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The overnight return puzzle and the “T+1” trading rule in Chinese stock markets[☆]

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ABSTRACT

Overnight returns in Chinese stock markets are on average negative. This overnight return puzzle appears to be unique to Chinese markets. We hypothesize that a particular arrangement in Chinese stock markets explains the puzzle: the “T+1” trading rule. T+1 trading prohibits traders from selling the shares they bought on the same day. This restriction leads to a discount on daily opening prices. We find empirical support that the T+1 induced discount explains the overnight return puzzle and estimate the average T+1 discount at 14 bps. In addition, we establish that the T+1 discount contributes significantly to overnight risk.

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1. Introduction

The expected return on risky assets should on average be positive according to conventional asset pricing theory, even for short time frames.¹ It is well documented that daily (24-h) returns based on closing prices, while highly volatile, are positive on average. However, we find that in Chinese stock markets the *overnight* return, which is based on the difference between today's opening price and yesterday's closing price, is on average negative and we show that this finding is highly robust. Moreover, this phenomenon seems to be unique to China, as we document that the overnight stock returns of other countries and regions are on average positive, as expected. It seems somewhat puzzling as to why this anomaly persists in the second largest capital market in the world. We propose, however, that a particular restriction in Chinese markets that prohibits an investor from selling shares purchased on the same day, the so-called “T+1” trading rule, can explain the overnight return puzzle.

Overnight returns have received considerable attention in the literature. Researchers utilize overnight returns to study information diffusion and financial contagion among different markets (e.g., Becker et al., 1990; Lin et al., 1994; Karolyi and Stulz, 1996; Wang and Firth, 2004). Consistent with theory, virtually all studies report that the average overnight return in stock mar-

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¹ Actually, the risk premium is expected to be positive, so the expected return should at least be larger than the risk-free rate, which historically has been negative on occasion in certain markets.

kets is positive (e.g., Lockwood and Mcinish, 1990; Masulis and Ng, 1995; Karolyi and Stulz, 1996; Chan et al., 1996; Gutierrez et al., 2009; Kang and Babbs, 2010; Kelly and Clark, 2011; Berkman et al., 2012; Riedel and Wagner, 2015; Liu and Tse, 2017; Lou et al., 2019). In contrast, a small number of studies report opposite findings for Chinese stock markets. For various market indices and sample periods, the average overnight return in China tends to be negative (e.g., Liu et al., 2015; Chen et al., 2016). While these studies do report this finding, they do not interpret it as a market anomaly or puzzle, but give it little to no attention or simply attribute it to a downward market trend in their particular sample, for example. However, we show that the overnight return puzzle is a pervasive phenomenon in Chinese stock markets, and robust to the choice of stock exchange, type of shares, and sample period. It is observed in both bull and bear markets, and persists across assets of small, medium, and large market capitalization.

We conjecture that the overnight return puzzle can be explained by the $T+1$ trading rule, a unique arrangement in China's stock markets. $T+1$ trading is an asymmetric restriction that prohibits traders from selling the shares they bought on the same day, yet they are allowed to buy shares they sold earlier in the day. The rule was implemented immediately when the Shanghai Stock Exchange and the Shenzhen Stock Exchange were established in December 1990. Initially intended as a temporary trading rule, regulators believe that this arrangement can efficiently reduce market price volatility. Previous studies on the $T+1$ trading rule focus mainly on its impact on price volatility and market liquidity (e.g., Guo et al., 2012; Wu and Qin, 2015). Little attention has been paid to its impact on asset prices and returns. An exception is Bian and Su (2010), who find that the $T+1$ trading rule reduces market liquidity, and in turn causes an illiquidity discount on asset prices.

Distinct from previous studies, we highlight the fact that the $T+1$ trading rule has asymmetric effects for buyers and sellers. If a trader buys a stock in the morning, and wants to "cash in" after the stock price has increased significantly during the day, he is not allowed to do so. A trader that bought the same stock just before yesterday's closing can however cash in after today's stock price increase. As a result, there should be a price discount for the stock at the opening relative to yesterday's closing of the market. If our conjecture is correct, we should not observe the overnight return anomaly for assets traded in China that are not subject to the $T+1$ trading rule. For bonds and futures markets the $T+1$ rule does not apply, and indeed we find that the average overnight return is on average positive for these asset classes. Also, Chinese stock markets were not subject to the $T+1$ rule during the period from January 1993 to December 1994, and all B-shares were not subject to the rule from March 2001 to November 2001. For these periods, we also find that the average overnight return is positive. So it seems that a negative average overnight return is empirically strongly associated with assets subject to the $T+1$ trading rule.

We propose a method to estimate the size of the opening discount in Chinese stock markets due to the $T+1$ trading rule. We argue that a good proxy for the "incentive to trade" is the daily log-price range, measured as the log-difference between the daily highest price and the daily lowest price. The log-price range should be correlated with the size of the $T+1$ discount. Our results show that the magnitude of the average daily $T+1$ discount is about 14 bps, and an alternative method using the return differences between futures (not subject to the trading rule) and the underlying index corroborates this finding. Moreover, we assess a lower and an upper bound of the $T+1$ discount's contribution to overnight risk. The $T+1$ discount variance contribution is between 5.02% and 10.04% of the total overnight return variance. As such, the introduction of the $T+1$ trading rule actually has had an adverse effect, because the introduction of the rule was motivated by the belief that it would reduce volatility. Both the opening discount and the associated additional risk are likely to be unintentional consequences of the $T+1$ trading rule.

To ensure that our range-based method is not detecting some other phenomenon, we conduct "placebo tests" by applying our methodology to stock markets from a number of other countries as well. Indeed, our method does not detect an opening discount for these countries. We also rule out some other behavioral explanations for the overnight return puzzle in China, namely investor overreaction and speculator manipulation.

The rest of this paper is structured as follows. In the next section, the overnight return puzzle in China's stock market is explored. In Section 3, we elaborate on the $T+1$ trading rule and provide evidence that this rule can explain the puzzle. In Section 4, we develop a method to estimate the size of the $T+1$ discount and show the results. In Section 5, we assess the $T+1$ discount's contribution to overnight risk. In Section 6, we discuss the placebo tests and rule out other explanations. Concluding remarks are in Section 7.

2. The overnight return puzzle in China's stock markets

In this section, we investigate overnight returns and daytime returns for the Chinese stock markets. Our main sample comes from the Tinysoft financial database.² We have daily data on opening prices, closing prices, lowest prices, and highest prices for the two main stock exchanges in China: the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The Shanghai Stock Exchange Composite Index (SSE Index) comprises all listed shares,³ and the Shenzhen Stock Exchange Index (Shencheng Index) consists of the top 500 listed stocks at the exchange. The sample period is from January 4, 2000 to May 31, 2019. Additionally, we have data for various asset classes, namely the B-share Index, the HS300 Index, the SSE50 Index, the M&S CAP Index, the SSE Total Return Index (dividend-reinvested price index), and the HS300 ETF. The B-share Index reflects the total capitalization of all domestically listed foreign shares traded at the Shanghai Stock Exchange. The HS300 and SSE50 are large-cap indices; the HS300 Index contains the top 300 stocks in terms of market capitalization traded at the Shanghai Stock Exchange and Shenzhen

² See <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>.

³ For details on the SSE Index's construction, see <http://www.sse.com.cn/market/sseindex/overview/>.

Table 1

Overnight returns and daily returns in Chinese stock markets.

	Overnight Return		Daily Return	
	# of Obs.	Mean (%)	# of Obs.	Mean (%)
SSE Index	4700	−0.064*** (−6.52)	4700	0.015 (0.67)
Shencheng Index	4700	−0.050*** (−4.76)	4700	0.020 (0.77)
B-share Index	4221	−0.039*** (−3.59)	4221	0.013 (0.44)
HS300 Index	4221	−0.072*** (−5.28)	4221	0.024 (0.92)
SSE50 Index	3743	−0.065*** (−5.20)	3743	0.027 (0.93)
M&S CAP Index	3402	−0.072*** (−5.20)	3402	0.050 (1.51)
SSE Total Return Index	2409	−0.093*** (−7.19)	2409	0.006 (0.19)
HS300 ETF	1505	−0.058** (−2.54)	1505	0.030 (0.70)
SSE Index (Bear Market)	1139	−0.124*** (−3.47)	1139	−0.011 (−0.13)
SSE Index (Bull Market)	3561	−0.045*** (−7.39)	3561	0.024 (1.42)

This table reports the average overnight return and daily return in Chinese stock markets. Overnight returns are calculated as $R_t^o = P_t^o - P_{t-1}^c$. Daily returns are calculated as $R_t = P_t^c - P_{t-1}^c$. P_t^o and P_t^c denote the logarithmic opening and closing price for trading day t , respectively. The SSE Index refers to the Shanghai Stock Exchange Composite Index, from January 4, 2000 to May 31, 2019. In addition we report the returns for the Shencheng Index (January 4, 2000 to May 31, 2019), B-share Index (January 4, 2002 to May 31, 2019), HS300 Index (January 4, 2002 to May 31, 2019), SSE50 Index (January 2, 2004 to May 31, 2019), M&S CAP Index (July 7, 2005 to May 31, 2019), SSE Total Return Index (July 3, 2009 to May 31, 2019) and HS300 ETF (March 25, 2013 to May 31, 2019). We also report the average overnight and daily return for the SSE Index during bearish periods and bullish periods. Market regimes (bear or bull) are identified by a two-regime Markov regime switching model for the SSE Index with a regime-based expected close-to-close 24-h return and conditional volatility. The Kalman filter probability serves to identify market regimes. The market is recognized as bearish if the Kalman filter probability of regime one is larger than $\frac{1}{2}$, otherwise it is recognized as bullish. All the data are collected from the Tinsysoft financial database; see <http://www.tinsysoft.com.cn/TSDN/HomePage.tsl>. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The t -statistics are in parentheses.

Stock Exchange; the SSE50 Index contains the top 50 largest stocks listed at the Shanghai Stock Exchange. The M&S CAP Index reflects the top 100 most liquid stocks with medium or small capitalization traded at the Shenzhen Stock Exchange. The SSE Total Return Index is the dividend-reinvested price index for all the shares traded at the Shanghai Stock Exchange. The HS300 ETF tracks the HS300 Index and allows for short selling. In addition, using a standard approach, we create a sample split to distinguish between bullish and bearish periods for the SSE Index.

We decompose the conventional daily close-to-close 24-h returns (R_t) into overnight returns (R_t^o) and daytime returns (R_t^d), that is:

$$R_t = R_t^o + R_t^d, \quad (1)$$

where $R_t = P_t^c - P_{t-1}^c$; $R_t^o = P_t^o - P_{t-1}^c$; $R_t^d = P_t^c - P_t^o$; P_t^o and P_t^c denote the logarithmic opening and closing prices for trading day t , respectively. The overnight return is thus the logarithmic difference between yesterday's closing price and today's opening price and should incorporate relevant information released during the non-trading period. The daily (24-h) return is simply the logarithmic difference between yesterday and today's closing price. Even though we are considering short time frames, conventional asset pricing theory predicts that the expectation of the overnight return and daily return are both positive (or at least larger than the risk-free rate).

Table 1 shows the average overnight returns R_t^o and daily returns R_t for various Chinese stock market indices and periods (bull/bear). Average overnight returns are significantly negative for all eight indices considered, around 6 bps. Daily returns are mostly positive (but insignificant). The last two rows of Table 1 provide results for the different market regimes (bear or bull). The market regimes are identified by a two-regime Markov regime switching model for the SSE Index with regime-based expected close-to-close 24-h returns and conditional volatility. The Kalman filter probability serves to identify market regimes. The market is recognized as bearish if the Kalman filter probability of regime one 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 (−0.124% and −0.045%, respectively). These findings suggest that the phenomenon of a negative expected overnight return is pervasive in China's stock markets. It is robust to various market regimes, sample periods, stock exchanges, types of shares and capitalization. This counter-intuitive phenomenon is labeled the "overnight return puzzle" in this paper.

To make a comparison with China's stock markets, a number of stock indices from other countries and regions are investigated as well. We consider stock indices from both developed and emerging markets, namely the Hang Seng Index (Hong Kong),

Table 2

Overnight returns and daily returns in various other stock markets.

	Overnight Return		Daily Return	
	# of Obs.	Mean (%)	# of Obs.	Mean (%)
Hang Seng Index (Hong Kong)	7183	0.045*** (4.13)	7183	0.031* (1.67)
S&P 500 ETF (United States)	6711	0.031*** (4.05)	6711	0.028** (2.02)
Nikkei 225 Index (Japan)	5074	0.045*** (3.27)	5074	−0.005 (−0.26)
TSEC Weighted Index (Taiwan)	6689	0.166*** (14.60)	6689	0.011 (0.64)
KOSPI Index (South Korea)	6073	0.057*** (4.69)	6073	0.010 (0.47)
FTSE 100 Index (United Kingdom)	7217	0.008*** (2.87)	7217	0.017 (1.35)
JSE Index (South Africa)	4231	−0.000 (−1.43)	4231	0.039** (2.14)
AORD Index (Australia)	4902	0.019 (1.50)	4902	0.028 (1.52)
SENSEX Index (India)	6837	0.127*** (11.64)	6837	0.054*** (2.78)
BOVESPA Index (Brazil)	7264	0.012*** (4.52)	7264	0.228*** (7.30)
DAX Index (Germany)	6609	0.344*** (33.98)	6609	0.029* (1.81)
RTS Index (Russia)	5911	0.042** (2.56)	5911	0.043 (1.33)
IPC Index (Mexico)	6499	0.003** (2.36)	6499	0.050*** (2.76)
STI Index (Singapore)	4967	0.609*** (26.33)	4967	0.007 (0.45)

This table reports the average overnight return and daily return for market indices from other countries and regions, i.e. Hang Seng Index (Hong Kong, April 2, 1990 to May 31, 2019), S&P 500 ETF (United States, January 29, 1993 to May 31, 2019), Nikkei 225 Index (Japan, August 8, 1988 to May 31, 2019), TSEC Weighted Index (Taiwan, March 12, 1992 to May 31, 2019), KOSPI Index (South Korea, October 31, 1994 to May 31, 2019), FTSE 100 Index (United Kingdom, November 5, 1990 to May 31, 2019), JSE Index (South Africa, June 24, 2002 to May 31, 2019), AORD Index (Australia, March 11, 1992 to May 31, 2019), SENSEX Index (India, January 2, 1991 to May 31, 2019), BOVESPA Index (Brazil, January 2, 1990 to May 31, 2019), DAX Index (Germany, April 22, 1993 to May 31, 2019), RTS Index (Russia, September 1, 1995 to May 31, 2019), IPC Index (Mexico, July 20, 1993 to May 31, 2019), and STI Index (Singapore, August 31, 1999 to May 31, 2019). All data from the Thomson Reuters EIKON Database. Overnight returns are calculated as $R_t^o = P_t^o - P_{t-1}^o$. Daily returns are calculated as $R_t = P_t^c - P_{t-1}^c$. P_t^o and P_t^c denote the logarithmic opening and closing price for trading day t , respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The t -statistics are in parentheses.

the S&P 500 ETF (United States),⁴ the Nikkei 225 Index (Japan), the TSEC Index (Taiwan), the KOSPI Index (South Korea), the FTSE 100 Index (United Kingdom), the JSE Index (South Africa), the AORD Index (Australia), the SENSEX Index (India), the BOVESPA Index (Brazil), the DAX Index (Germany), the RTS Index (Russia), the IPC Index (Mexico), and the STI Index (Singapore). Table 2 reports the summary statistics of their overnight returns and daily returns. For details on the data, see the notes of Table 2.

We observe that for all other markets in Table 2, both the average overnight returns and average daily returns are either positively significant, or insignificant, but never negatively significant. These findings are consistent with the conventional conjecture that the overnight returns of an aggregate market index should be positive on average. There are similar findings from various stock markets (e.g., Lockwood and Mcinish, 1990; Masulis and Ng, 1995; Chan et al., 1996; Karolyi and Stulz, 1996; Kang and Babbs, 2010; Kelly and Clark, 2011; Berkman et al., 2012; Liu and Tse, 2017; Lou et al., 2019). In addition, generally the overnight return appears to be larger on average than the daily return, indicating a reversal pattern (cf. Lou et al., 2019). So the overnight return puzzle seems to be a unique phenomenon in China's stock markets as we do not detect it in any other developed or emerging market.

3. The $T+1$ trading rule explains the overnight return puzzle

We argue that the $T+1$ trading rule causes a price discount for opening prices and can therefore explain the negative average overnight returns. The intuition is that the trading rule constrains short-term buyers' reversal trading, so that they require a discount to buy at the opening price. To investigate our hypothesis, we examine some Chinese securities that are not subject to the $T+1$ trading rule. Sometimes the lack of the rule is referred to as " $T+0$." In addition, shares in Chinese stock markets were

⁴ For the S&P 500, time series of opening prices are not available in CRSP, nor in Compustat, so we use data for an ETF. We thank Bruce Knuteson for this suggestion.

Table 3
Overnight and daily returns for Chinese securities that are not subject to $T+1$ trading.

	Overnight Return		Daily Return	
	# of Obs.	Mean (%)	# of Obs.	Mean (%)
SSE Index ($T+0$ Period)	508	0.234*** (2.84)	508	−0.045 (−0.25)
B-share Index ($T+0$ Period)	186	0.239** (2.20)	186	0.267 (1.14)
T-bill	3984	0.012*** (28.37)	3984	0.014*** (9.34)
Corporate Bond	3886	0.013*** (21.73)	3886	0.021*** (10.03)
Convertible Bond	1630	0.073*** (4.40)	1630	0.005 (0.12)
HS300 Index Future	2217	0.026* (1.89)	2217	0.002 (0.07)

This table shows the average overnight returns and daily returns of various security price indices in China's financial markets, and during different periods. These securities are all traded in $T+0$ environments, that is, they are not subject to the $T+1$ trading rule. Specifically, the Shanghai Stock Exchange Composite Index (from January 1, 1993 to December 31, 1994), the B-shares Index (from March 1, 2001 to November 31, 2001), the T-bill Index (from January 2, 2003 to May 31, 2019), the Corporate Bond Index (from June 9, 2003 to May 31, 2019) and the Convertible Bond Index (from September 12, 2012 to May 31, 2019), and the HS300 Index Future (from April 16, 2010 to May 31, 2019). All data are from the Tinysoft financial database; see <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>. Overnight returns are calculated as $R_t^o = P_t^o - P_{t-1}^o$. Daily returns are calculated as $R_t^d = P_t^c - P_{t-1}^c$. P_t^o and P_t^c denote the logarithmic opening and closing price for trading day t , respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The t -statistics are in parentheses.

not subject to the $T+1$ rule during the period from January 1993 to December 1994, and all B-shares were not subject to the rule from March 2001 to November 2001. We label these periods as the “ $T+0$ periods.” Table 3 shows average overnight returns and daily returns for Chinese securities not subject to the $T+1$ trading rule.

First, we investigate the overnight returns for the periods when the rule was not in effect. The first two rows of Table 3 show the results for the $T+0$ periods. The average overnight returns on the SSE Index and B-share Index are both significantly positive at the 5% level. This suggests that the overnight return puzzle disappears in China's stock market when the $T+1$ rule is not in effect.

Second, bond markets in China are not subject to the $T+1$ rule. The average overnight returns of the T-bill Index, the Corporate Bond Index, and the Convertible Bond Index are reported in Table 3 as well. The results show that all three average overnight returns are positive, and two of them are significant at the 1% level.

Third, futures markets are also not subject to the $T+1$ rule. The average overnight return on the HS300 Index Future is reported in the last row of Table 3. Here the daily overnight returns are calculated based on the prices of the futures contract with the closest maturity date. It shows that the average overnight return of the HS300 Index Future is significantly positive at the 10% level. It is worth mentioning that the average overnight return of the associated underlying (subject to the $T+1$ rule), the HS300 Index, exhibits a significantly negative overnight return during the same period instead, around −0.093%.

In sum, it seems there is a strong link between negative overnight returns and the presence of the $T+1$ trading rule, which we argue stems from an opening price discount.

4. Estimating the size of the $T+1$ discount

Clearly, the $T+1$ trading rule hardly affects long-term investors. We conjecture that the $T+1$ discount is generated by prohibiting buyers' intra-day buy-and-sell reversal trading. We assess the size of the discount by quantifying the strength of buyers' incentives to engage in buy-and-sell reversal trading. We classify these incentives into two general types: an incentive for profit taking and a stop-loss incentive. First, suppose a trader buys some shares at the opening price P^o and the price rises to $P > P^o$ later in the day. In this case, the buyer may be inclined to sell the shares to take his profit $P - P^o$. In fact, any buyer who sets his or her target profit price between P^o and P will be motivated to sell his or her shares. The larger the potential profit, the stronger the market-wide incentive to sell. Hence, $P - P^o$ can be used to proxy the strength of the profit taking incentive. Obviously, it reaches its daily maximum at $P^h - P^o$, where P^h is the highest price of the day. Second, if the share price decreases to $P < P^o$, buyers will be motivated to sell their shares to stop their potential loss $P^o - P$. Similar to the profit-taking incentive, all buyers who set their stop-loss target between P and P^o will be inclined to sell their shares. Thus, $P^o - P$ can be used to quantify the stop-loss incentive. The daily maximum of $P^o - P$ is $P^o - P^l$, where P^l is the lowest price of the trading day. To construct an integrated measure of the strength of these incentives, the impact of prices rising and dropping are assumed to be equal in size. The total strength of buyers' incentives to engage in buy-and-sell reversal trading can then be proxied by:

$$P^h - P^l = (P^h - P^o) + (P^o - P^l), \quad (2)$$

that is, the log-price range of the intra-day prices. We acknowledge that this simplified proxy ignores the potential asymmetric impact of prices rising versus dropping. But, as an integrated index, the log-price range will largely reflect buyers' incentives to conduct buy-and-sell reversal trading.

We hypothesize that the $T+1$ discount's magnitude is positively correlated with the expected log-price range. In a $T+1$ environment, buyers' reversal trading is 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 for not being able to do so (i.e., the $T+1$ discount). That is, when upon opening of the market potential buyers render it more likely that extreme price movements will occur and this results in hitting the stop-loss target, for example, they may postpone the transaction. Similarly, a buyer who expects the price to hit the profit-taking target during day t for a certain share cannot buy and sell the same share that day, so instead of buying at the opening of day t he or she will buy just before the close at day $t-1$ and take the overnight risk for granted. In both cases, the drop in demand in the morning will lead to a lower price. So the magnitude of the discount is expected to be positively related to the expected value of the strength of the incentives to (be able to) trade. If the log-price range indeed proxies the strength of buyers' incentives to conduct buy-and-sell reversal trading, the correlation between the expected log-price range (conditionally on an information set which is available at the opening bell) and the $T+1$ discount's magnitude should be positive.

An alternative but related interpretation of the connection between the log-price range and the size of the $T+1$ discount is the following. We can consider the log-price range as a rough measure of intra-day volatility. Day traders' or speculators' demand for trading tends to rise with volatility (Brogaard et al., 2014). However, traders aiming to buy low and sell high are not able to do so, while traders aiming at (short) selling high and buying low are not restricted. Relative to an unconstrained market, there is a drop in potential speculative buyers but not in potential speculative sellers. This asymmetry leads to an opening price discount.

In addition, the $T+1$ discount will slowly dissipate during the day and will be eliminated at the end of a trading day. If a buyer buys some shares at the closing bell, under the $T+1$ regulation he is still allowed to sell the shares the next morning or later, just like in a $T+0$ environment. In other words, shares bought just before the market close are not subject to any constraint under the $T+1$ rule, thus the closing price should not include a $T+1$ discount. The hypothesized periodic pattern of the $T+1$ discount is summarized in Assumption 1.

Assumption 1. In a $T+1$ trading environment, the logarithmic opening price of an asset is equal to the difference between the logarithm of the asset's fundamental opening value V_t^o at day t and a discount D_t ,

$$P_t^o = V_t^o - D_t. \quad (3)$$

Moreover, the logarithmic closing price of the asset P_t^c is equal to the logarithmic fundamental value at the closing bell, V_t^c ,

$$P_t^c = V_t^c, \quad (4)$$

where $D_t = \beta \times F_t$, $F_t = E(L_t | \mathcal{F}_t^-)$, $\mathcal{F}_t^-$ is the information set available at the opening bell of trading day t , and $L_t = P_t^h - P_t^l$ with P_t^h and P_t^l the logarithmic highest and lowest prices for trading day t .

According to Assumption 1, the fundamental value of the asset at opening, which is simply the expected discounted cash flow in absence of market frictions, is subject to a discount due to the $T+1$ trading rule. Assumption 1 also implies that there is a periodic pattern associated with the $T+1$ discount. In the morning, the $T+1$ discount is incorporated into the opening price. Its magnitude is proportional to the expected log-price range of the day. The sign of the expected log-price range is always positive, so the sign of the $T+1$ discount is the same as β . According to our previous discussion, β is expected to be positive. During daytime trading, the $T+1$ discount will be gradually reduced. At the end of the trading day, the discount is entirely eliminated.

The $T+1$ discount can thus explain the overnight return puzzle, given that the discount is large enough. The unconditional expected overnight return is given by:

$$E(R_t^o) = E(V_t^o - V_{t-1}^c) - E(D_t) = E(R_t^{o,V}) - E(D_t), \quad (5)$$

where $R_t^{o,V} = V_t^o - V_{t-1}^c$ is driven by fundamental value movements. $R_t^{o,V}$ reflects the fundamental overnight return, which is expected to be positive, and $E(D_t)$ is the expected $T+1$ discount, which is also expected to be positive. Hence, if $E(D_t) > E(R_t^{o,V})$, the expected overnight return will be negative and the overnight return puzzle appears. The challenge is how to estimate $E(D_t)$ and $E(R_t^{o,V})$.

Under Assumption 1, the overnight return can be written as:

$$R_t^o = R_t^{o,V} - D_t = R_t^{o,V} - \beta \times F_t. \quad (6)$$

The problem is that $R_t^{o,V}$ and F_t are both unobservable. Fortunately, there are some econometric approaches that can produce an estimate for F_t , but the fundamental overnight returns, $R_t^{o,V}$, are hard to obtain. A naïve idea to test whether there is a $T+1$ discount is regressing overnight returns R_t^o on F_t and omitting the unobserved variable $R_t^{o,V}$, i. e.,

$$R_t^o = \alpha - \beta F_t + \epsilon_t. \quad (7)$$

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

$$E(D_t) \approx \hat{\beta}E(F_t) = \hat{\beta}E(L_t), \quad (8)$$

where $\hat{\beta}$ is the estimated value of β derived from equation (7). However, the OLS estimation of the above regression is likely to be biased, due to the absence of $R_t^{o,V}$. The conditional expectation of the log-price range, F_t , is a simple proxy for expected intra-day volatility and, according to the volatility feedback hypothesis, there is a negative correlation between fundamental value and volatility (French et al., 1987; Campbell and Hentschel, 1992). Therefore, F_t is likely to be correlated with $R_t^{o,V}$. It means that omission of the variable $R_t^{o,V}$ will introduce an endogeneity problem in equation (7) and bias the OLS estimates of the naïve approach.

To obtain an unbiased estimate for β , we replace F_t with an expected value of L_t conditionally on a set of lagged information, i.e.,

$$F'_{t-1} = E(L_t | \mathcal{F}_{t-1}), \quad (9)$$

where $\mathcal{F}_{t-1}$ is the information set available at the end of trading day $t - 1$. Substituting it into equation (6), we obtain:

$$R_t^o = R_t^{o,V} - \beta(F'_{t-1} + \epsilon'_t) = R_t^{o,V} - \beta F'_{t-1} + e_t, \quad (10)$$

here $\epsilon'_t = F_t - F'_{t-1}$, and $e_t = -\beta\epsilon'_t$. Note that $\text{cov}(F'_{t-1}, e_t) = 0$, because the law of iterated expectations implies $E(e_t | \mathcal{F}_{t-1}) \equiv 0$. More importantly, the covariance between F'_{t-1} and $R_t^{o,V}$ is expected to be much smaller than the covariance between F_t and $R_t^{o,V}$. A large covariance between F'_{t-1} and $R_t^{o,V}$ would imply that the fundamental overnight returns are strongly predictable, because F'_{t-1} depends on $R_t^{o,V}$'s lagged information. Assuming efficient markets with the implication that daily returns are close to a “random walk” rules out the strong predictability of $R_t^{o,V}$. Although the risk premium is fairly predictable in the long run, its short-run predictability should be relatively weak. Therefore, it is possible to obtain a more accurate estimator of β by running the following regression:

$$R_t^o = \alpha - \beta F'_{t-1} + e_t. \quad (11)$$

Note that the α in equation (11) is the unconditional expectation of the fundamental overnight return, namely $E(R_t^{o,V})$.

Replacing F_t by F'_{t-1} can be interpreted as a two-stage least squares regression (2SLS), where F_t is the endogenous variable in equation (7) and F'_{t-1} is an instrumental variable. Conveniently, the coefficients in the auxiliary equation, $F_t = a + bF'_{t-1} + \epsilon_t$, are a priori known by the definition 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 way to estimate β is by examining the daytime returns. Combining equations (3) and (4), daytime returns can be written as:

$$R_t^d = (V_t^c - V_t^o) + D_t = R_t^{d,V} + D_t = R_t^{d,V} + \beta F_t, \quad (12)$$

where $R_t^{d,V} = V_t^c - V_t^o$ is the fundamental daytime return. Note that D_t is determined by the lagged information of $R_t^{d,V}$. Again, the efficient market hypothesis rules out the strong predictability of $R_t^{d,V}$, so the covariance between $R_t^{d,V}$ and D_t should not be too large. Therefore, a fairly good estimator of β can be derived from the following regression:

$$R_t^d = \alpha' + \beta' F_t + \epsilon_t, \quad (13)$$

where $\beta' = \beta$ and α' is the unconditional expected fundamental daytime return. However, for the sake of consistency in the use of regressors and obtaining a “safer”⁵ estimate for β , we again “instrument” F_t with F'_{t-1} . By doing so, equation (12) can be rewritten as:

$$R_t^d = R_t^{d,V} + \beta(F'_{t-1} + \epsilon'_t) = R_t^{d,V} + \beta F'_{t-1} - e_t. \quad (14)$$

The variable F'_{t-1} uses lagged information relative to F_t , so it is harder to predict the fundamental daytime return $R_t^{d,V}$ by using F'_{t-1} instead of F_t . In other words, replacing F_t by F'_{t-1} can further mitigate the endogeneity problem in equation (13) and delivers a “safer” estimate by running the following regression:

$$R_t^d = \alpha' + \beta' F'_{t-1} + \epsilon_t. \quad (15)$$

Referring to our previous analysis, if a $T+1$ discount exists, both $\alpha = E(R_t^{d,V})$ and $\beta' = \beta$ are expected to be positive. A summary of the justification for 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 conditional on the information set $\mathcal{F}_{t-1}$ which is available at the closing bell of trading day $t - 1$. $R_t^{o,V} = V_t^o - V_{t-1}^o$ is the logarithmic return driven by the movement of the asset's fundamental value

⁵ In the next section, we show that although the correlation between $R_t^{d,V}$ and D_t is small, it is not zero. We thank an anonymous referee for pointing this issue out.

Table 4Log-price range of the SSE Index and estimation of the $T+1$ discount.

Panel A: Summary Statistics of the Log-price Range of the SSE Index.					
	# of Obs.	Mean	S.D.	Max	Min
L_t	4701	0.018	0.012	0.003	0.106
Panel B: Quasi-Maximum Likelihood Estimation of CARR(1,1).					
	ω	θ	γ		
Coef.	0.000	0.167**		0.815***	
	[0.68]	[2.09]		[9.45]	
Panel C: Estimation of the $T+1$ Discount.					
$R_t^o = \alpha - \beta F'_{t-1} + \epsilon_t$		$R_t^d = \alpha' + \beta' F'_{t-1} + \epsilon_t$		$H_0: \beta = \beta'$	
$\alpha(\%)$	β	$\alpha'(\%)$	β'	χ^2 -stat	P-value
0.061**	0.069***	-0.066	0.081***	0.10	0.76
(2.53)	(5.66)	(-1.28)	(3.08)		

Panel A reports the summary statistics of the Shanghai Stock Exchange Composite Index's daily log-price range, which is calculated as $L_t = P_t^h - P_t^l$, where P_t^h and P_t^l are the logarithm of the highest price and lowest price for day t , respectively. The sample is from January 4, 2000 to May 31, 2019. The data are from the Tinysoft financial database; see <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>. Panel B Presents the estimates for the CARR(1,1) model. The z-statistics of the estimated coefficients are in square brackets. Panel C reports the OLS estimation of $R_t^o = \alpha - \beta F'_{t-1} + \epsilon_t$ and $R_t^d = \alpha' + \beta' F'_{t-1} + \epsilon_t$, where R_t^o is Shanghai Stock Exchange Composite Index's overnight return for day t ; R_t^d is its daytime return for day t ; F'_{t-1} is L_t 's forecasted value derived from the CARR(1,1) model. Overnight returns are calculated as $R_t^o = P_t^o - P_{t-1}^o$. Daytime returns are calculated as $R_t^d = P_t^c - P_{t-1}^c$. P_t^o and P_t^c denote the logarithmic opening and closing price for trading day t , respectively. The χ^2 -statistic for testing $\beta + \beta' = 0$ is estimated with GMM, where the two equations are estimated jointly. The sample period is from January 4, 2000 to May 31, 2019. The data are from the Tinysoft financial database; see <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The t -statistics are in parentheses.

during the overnight period. $R_t^{d,V} = V_t^c - V_t^o$ is the logarithmic return driven by the movement of the asset's fundamental value during the daytime period. We assume that both $\text{cov}(F'_{t-1}, R_t^{o,V})$ and $\text{cov}(F'_{t-1}, R_t^{d,V})$ are equal to zero.

Before we can estimate equations (11) and (15), a remaining problem is constructing a time series for F'_{t-1} . The conditional autoregressive range (CARR) model offers a solution to this problem. The CARR model's aim is to forecast asset price ranges by using lagged ranges (Chou, 2005). The CARR model is similar to a GARCH model or an ACD model (Engle, 1982; Bollerslev, 1986; Engle and Russell, 1998). We specify a CARR(1,1) to model L_t 's evolution, namely:

$$L_t = \lambda_t \epsilon_t, \quad (16)$$

$$\lambda_t = \omega + \theta L_{t-1} + \gamma \lambda_{t-1}, \quad (17)$$

where $\{\epsilon_t\}_{t=1}^T$ is a positively valued IID time series with unit mean. We assume it follows an exponential distribution. Referring to Engle and Russell (1998), and Chou (2005), if the error terms are exponentially distributed, a convenient property of the CARR model is that its quasi-maximum likelihood estimation can be conducted by specifying a GARCH model for the square root of the range with a normally distributed error term.

Based on our main sample, L_t is calculated for the daily highest and lowest log-prices of the SSE index, from January 4th, 2000 to May 31st, 2019. Panels A and B of Table 4 report the summary statistics of L_t and the quasi-maximum likelihood estimates for the CARR(1,1) model.

Panel A shows that the mean of L_t is about 1.80%. This number is used to calculate the $T+1$ discount based on equation (8). Panel B shows that the estimated parameters θ and γ for the CARR(1,1) model are both positive and significant. This finding implies that the daily range exhibits clustering; a large range is likely to be followed by a large range. Note that L_t 's forecasted value λ_t is determined by the information available at the closing bell of trading day $t-1$. Thus, F'_{t-1} can be estimated by $\hat{\lambda}_t = \hat{\omega} + \hat{\theta} L_{t-1} + \hat{\gamma} \hat{\lambda}_{t-1}$ iteratively.

Equations (11) and (15) are estimated by substituting $\hat{\lambda}_t$ for F'_{t-1} . The estimates are reported in Panel C of Table 4. We first focus on the estimates for β and β' . The sign and significance of β and β' are both in line with our expectations. The estimate for β is around 0.069, and significant at the 1% level and the estimate for β' is about 0.081, and significant at the 1% level too. In addition, a chi-square test shows that we cannot reject the hypothesis $\beta' = \beta$ (based on a GMM estimation where we estimate the two equations jointly). It is also consistent with our previous analysis that β should be equal to β' . Referring to equation (8), an estimate for the average $T+1$ discount can be obtained by using the estimate for β . With $\beta \approx 0.069$ and $E(L_t) \approx 0.018$, equation (8) gives that $E(D_t) = \beta E(L_t) \approx 0.124\%$. This implies an annualized loss of around $0.124\% \times 240 = 29.81\%$. Another

estimate of the average $T+1$ discount can be derived by $E(D_t) = \beta' E(L_t)$, which is around 0.146%. The two estimates are in the same ballpark. We conclude that the $T+1$ discount is both statistically and economically significant for China's SSE Composite Index, and its daily magnitude is around 14 bps on average.

It is also interesting to look at the estimates for α and α' . Recall that α and α' can be interpreted as the unconditional expectations of the fundamental overnight return and fundamental daytime return, respectively. Both of them are expected to be positive. Panel C of Table 4 shows that the estimate of α is about 0.061%, and significant at the 5% level. This finding is consistent with our conjecture that the expected fundamental overnight return is positive. However, the value is smaller than the average $T+1$ discount, which is about 14 bps. As mentioned before, if $E(D_t) > E(R_t^{o,V})$, it will produce a negative expected overnight return. This finding verifies that the $T+1$ discount provides explanatory power for the overnight return puzzle in China's stock market, as it significantly contributes to the expectation of the overnight return. Moreover, though the estimate of α' is -0.066% , it is not significant at the 10% level, which suggests that overnight returns more significantly reflect fundamental value movements compared to daytime returns, in line with findings for other markets (e.g., Knuteson, 2018; Lou et al., 2019).

We propose another way to estimate the $T+1$ discount, by comparing the overnight returns with the HS300 Index future's overnight returns. Our approach is similar that of Stephan and Whaley (1990). According to the no-arbitrage condition, the spot price should equal the discounted value of the future price, namely:

$$p_t^F = e^{(T-t)r} v_t, \quad (18)$$

where r is the risk-free rate; p_t^F denotes the future price; and v_t is the spot price. However, if the equation does not hold and there is an arbitrage opportunity, it cannot be exploited due to the $T+1$ trading rule. The HS300 Index future is traded in a $T+0$ environment, so the spot price v_t should be an unobservable spot price in a $T+0$ environment, without the $T+1$ discount. Thus, v_t is simply the fundamental value of the HS300 Index. Taking the derivative and using Itô's lemma, we have:

$$\frac{dp_t^F}{p_t^F} = \frac{dv_t}{v_t} - rdt. \quad (19)$$

In particular, for the return during the overnight period, $\frac{dp_t^F}{p_t^F}$ is the HS300 Index future's overnight return $R_t^{o,F}$; $\frac{dv_t}{v_t}$ is the HS300 Index fundamental overnight return $R_t^{o,V}$; and rdt is the overnight risk-free rate rf_t^o . Hence, equation (19) can be expressed as

$$R_t^{o,F} = R_t^{o,V} - rf_t^o. \quad (20)$$

Combining equations (6) and (20), the average $T+1$ discount is:

$$E(D_t) = E(R_t^{o,F}) + E(rf_t^o) - E(R_t^o). \quad (21)$$

The Shanghai Interbank Offered Rate (SHIBOR) is used to proxy rf_t^o . SHIBOR is the rate based on the interbank interest rates in the money market.⁶ The daily SHIBOR overnight rate is calculated by dividing the annualized SHIBOR over-night rate by 360. Its average value in the period matching the sample of the HS300 Index future is about 0.007%. The average $T+1$ discount can be estimated by $E(D_t) = E(R_t^{o,F}) + E(rf_t^o) - E(R_t^o) \approx 0.126\%$. This estimated value is also close to our previous results, around 14 bps. Based on these findings, we conclude that our estimate for the $T+1$ discount rate is robust to various estimation methods.

5. The $T+1$ discount's contribution to overnight risk

In this section, we estimate the $T+1$ discount's contribution to overnight risk, which is measured as the unconditional variance of the overnight return. An assessment of the potential additional risk due to the $T+1$ trading rule is important, because the introduction of the $T+1$ trading rule was motivated by the belief that the rule could reduce market volatility. However, we conjecture that the rule may have unintentional consequences by actually increasing volatility.

According to equation (6), the total variance of the overnight return in a $T+1$ environment can be written as:

$$\text{var}(R_t^o) = \text{var}(R_t^{o,V} - D_t) \quad (22)$$

$$= \text{var}(R_t^{o,V}) + (\text{var}(D_t) - 2\text{cov}(R_t^{o,V}, D_t)), \quad (23)$$

where $\text{var}(R_t^{o,V})$ is the risk due to fundamental value movements (i.e., the total variance of the overnight return in a $T+0$ environment). The additional variance caused by the $T+1$ discount is thus:

$$\text{var}(D_t) - 2\text{cov}(R_t^{o,V}, D_t),$$

⁶ For further details of the SHIBOR rate, see <http://www.shibor.org/>.

Table 5

Variance-covariance matrix of total returns, overnight returns and daytime returns.

	R_t	R_t^o	R_t^d
R_t	2.49×10^{-4}	4.30×10^{-5}	2.06×10^{-4}
R_t^o		4.50×10^{-5}	-2.30×10^{-6}
R_t^d			2.08×10^{-4}

This table reports the variance-covariance matrix of daily returns (R_t), overnight returns (R_t^o) and daytime returns (R_t^d), based on the Shanghai Stock Exchange Composite Index, from January 4, 2000 to May 31, 2019. Daily, overnight, and daytime returns are defined as $R_t = P_t^c - P_{t-1}^c$, $R_t^o = P_t^o - P_{t-1}^o$, and $R_t^d = P_t^c - P_t^o$. P_t^o and P_t^c denote the logarithmic opening and closing price for trading day t , respectively. All data are from the Tinysoft financial database; see <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>.

where $\text{var}(D_t)$ is the variance of the $T+1$ discount, and $\text{cov}(R_t^{o,V}, D_t)$ captures the volatility feedback effect. We expect $\text{cov}(R_t^{o,V}, D_t)$ to be negative and $\text{var}(D_t)$ is positive, so that the total additional variance is positive.

It is difficult to obtain a point estimate of the $T+1$ discount's variance contribution, but it is possible to derive an upper bound and a lower bound. Comparing equation (6) and equation (12), the covariance between the overnight return and daytime return is:

$$\text{cov}(R_t^o, R_t^d) = (\text{cov}(R_t^{o,V}, D_t) - \text{var}(D_t)) - \text{cov}(R_t^{d,V}, D_t) + \text{cov}(R_t^{o,V}, R_t^{d,V}). \quad (24)$$

If the fundamental values V_{t-1}^c , V_t^o , and V_t^c exhibit independent increments, the last term of equation (24), $\text{cov}(R_t^{o,V}, R_t^{d,V})$, is equal to zero. Hence, we ignore this term and obtain:

$$\text{cov}(R_t^o, R_t^d) \approx (\text{cov}(R_t^{o,V}, D_t) - \text{var}(D_t)) - \text{cov}(R_t^{d,V}, D_t).$$

An upper bound of the $T+1$ discount's variance contribution is given by:

$$\begin{aligned} \text{var}(D_t) - 2\text{cov}(R_t^{o,V}, D_t) &< 2(\text{var}(D_t) - \text{cov}(R_t^{o,V}, D_t)) \\ &\approx -2\text{cov}(R_t^o, R_t^d) - 2\text{cov}(R_t^{d,V}, D_t). \end{aligned} \quad (25)$$

Similarly, a lower bound of the $T+1$ discount's variance contribution is:

$$\begin{aligned} \text{var}(D_t) - 2\text{cov}(R_t^{o,V}, D_t) &> \text{var}(D_t) - \text{cov}(R_t^{o,V}, D_t) \\ &\approx -\text{cov}(R_t^o, R_t^d) - \text{cov}(R_t^{d,V}, D_t). \end{aligned} \quad (26)$$

So in order to assess a lower and upper bound for the additional variance due to the $T+1$ trading rule, we need estimates for $\text{cov}(R_t^o, R_t^d)$ and $\text{cov}(R_t^{o,V}, D_t)$.

An estimate for the first term, $\text{cov}(R_t^o, R_t^d)$, is straightforward, since both R_t^o and R_t^d are observable. Based on our main sample of the SSE Index, the variance-covariance matrix of R_t , R_t^o , and R_t^d is reported in Table 5. The covariance between the overnight return and daytime return is about -2.3×10^{-6} . To estimate the covariance between the daytime return of the fundamental value and the $T+1$ discount, $\text{cov}(R_t^{d,V}, D_t)$, we need to construct time series for $R_t^{d,V}$ and D_t . First, we specify a CARR(1,1)-X model for the daily log-price range, L_t :

$$L_t = \lambda_t \epsilon_t, \quad (27)$$

$$\lambda_t = \omega + \theta L_{t-1} + \gamma \lambda_{t-1} + b_1 R_t^o + b_2 (R_t^o)^2 + b_3 |R_t^o|, \quad (28)$$

where R_t^o , $(R_t^o)^2$, and $|R_t^o|$ are exogenous variables to capture the effect of the overnight information. The quasi-maximum likelihood estimation results of the CARR(1,1)-X model are reported in Panel A of Table 6. The $T+1$ discount is then estimated as $\hat{D}_t = \beta \times F_t = \beta \times \tilde{\lambda}_t$, where $\tilde{\lambda}_t$ is the fitted value of λ_t of the CARR(1,1)-X model. According to the results in Table 4, β is around 0.069. The daytime return on the fundamental value can be estimated as $\hat{R}_t^{d,V} = R_t^d - \hat{D}_t$. The summary statistics of $\hat{D}_t$ and $\hat{R}_t^{d,V}$, including the estimate of interest, $\text{cov}(\hat{R}_t^{d,V}, D_t)$, are presented in Panel B of Table 6.

The overnight return's total variance is around 4.50×10^{-5} . Using our estimates for $\text{cov}(R_t^o, R_t^d)$ and $\text{cov}(R_t^{d,V}, D_t)$, and the expressions for the upper and lower bound, equations (25) and (26), the $T+1$ discount's variance contribution relative to the total overnight return variance is between $\frac{2.3 \times 10^{-6} - 4.0 \times 10^{-8}}{4.5 \times 10^{-5}} = 5.02\%$ and $\frac{2 \times 2.3 \times 10^{-6} - 2 \times 4.0 \times 10^{-8}}{4.5 \times 10^{-5}} = 10.04\%$. This indicates that the $T+1$ discount's variance significantly contributes to the total overnight return variance.

Table 6

Estimation of the covariance between the fundamental daytime returns and the daily T+1 discount.

Panel A: Quasi-Maximum Likelihood Estimation of CARR(1,1)-X.						
	ω	θ	γ	b_1	b_2	b_3
Coef.	-7.298*** (-7.21)	0.180* (1.88)	0.762*** (6.78)	-4.670 (-0.15)	-1045.438 (-0.63)	108.257 (1.29)
Panel B: Summary Statistics of $\widehat{D}_t$ and $\widehat{R}_t^{d,V}$.						
	$\widehat{D}_t$ (%)	$\widehat{R}_t^{d,V}$ (%)	$cov(\widehat{D}_t, \widehat{R}_t^{d,V})$		$corr(\widehat{D}_t, \widehat{R}_t^{d,V})$	
	0.125 [0.059]	-0.046 [1.441]	4.0×10^{-8}		0.005	

Panel A presents the parameter estimates for the following CARR(1,1)-X' model specification:

$$L_t = \lambda_t \epsilon_t,$$

$$\lambda_t = \omega + \theta L_{t-1} + \gamma \lambda_{t-1} + b_1 R_t^o + b_2 R_t^{o2} + b_3 |R_t^o|,$$

where R_t^o is the overnight return; L_t is the daily log-price range. The z-statistics of the estimated coefficients are in parentheses. Panel B presents the summary statistics of $\hat{D}_t$ and $\hat{R}_t^{d,V}$, where $\hat{D}_t = \beta \times \tilde{\lambda} = 0.069 \times \tilde{\lambda}$; $\tilde{\lambda}$ is the fitted value of λ ; $\hat{R}_t^{d,V} = R_t^d - \hat{D}_t$; and R_t^d is the overnight return. Standard deviations are in square brackets. Our sample period is from January 4, 2000 to May 31, 2019. The data are from the Tinysoft financial database; see <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7

Placebo tests: Estimating the T+1 discount for markets in a T+0 environment.

	$R_t^o = \alpha - \beta F'_{t-1} + \epsilon_t$		$R_t^d = \alpha' + \beta' F'_{t-1} + \epsilon_t$	
	α (%)	β	α' (%)	β'
S&P 500 ETF (United States)	0.042*** (2.63)	0.008 (0.76)	-0.032 (-1.33)	0.023 (1.39)
JSE Index (South Africa)	-0.002 (-1.51)	-0.001 (-1.06)	0.004 (0.08)	0.026 (0.80)
FTSE 100 Index (United Kingdom)	0.007 (1.05)	-0.001 (-0.26)	-0.033 (-1.17)	0.033* (1.71)
Hang Seng Index (Hong Kong)	0.021 (0.77)	-0.016 (-0.97)	-0.011 (-0.31)	-0.002 (-0.10)
KOSPI Index (South Korea)	0.023 (0.94)	-0.020 (-1.56)	-0.081** (-2.29)	0.021 (1.13)
Nikkei 225 Index (Japan)	-0.001 (-0.04)	-0.031 (-1.44)	-0.078 (-1.43)	0.019 (0.57)
TSEC Weighted Index (Taiwan)	0.154*** (5.15)	-0.008 (-0.41)	-0.194*** (-5.26)	0.028 (1.15)
AORD Index (Australia)	0.028 (0.85)	0.009 (0.29)	0.018 (0.58)	-0.009 (-0.31)
SENSEX Index (India)	0.076*** (2.85)	-0.031** (-2.12)	-0.024 (-0.60)	-0.030 (-1.38)
BOVESPA Index (Brazil)	0.017*** (2.70)	0.002 (0.89)	-0.232*** (-3.14)	0.171*** (6.68)
DAX Index (Germany)	0.011 (0.58)	-0.248*** (-21.16)	0.011 (0.45)	-0.243*** (-15.39)
RTS Index (Russia)	0.053* (1.74)	0.005 (0.43)	0.081 (1.64)	-0.038* (-1.91)
IPC Index (Mexico)	0.004 (1.28)	0.001 (0.36)	-0.036 (-0.81)	0.051** (2.04)
STI Index (Singapore)	-0.638*** (-16.77)	-0.697*** (-38.75)	0.609*** (14.93)	-0.677 (-35.08)

This table reports estimates for the expected range based prediction using overnight returns and daytime returns for various countries/regions, for details of the data see the note of Table 2. The expected range, L_t , is estimated by using the CARR(1,1)'s quasi-maximum likelihood estimation. We report the OLS estimates of $R_t^o = \alpha + \beta F'_{t-1} + \epsilon_t$ and $R_t^d = \alpha' + \beta' F'_{t-1} + \epsilon_t$, where R_t^o is the overnight return for day t ; R_t^d is the daytime return for day t ; F'_{t-1} is L_t 's forecasted value derived by the CARR(1,1) model. 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 price for trading day t , respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

Table 8
Analysis of overnight returns and closing bubbles.

B_{t-1}^c	$P_{t-1}^c - \frac{P_{t-1}^l + P_{t-1}^h}{2}$		$P_{t-1}^c - P_{t-1}^l$		R_{t-1}^d	
	$\alpha(\%)$	$\beta(\%)$	$\alpha(\%)$	$\beta(\%)$	$\alpha(\%)$	$\beta(\%)$
Coef.	-0.080*** (-8.22)	15.103*** (12.66)	-0.129*** (-9.41)	6.435*** (6.76)	-0.071*** (-7.40)	9.153*** (13.74)

This table reports the OLS estimation of the following equation:

$$R_t^o = \alpha + \beta B_{t-1}^c + \epsilon_t.$$

Overnight returns are calculated as $R_t^o = P_t^o - P_{t-1}^c$. P_t^o and P_{t-1}^c denote the logarithmic opening and closing price of the Shanghai Stock Exchange Composite Index, respectively. The closing bubbles B_{t-1}^c are proxied by $P_{t-1}^c - \frac{P_{t-1}^l + P_{t-1}^h}{2}$, $P_{t-1}^c - P_{t-1}^l$, and $R_{t-1}^d = P_t^c - P_t^o$, where P_{t-1}^c , P_{t-1}^l , and P_{t-1}^h refer to the logarithmic closing price, lowest price and highest price, respectively. The sample period is from January 4, 2000 to May 3, 2019. The data are from the Tinysoft financial database; see <http://www.tinysoft.com.cn/TSDN/HomePage.tsl>. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The t -statistics are in parentheses.

6. Placebo tests and alternative explanations for the overnight return puzzle

In this section, we first try to rule out the possibility that our range-based regression approach is detecting some other market phenomenon, unrelated to the opening discount. To do so, we conduct placebo tests by applying our methodology to stock markets from a number of other countries/regions. If our method is indeed able to detect the $T+1$ discount, it should not find anything for stock markets in a $T+0$ environment. The results are presented in Table 7. The estimates for β and β' are insignificant for almost all markets. Additionally, the signs and magnitudes of β and β' are inconsistent with the existence of a $T+1$ discount, in the sense that they are never significantly positive and/or of the same magnitude. These findings imply that we do not find an opening discount for these markets.

In addition, we want to rule out two alternative behavioral explanations for the overnight return puzzle in China's stock markets: investor overreaction and speculator manipulation. First, investors may overreact to bad news that 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 in the Chinese markets. If investors' overreaction responses to good news and bad news occur symmetrically, the average overnight return should not deviate too much from the rational mean return driven by fundamental value movements, which is expected to be positive. In addition, why would investors' overreactions exclusively exist in China's stock markets? Perhaps a cultural phenomenon drives this type of behavior; then again, we do not observe it in any other Asian market we examine.

Second, speculators may try to manipulate prices at the end of a trading day. That is, if speculators with significant market power have some motivation to present "good" closing prices to the public, they may somehow drive up the assets' prices at the closing bell, so that price "bubbles" are generated, which could be called "closing bubbles." So then the explanation of the overnight return puzzle is that the negative average overnight return is caused by the "bursting" of the "closing bubbles." However, this explanation neglects that speculators could have a similar motivation to drive down the assets' prices and try to realize "bad" closing prices. Besides, it is hard to believe that such speculators keep on employing this failing strategy for more than 20 years on a daily basis. In addition, price manipulation cannot explain why the overnight return puzzle is unique to China.

Moreover, if closing bubbles indeed explain the overnight return puzzle, we can try to test this. If the price drop reflects the bursting of a bubble, overnight returns should be negatively correlated with the sizes of the closing bubbles. This relation can be examined with the following regression,

$$R_t^o = \alpha + \beta B_{t-1}^c + \epsilon_t, \quad (29)$$

where B_{t-1}^c is a proxy for a closing bubble on trading day $t - 1$. Table 8 shows the estimation with three proxies of closing bubbles, i.e., $P_{t-1}^c - \frac{P_{t-1}^l + P_{t-1}^h}{2}$, $P_{t-1}^c - P_{t-1}^l$, and $R_{t-1}^d = P_{t-1}^c - P_{t-1}^o$, where P_{t-1}^c , P_{t-1}^l , and P_{t-1}^h refer to the logarithmic closing price, the lowest price and the highest price for trading day $t - 1$, respectively.

In contrast to the closing bubbles hypothesis, Table 8 shows that the estimates of β are consistently positive and significant at the 1% level. This implies that there is a strong positive relation between overnight returns and "closing bubbles." The analysis above thus shows no support for the notion that the overnight return puzzle stems from closing bubbles.

7. Conclusion

In this paper, we report a puzzling phenomenon, namely that the average overnight return, defined as the difference between yesterday's closing price and today's opening price, is significantly negative for the Shanghai Stock Exchange and the Shenzhen Stock Exchange. This finding violates traditional asset pricing theory. Furthermore, we show that this finding is unique to China. For various financial markets from other countries and regions, the average overnight return is positive as expected. We label

this finding the overnight return puzzle.

We hypothesize that the so-called $T+1$ trading rule in China can explain the puzzle. Specifically, the $T+1$ trading rule constrains buyers' buy-and-sell intra-day reversal trading, but does not put any constraint on sellers. Hence, buyers require a discount at the opening bell, which we call the $T+1$ discount. This discount can explain the negative overnight returns. To provide empirical support for our hypothesis that the $T+1$ rule explains the negative overnight return, we investigate Chinese securities and time periods not subject to the $T+1$ rule. We find that for periods when the $T+1$ rule was not effective, Chinese markets also exhibit positive overnight returns. In addition, Chinese securities that are not subject to the rule, such as bonds and futures, also show positive average overnight returns. We conclude that there is a tight link between negative overnight returns and the $T+1$ trading rule.

We estimate the daily $T+1$ discount at 14 bps, which is large enough to offset the fundamental overnight return, estimated at about 9 bps. The relatively large opening discount results in a negative overnight return, and thus explains the puzzle. In addition, we assess the contribution of the $T+1$ discount to overnight risk. We estimate that the variance contribution of the $T+1$ discount is between 5.02% and 10.04%. While the $T+1$ trading rule was motivated by the belief that it would reduce volatility, we show that it actually increases volatility. Both the discount and the associated additional risk are likely to be unintentional consequences of the $T+1$ trading rule.

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