise to \( P > p_{o} \) at a later time of the day. In this case, the buyers will be motivated to sell the shares for taking their potential profit \( P - p_{o} \). Actually, all of the buyers who set their taking profit lines between \( p_{o} \) and \( P \) will be motivated to sell the shares. The larger the profit is, the stronger the incentive is. Hence, \( P - p_{o} \) can be used to proxy the strength of their incentive of taking profit. Obviously, it reaches its maximum at \( p_{h} - p_{o} \), where \( p_{h} \) is the logarithmic highest price of the day. Secondly, if the asset prices decrease to \( P \) which is lower than \( p_{o} \), the buyers will be motivated to sell the shares for stopping their potential loss \( p_{o} - P \). Similarly, all the buyers who set their stopping loss line between \( P \) and \( p_{o} \) will be motivated to sell the shares for stopping loss. Thus, \( p_{o} - P \) can be used to quantify their incentive for stopping loss. The maximum of \( p_{o} - P \) is \( p_{o} - p_{l} \), where \( p_{l} \) is the logarithmic lowest price of the day. Furthermore, for constructing an integrated measure, the impacts of prices rising and dropping are assumed to be perfectly substitutable for each other. Then the total strength of buyers’ incentive of buy-and-sell reversing trading can be proxied by

\[
(5) \quad p_{h} - p_{l} = (p_{h} - p_{o}) + (p_{o} - p_{l})
\]

namely the log-range of the intro-day prices. It implies that same scales of prices rising and dropping will result in identical incentives of buyers’ reversal trading. This simplified arrangement ignores the asymmetric impacts of prices rising and dropping. But, as an integrated index, the log-range is supposed to substantially reflects buyers’ incentive of buy-and-sell reversal trading.

\( T+1 \) discount’s magnitude is positively correlated with log-range’s forecasting value. In \( T+1 \) environment, buyers’ reversal trading is absolutely constrained.
Therefore, at the opening bell, rational buyers will forecast the strength of the incentive to do buy-and-sell reversal trading, and require an extra compensation, i.e. T+1 discount. The magnitude of the discount is expected to be positively related with the forecasting value of the strength. If log-range proxies the strength of buyers’ incentive of buy-and-sell reversal trading, the correlation between log-range’s forecasting value (conditionally on an information set which is available at the opening bell) and T+1 discount’s magnitude should be positive.

Another interesting fact is that T+1 discount will be eliminated at the end of a trading day. Actually, if a buyer bought $N$ shares of the asset at the closing bell, T+1 allows him to sell the shares tomorrow morning or later, just like T+0 environment. It means that T+1 trading rule does not impose any constraint on him, thus the closing price shouldn’t include T+1 discount. The periodic pattern of T+1 discount is summarized in Assumption 1.

**ASSUMPTION 1:** In a market adopting T+1 trading rule, the logarithmic opening price of an asset can be decomposed into two opponents

\[ P_t^o = V_t^o + D_t, \]

where $V_t^o$ is the logarithm of the asset’s fundamental value at the opening bell of trading day $t$, which is simply the discounted cash flow; and $D_t$ is a discount caused by T+1 trading rule, which is a linear function of conditional expectation of the logarithmic range of the intro-day prices, namely

\[ D_t = \beta \times F_t, \]

\[ F_t = E(L_t|\mathcal{F}_t^-), \]

where $L_t = P_t^h - P_t^l$; $P_t^h$ and $P_t^l$ are logarithmic highest and lowest prices for day $t$; and $\mathcal{F}_t^-$ is a set of information which is available at the opening bell of day $t$. Besides, the
closing price of the asset is simply its fundamental value, namely

\[ P_t^c = V_t^c, \]  

where \( P_t^c \) is its logarithmic closing price of day \( t \); and \( V_t^c \) is the logarithm of its fundamental value at the closing bell of day \( t \).

Assumption 1 presents a periodic pattern of T+1 discount. In the morning of a day, T+1 discount is incorporated into the opening price. Its magnitude is proportional to expected log-range of the day. The sign of expected log-range is constantly positive, then the sign of T+1 discount is same as \( \beta \). According to our previous discussion, \( \beta \) is expected to be negative. During the daytime trading, T+1 discount will be reduced gradually. At the end of the day, it is entirely eliminated.

China’s stock market’s overnight return puzzle can be explained by T+1 discount potentially. According to the above assumption, unconditional expected overnight return is represented as

\[ E(R_o) = E(V_t^o - V_{t-1}^o) + E(D_t) = E(R_t^{o,V}) + E(D_t), \]  

where \( R_t^{o,V} = V_t^o - V_{t-1}^o \) is driven by the movement of fundamental value. \( R_t^{o,V} \) can be called as overnight fundamental return, which is expected to be positive due to agents’ risk aversion. \( E(D_t) \) is the expected T+1 discount which is expected to be negative. Hence, \( E(R_t^o) = |E(R_t^{o,V})| - |E(D_t)| \). If \( |E(D_t)| > |E(R_t^{o,V})| \), the expected overnight return will be negative, then overnight return puzzle appears. Now the question boils down to estimate \( E(D_t) \) and \( E(R_t^{o,V}) \).

Overnight return can be written as

\[ R_t^o = R_t^{o,V} + D_t = R_t^{o,V} + \beta \times F_t. \]
An intractable problem is that \( R_{t}^{o,V} \) and \( F_{t} \) are both unobservable. Fortunately, there are some existing econometric approaches can produce an estimate for \( F_{t} \), but the overnight fundamental returns are very hard to obtain. A naive idea for testing T+1 discount is regressing overnight return \( R_{t}^{o} \) on \( F_{t} \) and omit the unobserved variable \( R_{t}^{o,V} \), namely

\[
R_{t}^{o} = \alpha + \beta F_{t} + \epsilon_{t}. \tag{12}
\]

Then, the mean of T+1 discount can be calculated as

\[
E(D_{t}) \approx \hat{\beta}E(F_{t}) = \hat{\beta}E(L_{t}), \tag{13}
\]

where \( \hat{\beta} \) is the estimated value of \( \beta \) derived from Eq. (12). However, the OLS estimation of the above regression will be biased, because of the absence of \( R_{t}^{o,V} \). Actually, \( F_{t} \) is the conditional expectation of log-rang which is naturally a measure of volatility. Volatility feedback hypothesis claims that there is a negative correlation between fundamental value and volatility; see Campbell and Hentschel (1992), French et al. (1987). Therefore, \( F_{t} \) must be correlated with \( R_{t}^{o,V} \). It means that the missing of \( R_{t}^{o,V} \) will introduce an endogenous problem in Eq. (12), and disturbs our OLS estimation.

To obtain an unbiased estimator of \( \beta \), it is suggested to replace \( F_{t} \) by an expected value of \( L_{t} \) conditionally on a set of lagged information, i.e.

\[
F_{t-1}' = E(L_{t}|\mathcal{F}_{t-1}), \tag{14}
\]

where \( \mathcal{F}_{t-1} \) is a set of information that is available at the end of trading day \( t-1 \). Plug it into Eq. (11), we obtain

\[
R_{t}^{o} = R_{t}^{o,V} + \beta(F_{t-1}' + \epsilon_{t}') = R_{t}^{o,V} + \beta F_{t-1} + \epsilon_{t}, \tag{15}
\]
here $e'_t = F_t - F'_{t-1}$, and $e_t = \beta e'_t$. Note that $cov(F'_{t-1}, e_t) = 0$, because $E(e_t | \mathcal{F}_{t-1}) \equiv 0$. Additionally, more important, the covariance between $F'_{t-1}$ and $R_{t}^{o,V}$ is expected to be much smaller than the covariance between $F_t$ and $R_{t}^{o,V}$. Actually, a large covariance between them implies that the overnight fundamental returns are strongly predictable, because $F'_{t-1}$ depends on $R_{t}^{o,V}$'s lagged information. In an efficient market, the price should fully reflect all available information, thus it rules out the strong predictability of $R_{t}^{o,V}$. Although the risk premium is predictable to some extent, its predictability should be relatively weak. Therefore, it is possible to obtain a more accurate estimator of $\beta$ by running the regression

$\begin{equation}
R_t^o = \alpha + \beta F'_{t-1} + \epsilon_t. \tag{16}
\end{equation}$

It is worth noting that the $\alpha$ in Eq. (16) is the unconditional expectation of overnight fundamental return, namely $E(R_{t}^{o,V})$.

Replacing $F_t$ by $F'_{t-1}$ can be interpreted as a two-stage least square regression (2SLS). $F_t$ is the endogenous variable in Eq. (12), and $F'_{t-1}$ is an instrumental variable. The convenience is that the coefficients in auxiliary equation, $F_t = a + b F'_{t-1} + \epsilon_t$, are known according to the financial interpretation of $F_t$ and $F'_{t-1}$. The constant $a$ is zero, and the slope $b$ is one. Thus it is not necessary to estimate them in our case.

Another alternative way to estimate $\beta$ is using daytime return. Combining Eq. (6) and (9), daytime return can be written as

$\begin{equation}
R_t^d = (V_t^c - V_t^o) - D_t = R_t^{d,V} - D_t = R_t^{d,V} - \beta F_t, \tag{17}
\end{equation}$

where $R_t^{d,V} = V_t^c - V_t^o$ can be called daytime fundamental return, which is driven by the movement of fundamental value during the daytime period. Be noticed, $D_t$ is determined by lagged information of $R_t^{d,V}$. Similarly, efficient market hypothesis rules out the strong predictability of $R_t^{d,V}$, then the covariance
between $R_{t}^{d,V}$ and $D_{t}$ should not be too large. Therefore, a fairly good estimator of $\beta$ can be derived from the regression

$$R_{t}^{d} = \alpha' + \beta' F_{t} + \epsilon_{t}, \quad (18)$$

where $\beta' = -\beta$; $\alpha'$ is the unconditional expected daytime fundamental return. However, for keeping the consistency of regressors and getting a "safer" estimator of $\beta$, it is still suggested to replace $F_{t}$ by $F_{t-1}'$. Actually, Eq. (17) can be rewritten as

$$R_{t}^{d} = R_{t}^{d,V} - \beta(F_{t-1}' + \epsilon_{t}') = R_{t}^{d,V} - \beta F_{t-1}' - \epsilon_{t}. \quad (19)$$

Note that $F_{t-1}'$ is more lagged than $F_{t}$. Hence, daytime fundamental return $R_{t}^{d,V}$ is more difficult to be predicted by using $F_{t-1}'$ than using $F_{t}$. In another word, replacing $F_{t}$ by $F_{t-1}'$ can further weaken the endogenous problem in Eq. (18). Therefore, it is a possible way to obtain a more reliable estimator by running the regression

$$R_{t}^{d} = \alpha' + \beta' F_{t-1}' + \epsilon_{t}, \quad (20)$$

Referring to our previous analysis, if T+1 discount exists, both $\alpha = E(R_{t}^{d,V})$ and $\beta' = -\beta$ are expected to be positive. A summary of the above analysis is formally presented in Assumption 2.

**ASSUMPTION 2:** Suppose $F_{t-1}' = E(L_{t} | \mathcal{F}_{t-1})$ is the expectation of $L_{t}$ conditionally on a set of information $\mathcal{F}_{t-1}$ which is available at the closing bell of day $t-1$. $R_{t}^{o,V} = V_{t} - V_{t-1}$ is the logarithmic return driven by the movement of asset’s fundamental value, during the overnight period. $R_{t}^{d,V} = V_{t}^{c} - V_{t}^{o}$ is the logarithmic return driven by the movement of asset’s fundamental value, during the daytime period. Then, both $\text{cov}(F_{t-1}', R_{t}^{o,V})$ and $\text{cov}(F_{t-1}', R_{t}^{d,V})$ equal to zero.
Before estimate Eq. (16) and (20), a remaining problem is constructing a time series for $F_{t-1}'$. Conditional Autoregressive Range (CARR) Model is a feasible approach which aims to forecast the ranges of assets’ prices by using lagged ranges; see Chou (2005). Essentially, CARR model is an analogue of GARCH model or ACD model; see Engle (1982), Bollerslev (1986), Engle and Russell (1998). CARR(1,1) is specified to model $L_t$’s evolution, namely

\begin{align}
L_t &= \lambda_t \epsilon_t, \quad (21) \\
\lambda_t &= \omega + \theta L_{t-1} + \gamma \lambda_{t-1}, \quad (22)
\end{align}

where $\{\epsilon_t\}_{t=1}^T$ is a positive valued IID time series with unit mean. In this paper, it is assumed to follow an exponential distribution. Referring to Chou (2005), Engle and Russell (1998), if the error terms are exponentially distributed, one desirable property of CARR model is that the quasi-maximum likelihood estimation can be derived by specifying a GARCH model for the square root of range with normal distributed error term.

Based on our main empirical sample, $L_t$ is calculated by the daily highest and lowest log-prices of SSE index, from January 4th, 2000 to July 3th, 2017. Panel A and B of Table 4 report the summary statistics of $L_t$ and quasi-maximum likelihood estimation of CARR(1,1) model. Panel A of Table 4 shows that the mean of $L_t$ is about 1.90%. This number will be used later for calculating T+1 discount referring to Eq. (13). Panel B of Table 4 presents that $\theta$ and $\gamma$ are both positively significant. This finding implies that daily range exhibits clustering effect: large range follows large range. Note that $L_t$’s forecasting value $\lambda_t$ is determined by the information that is observable at the closing bell of day $t-1$. Thus, $F_{t-1}'$ can be estimated by $\hat{\lambda}_t = \hat{\omega} + \hat{\theta} L_{t-1} + \hat{\gamma} \hat{\lambda}_{t-1}$ recursively.

Eq. (16) and (20) are estimated by using $\hat{\lambda}_t$ to substitute $F_{t-1}'$. The estimations are reported in Panel C of Table 4. We first focus on the estimators of $\beta$ and...
**Panel A: Summary Statistics of Log-range of SSE Index.**

<table>
<thead>
<tr>
<th>L_t</th>
<th># of Obs.</th>
<th>Mean</th>
<th>S.D.</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4,229</td>
<td>0.019</td>
<td>0.012</td>
<td>0.003</td>
<td>0.106</td>
</tr>
</tbody>
</table>

**Panel B: Quasi-Maximum Likelihood Estimation of CARR(1,1).**

<table>
<thead>
<tr>
<th>Estimator</th>
<th>ω</th>
<th>θ</th>
<th>γ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.000</td>
<td>0.161**</td>
<td>0.821***</td>
</tr>
<tr>
<td></td>
<td>(0.640)</td>
<td>(1.990)</td>
<td>(9.370)</td>
</tr>
</tbody>
</table>

**Panel C: Expected Range Based Estimation for T+1 Discount.**

\[
R_{ot} = \alpha + \beta L_{t-1} + \epsilon_t \\
R_{dt} = \alpha' + \beta' L_{t-1} + \epsilon_t \\
H_0: \beta + \beta' = 0
\]

<table>
<thead>
<tr>
<th>α (%)</th>
<th>β</th>
<th>α' (%)</th>
<th>β'</th>
<th>χ^2-stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.084***</td>
<td>-0.077***</td>
<td>-0.081</td>
<td>0.086***</td>
<td>0.050</td>
<td>0.819</td>
</tr>
<tr>
<td>(3.220)</td>
<td>(-5.930)</td>
<td>(-1.430)</td>
<td>(3.050)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Panel A reports the summary statistics of Shanghai Stock Exchange Composite Index’s daily log-range, which is calculated as \( L_t = \log P_h - \log P_l \), where \( P_h \) and \( P_l \) are logarithmic highest price and lowest price for day \( t \), respectively. The sample is from January 4th, 2000 to July 3rd, 2017. The data are collected from Tinysoft financial database; see http://www.tinysoft.com.cn/TSDN/HomePage.tsl. Panel B Presents the CARR(1,1)’s quasi-Maximum likelihood estimation, which is derived by specifying a GARCH model for the square root of range with normal distributed error term, \( \sqrt{L_t} = \lambda_t \epsilon_t \), \( \lambda_t = \omega + \theta L_{t-1} + \gamma \lambda_{t-1} \).

The z-statistics of coefficients’ estimators are reported in the brackets. Panel C reports the OLS estimation of \( R_{ot} = \alpha + \beta F'_{t-1} + \epsilon_t \) and \( R_{dt} = \alpha' + \beta' F'_{t-1} + \epsilon_t \), where \( R_{ot} \) is Shanghai Stock Exchange Composite Index’s overnight return for day \( t \); \( R_{dt} \) is its daytime return for day \( t \); \( F'_{t-1} \) is \( L_t \)’s forecasting value derived by CARR(1,1) model. Overnight returns are calculated as \( R_{ot} = P_o^t - P_c^{t-1} \). Daytime returns are calculated as \( R_{dt} = P_c^t - P_o^{t-1} \). \( P_o^t \) and \( P_c^t \) denote the logarithmic opening and closing prices for trading day \( t \), respectively. The \( \chi^2 \)-statistic for testing \( \beta + \beta' = 0 \) is derived by a GMM estimation involves the two equation jointly, i.e. four population moments. The t-statistics of coefficients’ estimators are presented in the brackets. The sample period is from January 4th, 2000 to July 3th, 2017. The data are collected from Tinysoft financial database; see http://www.tinysoft.com.cn/TSDN/HomePage.tsl. *, ** and *** denote 10%, 5% and 1% significance respectively.

The signs and significance of \( \beta \) and \( \beta' \) are both consistent with our expectation. The estimator of \( \beta \) is around -0.077, and significant at 1% level; meanwhile, the estimator of \( \beta' \) is about 0.086, and significant at 1% level too. Besides, \( \chi^2 \) test shows that we cannot reject the hypothesis \( \beta' + \beta = 0 \) (derived by a GMM estimation involves the two equation jointly, i.e. four population moments). It is also consistent with our previous analysis that \( \beta \) equals to \(-\beta'\). Referring to Eq. (13), an estimate for of average T+1 discount can be derived by using the estimator of \( \beta \). Plug \( \beta \approx -0.077 \) and \( E(L_t) \approx 0.019 \) into Eq. (13), it is ob-
tained that $E(D_t) = \beta E(L_t) \approx -0.146\%$. This implies an annualized loss around $-0.159\% \times 240 = 38.15\%$. Besides, another estimate of average T+1 discount can be derived by $E(D_t) = -\beta' E(L_t)$, which is around -0.159\%. The two estimates are very close. Therefore, It is discreetly concluded that T+1 discount is both statistically and economically significant in China’s stock market, and its magnitude is around 15 basis points on average.

Another interesting finding is the estimators of $\alpha$ and $\alpha'$. Once again, $\alpha$ and $\alpha'$ can be interpreted as the unconditional expectations of fundamental returns during overnight period and daytime period, respectively. Both of them are expected to be positive. Panel C shows that the estimator of $\alpha$ is about 0.084\%, and significant at 1% level. This finding is consistent with our conjecture that the expected overnight fundamental return is positive due to agents’ risk aversion. But this value is quite smaller than average T+1 discount, 15 basis points (about half of it). According to our previous analysis, if $|E(D_t)| > |E(R_t^{0,V})|$, it will produce a negative expected overnight return. Therefore, it is empirically verified that T+1 discount explains overnight return in China’s stock market, and it significantly contributes to overnight return’s expectation. Besides, the estimator of $\alpha'$ is -0.081\%, but it is not significant at 10% level. It suggests that overnight returns more significantly reflect the movements of assets’ fundamental value than daytime returns.

IV. Supplementary Evidence

This section will present some more direct evidence to support that T+1 discount causes overnight return puzzle in China’s stock market. The summary statistics of the overnight returns of some other China’s security market indices are shown in Table 5. Be noticed that all of these securities are traded in T+0 environments, instead of T+1.

Firstly, all of the shares in China’s stock market adopt T+0 trading rule dur-
T+1 RULE AND OVERNIGHT RETURN PUZZLE IN CHINA’S STOCK MARKET

Table 5—Summary Statistics for Overnight/Daytime Return for Securities Adopting T+0

<table>
<thead>
<tr>
<th>Security Type</th>
<th># of Obs.</th>
<th>Overnight Return</th>
<th>Daytime Return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean (%)</td>
<td>Mean (%)</td>
</tr>
<tr>
<td>SSE Index (T+0 Period)</td>
<td>514</td>
<td>0.214***</td>
<td>-0.237</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.81)</td>
<td>(-1.52)</td>
</tr>
<tr>
<td>B-share Index (T+0 Period)</td>
<td>188</td>
<td>0.248**</td>
<td>0.135</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.92)</td>
<td>(0.62)</td>
</tr>
<tr>
<td>T-bill</td>
<td>2983</td>
<td>0.014***</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5.57)</td>
<td>(0.76)</td>
</tr>
<tr>
<td>Corporate Bond</td>
<td>2944</td>
<td>0.014***</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.67)</td>
<td>(3.45)</td>
</tr>
<tr>
<td>Convertible Bond</td>
<td>2777</td>
<td>0.000</td>
<td>0.032*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(1.77)</td>
</tr>
<tr>
<td>CSI300 Future Index</td>
<td>1445</td>
<td>0.032**</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.46)</td>
<td>(-0.06)</td>
</tr>
</tbody>
</table>

Note: This table shows the average overnight returns and daytime returns of various security price indices in China’s financial market, during different periods. These securities are all traded in T+0 environments. They are Shanghai Stock Exchange Composite Index (from December 1992 to December 1995), B-shares Index (from March 2001 to November 2001), T-bill Index (from April 4th, 2003 to June 30th), Corporate Bond Index (from June 10th, 2003 to June 30th, 2017) and Convertible Bond Index (from January 2th, 2004 to June 30th, 2017). All the data are collected from Tinysoft financial database; see http://www.tinysoft.com.cn/TSDN/HomePage.tsl. Overnight returns are calculated as \( R_t^o = P_t^o - P_{t-1}^o \). Daytime returns are calculated as \( R_t^d = P_t^c - P_t^o \). \( P_t^o \) and \( P_t^c \) denote the logarithmic opening and closing prices for trading day \( t \), respectively. *, ** and *** denote 10%, 5% and 1% significance respectively. The t-statistics of coefficients' estimators are presented in the brackets.

ing the period from December 1992 to December 1995, and all the B-shares are traded under T+0 rule from March 2001 to November 2001. The average overnight returns on SSE Index and B-share Index during T+1 period are reported at first. Both of them are significantly positive at 5% level. It suggests that overnight return puzzle disappears in China’s stock market during T+0 periods. Furthermore, the average daytime return of SSE Index is -0.237%. Its absolute value is larger than SSE Index’s average overnight return during same period. Hence, the average 24-hour return of SSE Index, during T+0 period, is negative. That is to say, the positive sign of average overnight return in T+0 period cannot be attributed to selection bias, because the market exhibits a downward trend during the sample period.

Secondly, the bond markets in China consistently adopt T+0 trading rule.
The average overnight returns of T-bill Index, Corporate Bond Index and Convertible Bond Index are reported in in Table 5 as well. Their sample periods are presented in the footnotes of Table 5. The results show that, in T+0 environment, all of the three average overnight returns are positive, and two of them are significant in 1% level.

Thirdly, the average overnight return on CSI300 Index Future is reported at last. The sample period is from April 16th, 2010 to June 30th, 2017. Its daily overnight returns are calculated based on the prices of the future contract with the most nearby maturity date. It shows that the average overnight return of CSI300 Index Future is significantly positive at 5% level. It is worth noting that the average overnight return of CSI300 Index during the same period is still significantly negative, around -0.094%.

CSI300 Index Future’s overnight returns can be used to re-estimate average T+1 discount. Our approach is similar with Stephan and Whaley (1990). Traditional asset pricing theory states that the spot price should equal to the discounted value of future price, namely

$$p_t^F = e^{(T-t)r} v_t, \quad (23)$$

where $r$ is the risk-free rate; $p_t^F$ denotes the future price; $v_t$ is the spot price. Note that CSI300 Index Future is traded in T+0 environment, then the $v_t$ at here should be an unobservable spot price in T+0 environment, which excludes the T+1 discount. Thus, $v_t$ is simply the fundamental value of CSI300 Index. Taking the derivative and using Ito lemma, it is obtained that

$$\frac{dp_t^F}{p_t^F} = \frac{dv_t}{v_t} - r dt. \quad (24)$$

In particular, for the return during overnight period, $\frac{dp_t^F}{p_t^F}$ is the CSI300 Index Future’s overnight return $R_t^{o,F}$; $\frac{dv_t}{v_t}$ is CSI300 Index’s overnight fundamental return.
$R_t^{o,F}$; $r_{fd}$ is the overnight risk-free rate $rf_t^o$. Hence, Eq. (24) can be expressed as

\begin{equation}
R_t^{o,F} = R_t^{o,V} - rf_t^o.
\end{equation}

Combining with Eq. (11), the average T+1 discount is

\begin{equation}
E(D_t) = E(R_t^o) - E(R_t^{o,F}) - E(r_f).
\end{equation}

Shanghai Interbank Offered Rate (Shibor) is used to proxy $rf_t$. Shibor is the rate based on the interbank interest rates in money market. The daily Shibor overnight rate is calculated by dividing annualized Shibor overnight rate by 360. For further details of Shibor rate, see http://www.shibor.org/. Its average value in the period matching the sample of CSI300 Index Future is about 0.008%. The average T+1 discount can be estimated by $E(D_t) = E(R_t^o) - E(R_t^{o,F}) - E(r_f) \approx -0.134\%$. This estimated value is also close to our previous results, around 15 basis points.

V. T+1 Discount’s contribution to Overnight Risk

Previous sections have shown that the average T+1 discount is approximately 15 basis points, which significantly contributes to the expectation of overnight return. This section aims to estimate T+1 discount’s contribution to overnight risk, which is measured in unconditional variance of overnight return.

According to Eq. (11), the total variance of overnight return in T+1 environment can be written as

\begin{align}
\text{var}(R_t^o) &= \text{var}(R_t^{o,V} + D_t) \\
&= \text{var}(R_t^{o,V}) + (\text{var}(D_t) + 2\text{cov}(R_t^{o,V}, D_t)).
\end{align}

$\text{var}(R_t^{o,V})$ is the risk brought by fundamental value movements. Hence, it is the
total variance of overnight return in T+0 environment. That is to say, the extra variance caused by T+1 discount is

\begin{equation}
\var(D_t) + 2\cov(R_t^{o,V}, D_t).
\end{equation}

\( \var(D_t) \) is the variance of T+1 discount, and \( \cov(R_t^{o,V}, D_t) \) captures the volatility feedback effect. Both \( \var(D_t) \) and \( \cov(R_t^{o,V}, D_t) \) are expected to be positive.

It is very hard to derive an exact value of T+1 discount’s variance contribution, but it is possible to derive an upper bound. Comparing Eq. (11) and Eq. (17), the covariance between overnight return and daytime return is

\begin{equation}
\cov(R_t^{o}, R_t^{d}) = -\cov(R_t^{o,V}, D_t) - \var(D_t) + \cov(R_t^{d,V}, R_t^{o}).
\end{equation}

If the predictability of daytime fundamental return is assumed to very weak, \( \cov(R_t^{d,V}, R_t^{o}) \) can be ignored in Eq. (30),

\begin{equation}
\cov(R_t^{o}, R_t^{d}) \approx -\cov(R_t^{o,V}, D_t) - \var(D_t).
\end{equation}

Hence, an upper bound of T+1 discount’s variance contribution is given by

\begin{equation}
\var(D_t) + 2\cov(R_t^{o,V}, D_t) < 2(\var(D_t) + \cov(R_t^{o,V}, D_t)) \approx -2\cov(R_t^{o}, R_t^{d}).
\end{equation}

Both \( R_t^{o} \) and \( R_t^{d} \) are observable. Based on the our main sample of SSE Index, the variance-covariance matrix of \( R_t \), \( R_t^{o} \) and \( R_t^{d} \) is reported in Table 6. The covariance between overnight return and daytime return shows an empirical value around \(-3.10 \times 10^{-6}\). Meanwhile, the empirical value of overnight return’s total variance is around \(4.70 \times 10^{-5}\). Therefore, T+1 discount’s variance contribution rate is less than \( \frac{2 \times 3.1 \times 10^{-6}}{4.7 \times 10^{-5}} = 13.19\% \). It indicates that T+1 discount’s variance
contribution is quite small, and less than fundamental value movements’ contribution, although it significantly contributes to overnight return’s expectation.

**Table 6—Variance-Covariance Matrix of Total Return, Overnight Return and Daytime Return**

<table>
<thead>
<tr>
<th></th>
<th>( R_t )</th>
<th>( R^2_o )</th>
<th>( R^2_d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_t )</td>
<td>( 2.61 \times 10^{-4} )</td>
<td>( 4.40 \times 10^{-5} *** )</td>
<td>( 2.17 \times 10^{-4} *** )</td>
</tr>
<tr>
<td></td>
<td>(28.03)</td>
<td>(138.83)</td>
<td></td>
</tr>
<tr>
<td>( R^2_o )</td>
<td></td>
<td>( 4.70 \times 10^{-5} )</td>
<td>( -3.10 \times 10^{-6} ** )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-2.00)</td>
<td></td>
</tr>
<tr>
<td>( R^2_d )</td>
<td></td>
<td></td>
<td>( 2.21 \times 10^{-4} )</td>
</tr>
</tbody>
</table>

*Note:* This table reports the variance-covariance matrix of total return (\( R_t \)), overnight return (\( R^2_o \)) and daytime return (\( R^2_d \)), based on Shanghai Stock Exchange Composite Index, from January 4th, 2000 to July 3rd, 2017. \( R_t = P_o^t - P_{c,t-1} \); \( R^2_o = P_{c,t} - P^t_o \); \( R^2_d = P^t_o - P^t_c \). \( P^t_o \) and \( P^t_c \) denote the logarithmic opening and closing prices for trading day \( t \), respectively. All the data are collected from Tinysoft financial database; see http://www.tinysoft.com.cn/TSDN/HomePage tsl. *, ** and *** denote 10%, 5% and 1% significance respectively. The t-statistics for testing the null hypothesis that the covariance doesn’t significantly deviate from zero are presented in the brackets.

**VI. Conclusion**

We firstly report an interesting puzzle that the average overnight return on market portfolio is significantly negative in China’s stock market. This finding violates traditional assets pricing theory and the evidence from various financial markets from other countries and regions. T+1 trading rule in China’s stock market is used to explain this anomaly. Specifically, T+1 trading rule constrains buyers’ buy-and-sell intro-day reversal trading, but does not give any constraint on sellers. Hence, buyers require a discount at the opening bell, which is named T+1 discount. By using daily high-low range to proxy buyers’ strength of incentive of buy-and-sell intro-day reversal trading, T+1 discount’s significance and magnitude are estimated empirically. Some interesting findings are reported.

Firstly, T+1 discount presents a periodical pattern: it is incorporated in the
opening price every morning, and eliminated at the end of the day.

Secondly, empirical results show that the average T+1 discount is around 15 basis points, which is almost two times of the average overnight fundamental return. Thus, T+1 discount indeed explains overnight return puzzle in China’s stock market, and significantly contributes to overnight return’s expectation.

Thirdly, in China’s financial market, all the price indices for those securities traded in T+0 environment consistently generate positive average overnight returns. This finding more directly reveals that overnight return puzzle stems from T+1 trading rule.

Fourthly, using CSI300 Index Future, the T+1 discount is re-estimated. A similar estimate confirms our previous results.

Finally, T+1 discount’s contribution to overnight risk is evaluated. An upper bound of its variance contribution rate is presented around 13.19%. This finding indicates that T+1 discount’s variance contribution is very small, although its contribution to overnight return’s expectation is very significant.
References


