A unique “T + 1 trading rule” in China: Theory and evidence

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1. Introduction

The Chinese stock market opened in December 1990, with two separate sub-markets: an A-share market (for domestic investors) and a B-share market (for foreign investors). Initially, both adopted the “T + 0 trading rule”, which allows an investor to sell stocks bought the same day. However, in January 1995, the China Securities Regulatory Commission (CSRC) abandoned this “T + 0 trading rule” for A-share stocks and replaced it with a “T + 1 trading rule” – a unique institutional arrangement found nowhere else in the world. The “T + 1 trading rule” requires an investor to sell only stocks he purchased at least one day prior, and forbids him from selling stocks bought the same day. In China’s official newspaper, Renmin Daily, the authority claimed that the “T + 1 trading rule” would effectively prevent excessive speculative trading and thus would be in line with the interests of retail investors.1 In 2000, China’s B-share stock market abandoned the “T + 0 trading rule”, and adopted the “T + 1 trading rule” as well. Despite the longstanding arguments in favor of the “T + 1 trading rule”, few theoretical models and little empirical evidence have been provided to explain and analyze this unique trading arrangement. Our paper may be the first to explore the effects of the “T + 1 trading rule” on the welfare of various investors, the stock prices, and volumes, from both theoretical and empirical perspectives.

We develop a parsimonious trade-based price manipulation model in which there are three types of traders: a strategic trader, mechanical trend chasers, and competitive risk-averse liquidity providers. The risk-averse liquidity providers passively clear the market by taking orders submitted by the strategic trader and trend chasers. The strategic trader maximizes her expected utility by manipulating the stock prices to induce trend chasers to follow her trading, whereas the trend chasers follow a pre-specified trading rule.2 The stock price is affected by the strategic trader’s manipulation trades as well as by the trend chasers’ trend-following behavior. We show that, compared with the “T + 0 trading rule”, adopting the “T + 1 trading rule” effectively reduces the total trading volume, as well as price volatility, and improves the trend chasers’ welfare if trend-chasing is strong. We test the model’s predictions by comparing trading volume and stock price volatility before and after the implementation of “T + 1”, using data from China’s B-share market. We also check the robustness of our test by examining different measures of stock volatility and by controlling the effect of the “Opening-up” policy, which was introduced about the same time as the introduction of the “T + 1 trading rule”. The empirical results support our hypotheses.

1 Due to the lack of rigorous regulation in the early 1990s, China’s stock market is dominated by speculative trading, as in most emerging markets.

2 Trend-following behavior is common in emerging markets, see Gelos and Wei (2002) and Khwaja and Mian (2005). It is very common among retail investors in China as well.
Our paper is closely related to the literature on stock market manipulation. Allen and Gale (1992) classify stock market manipulation into three categories: action-based manipulation, information-based manipulation, and trade-based manipulation. Our theory falls into the trade-based manipulation category, in which a trader manipulates a stock simply by buying and selling, without taking any publicly-observable action to change the firm's value, or releasing any information to affect the price. Hart (1977) shows, in a dynamic deterministic setting, that trade-based manipulation is profitable when the stationary equilibrium is unstable or demand functions are nonlinear. Jarrow (1992) extends Hart (1977) to a stochastic environment and shows that the manipulation can be profitable if there exists a “price momentum”, or when the speculator can corner the market. In these papers, the demand functions are exogenously given and their frameworks are thus of partial equilibria. We take a general equilibrium approach here. In our paper, there exist risk-averse liquidity providers who clear the markets so that the demand function is endogenously determined. In addition, we assume there exist trend chasers, who follow an exogenously-given trading rule. The rule requires them to buy stocks when the price goes up and sell stocks when the price goes down. DeLong et al. (1990) classifies this type of trading as positive feedback trading. They cite various empirical evidence to support this assumption. Our model is similar to DeLong et al. (1990) in that we also assume the rational strategic trader can manipulate the positive feedback trader to make a profit. However, our paper differs from theirs in two aspects. First, our model assumes information symmetry among traders because we focus on the effects of the “T + 1 trading rule”. In contrast, DeLong et al. (1990) assume information asymmetry among different types of traders, aiming primarily at manipulative behavior. Second, in their paper, the equilibrium price is obtained by directly specifying demand functions for passive traders, while in our model, the demand of the passive traders, or, risk-averse liquidity providers, is determined by their own utility maximization, following Subrahmanyam (1991).

Several papers document empirical evidence of market manipulation for both emerging and developed markets. Using trade-level data from Pakistan stock market, Khwaja and Mian (2005) find that brokers earn at least 8% higher returns on their own trades through a specific trade-based “pump and dump” price manipulation scheme. Mei et al. (2004) empirically test a price manipulation pattern based on investors’ behavioral biases, using data on Securities and Exchange Commission (SEC) prosecution of “pump and dump” manipulation cases. Aggarwal and Wu (2006) also provide empirical evidence from 142 litigation cases of stock price manipulation in the U.S. from 1990 to 2001.

The rest of this paper is organized as follows. Section 2 specifies the assumptions of the model. Section 3 solves the equilibrium for the case of the “T + 1 trading rule”. Section 4 solves the equilibrium for the case of the “T + 0 trading rule”. In Section 5, we compare the equilibrium features of these two cases with regard to trading volume, price volatility, and investors’ welfare. Section 6 tests for the predictions in Section 5, using data from China’s B-share market. Section 7 concludes the paper.

2. The model

For tractability, we consider a two-day model in which there are three types of traders: a risk-averse strategic trader, trend chasers, and risk-averse liquidity providers. There are one risk-free bond and one risky stock available for trading. Without loss of generality, we assume that the interest rate for the bond is zero. Therefore, the bond’s price is always equal to 1.

The model involves two days, in which day 1 comprises periods 1–4, and the stock payoff is realized and the stock is liquidated in day 2. Before period 1, the strategic trader and the risk-averse liquidity providers know that the stock’s payoff is $D_0$. Uncertainty about the stock’s payoff arises in period 1 and ends in the second day. From periods 1 to 4, the strategic trader and the risk-averse liquidity providers know only that the stock payoff $D$ follows a normal distribution with a mean $D_0$ and a variance $\sigma^2$. The uncertainty is resolved in day 2 and the stock payoff $D$ is realized.

The strategic trader chooses her optimal trading strategy, while trend chasers follow an exogenously-given rule. Risk-averse liquidity providers trade passively to provide immediacy to other investors for liquidity premium, and set equilibrium prices competitively based on the order flows submitted by the strategic trader and trend chasers. Note that because there is no information asymmetry, it does not make any difference to risk-averse liquidity providers whether they observe the order flows separately or in total.

Since the liquidity providers are risk averse, the order flows submitted by the strategic trader and trend chasers affect the stock prices in equilibrium. As a result, the strategic trader chooses her optimal trading strategies by taking into account the impact of her trades on prices. The strategic trader has an exponential utility of the form $-\exp(-\gamma W)$, where $\gamma$ is her risk-aversion coefficient. We also assume an exponential utility $-\exp(-\gamma W)$ for risk-averse liquidity providers. Without loss of generality, we normalize the number of risk-averse liquidity providers to be 1. The stock price in period $i$ is denoted by $P_i$, where $i \in \{1,2,3,4,5\}$. Since there is no uncertainty in period 5 (day 2), the price in period 5 satisfies $P_5 = D_0$. Since there is no uncertainty before period 1, the stock price before period 1 is equal to $D_0$.

We assume that the strategic trader’s initial stock endowment is $X_0$, where $X_0$ is a positive constant. The initial endowments of risk-averse liquidity providers are assumed to be zero and their holding in period $i$, where $i \in \{1,2,3,4\}$, is denoted by $Q_i$.

For simplicity, we assume that the strategic trader trades in periods 1 and 3, and the quantities she trades are denoted by $X$ and $X$, respectively. The trend chasers follow the strategic trader’s trading and trade in periods 2 and 4. The quantities chosen by them in these two periods are denoted by $Y$ and $T$, respectively. They are given by the following rule:

$$Y = g(P_1 - D_0),$$

and

$$T = g(P_3 - P_2),$$

where $g$ is a positive constant. As in DeLong et al. (1990), $g$ represents the intensity of the bullishness of trend chasers.

We now introduce the “T + 1 trading rule” into the model. Under the “T + 1 trading rule”, the quantities an investor sells in day 1 cannot be more than his initial position at the beginning of day 1. This rules out the case where an investor buys a large number of stocks and sells this quantity during the same day.

\[ \text{In essence, we only focus on the intra-day trading behaviors of the investors, to study the effect of the “T + 1 trading rule”. However, our results should be robust in a more complicated setup.} \]

\[ \text{It is worth noting that individual investors also provide liquidity in other markets, as empirical evidence has indicated. Kaniel et al. (2008, 2009) have shown that risk-averse individual investors provide liquidity to institutional investors in the U.S. Therefore, it is reasonable to assume that the risk-averse liquidity providers (individual investors) clear the market at the equilibrium price. Technically, many papers assume exogenous demand functions of risk-averse liquidity providers, for tractability reasons. For example, Brunnermeier and Pedersen (2005) incorporate the price impacts of order flows and downward-sloping demands of risk-averse liquidity providers into asset pricing models. In their paper, the demand curve is exogenously given. Our paper, on the other hand, endogenizes the demands of the liquidity providers when incorporating the price impacts of order flows.} \]
3. Equilibrium under the “T + 1 trading rule”

In this section, we solve for the equilibrium under the “T + 1 trading rule”.

3.1. Equilibrium prices

Since the risk-averse liquidity providers’ goal is to clear the markets in each period, the sum of the positions of the strategic trader, trend chasers, and risk-averse liquidity providers must be equal to zero. We thus obtain

\[
\begin{align*}
0 &= Q_1 + X, \\
0 &= Q_2 - Q_1 + Y, \\
0 &= Q_3 - Q_2 + \bar{X}, \\
0 &= Q_4 - Q_3 + Y.
\end{align*}
\]

The risk-averse liquidity providers set prices competitively to clear the market. Following Subrahmanyam (1991), the quantities traded by risk-averse liquidity providers satisfy:

\[
E[Q_t(D - P_t)] - \frac{1}{2} \gamma \lambda^2 Q_t = 0.
\]

With the above equation, we establish the relationship between the equilibrium prices and the risk-averse liquidity providers’ holdings, in the following proposition.

**Proposition 1.** The stock price in period \( t \) is

\[
P_t = D_0 - \frac{1}{2} \gamma \lambda^2 Q_t, \quad t = 1, 2, 3, 4.
\]

**Proof.** Since \( D \sim N(D_0, \sigma^2) \), substituting \( E[Q_t(D - P_t)] = Q_t(D_0 - P_t) \) and \( \frac{1}{2} \gamma \lambda^2 Q_t \) into (4) yields

\[
P_t = D_0 - \frac{1}{2} \gamma \lambda^2 Q_t, \quad t = 1, 2, 3, 4.
\]

Define \( \lambda = \frac{1}{2} \gamma \lambda^2. \) Using equations (3) and Proposition 1, we obtain

\[
\begin{align*}
P_1 &= D_0 + \lambda X, \\
P_2 &= D_0 + \lambda (X + Y), \\
P_3 &= D_0 + \lambda (X + Y + \bar{X}), \\
P_4 &= D_0 + \lambda (X + Y + \bar{X} + Y).
\end{align*}
\]

Substituting (5) into (1) and (2) yields the quantities traded by trend chasers in periods 2 and 4, which are given by

\[
Y = g(P_1 - D_0) = g \lambda X
\]

and

\[
\bar{Y} = g(P_3 - P_2) = g \lambda \bar{X}.
\]

3.2. The strategic trader’s optimization problem

In day 1 (periods 1–4), the strategic trader trades in periods 1 and 3 to maximize her expected utility in day 2 (period 5). We use the backward induction method to solve for her optimal trading strategies. We first solve the optimization problem of the strategic trader in period 3 and then solve for her optimal trading in period 1.

3.2.1. The maximization problem in period 3

In period 3, the strategic trader maximizes her expected utility in period 5 based on the information available in period 3. With the “T + 1 trading rule”, the quantity that the strategic trader sells cannot be more than \( X_0 \). Therefore, we have the following constraint:

\[
\bar{X} \geq -X_0.
\]

where \( \bar{X} \) is the quantity she trades in period 3 and \( X_0 \) is her initial position.

Simple derivation yields the strategic trader’s budget constraint in period 3:

\[
W_5 - W_2 = (X_0 + X)(P_5 - P_2) + \bar{X}(P_5 - P_3).
\]

Her maximization problem in period 3 is then given by:

\[
\max_{\bar{X}} E[W_5|F_3] - \frac{1}{2} \gamma \lambda^2 Var(W_5|F_3)
\]

\[
s.t. \begin{align*}
(a) & \quad W_5 - W_2 = (X_0 + X)(P_5 - P_2) + \bar{X}(P_5 - P_3) \\
(b) & \quad \bar{X} \geq -X_0,
\end{align*}
\]

where \( F_3 \) denotes her information set in period 3. Since her objective function is quadratic, we need only to solve the optimization problem in (10) without constraint (b) and then determine whether the solution is larger than \(-X_0\).

The optimization problem without constraint (b) is given by:

\[
\max_{\bar{X}} E[W_5|F_3] - \frac{1}{2} \gamma \lambda^2 Var(W_5|F_3)
\]

\[
s.t. \begin{align*}
(a) & \quad W_5 - W_2 = (X_0 + X)(P_5 - P_2) + \bar{X}(P_5 - P_3) \\
(b) & \quad \bar{X} \geq -X_0,
\end{align*}
\]

Substituting (5), (1), and constraint (a) into the objective function in (11) yields:

\[
\max_{\bar{X}} W_5 - \bar{X}X_0 + X(1 + g \lambda)X - \bar{X}X + g \lambda X + \bar{X} - \bar{X}X_0 + X + \bar{X}^2.
\]

\[
\max_{\bar{X}} W_5 - \bar{X}X_0 + X(1 + g \lambda)X - \bar{X}X + g \lambda X + \bar{X} - \bar{X}X_0 + X + \bar{X}^2.
\]

\[
\bar{X} = \max(-X_0, \bar{X}).
\]

It is easy to check that the second-order condition is negative. Thus, the solution (13) is the optimal one. If \( \bar{X} \geq -X_0 \), then (13) is also the solution to the constrained optimization problem given by (10). If \( \bar{X} < -X_0 \), because the objective function is quadratic and concave, the constraint will be binding at \(-X_0\). Therefore, combining the above two cases, we can write the optimal solution to problem (10) as:

\[
\bar{X} = \max(-X_0, \bar{X}).
\]

Eq. (14) shows that the strategic trader’s optimal strategy in period 3 is a nonlinear function of her initial endowment \( X_0 \) and her chosen quantity \( X \) in period 1. Eq. (15) shows that \( \bar{X} \) is negatively correlated with \( X \). The implication is that the strategic trader tends to trade in the opposite directions in periods 1 and 3 to manipulate markets and obtain trading profit by inducing trend chasers to follow her transaction. An example is that she buys low and sells high. Note that \( \bar{X} \) is also negatively correlated with her initial endowment \( X_0 \) because the risk-averse strategic trader tends to hold a position with a smaller magnitude to reduce the risk. In addition, Eq. (14) shows that the quantities she sells in period 3 are up-bounded, which is consistent with the “T + 1 trading rule”.

3.2.2. The maximization problem in period 1

In period 1, the strategic trader’s budget constraint is given by

\[
W_5 - W_0 = X_0(P_5 - D_0) + \bar{X}(P_5 - P_1) + \bar{X}(P_5 - P_3),
\]

and her optimization problem is:

\[\text{Maximize } E[W_5|F_0] \text{ subject to } W_5 - W_0 = X_0(P_5 - D_0) + \bar{X}(P_5 - P_1) + \bar{X}(P_5 - P_3).\]

Given \( u(W) = -\exp(-\gamma W) \), \( E[u(W)] \) is equivalent to \( \max E[W] - \frac{1}{2} \gamma \lambda^2 Var(W) \).
The strategic trader has two optimal trading strategies. The first one is:

\[ X' = \frac{1}{2} X_0 - \frac{(g \lambda + 3) X}{4}, \]  

where \( X \) is the strategic trader’s information set in period 1. Substituting constraint (a), (1) and (5) into its objective function (16) yields:

\[ \max_X - X'^2 + g X' + X - (X_0 + X + X)^2 \]

\[ X \geq -X_0, \]  

(17)

where \( X' = \max(-X_0, X) \), we solve the optimization problem given in (17) by considering \(-X_0 \geq X'\) and \(-X_0 < X'\), respectively. We summarize the results in the following proposition.

**Proposition 2.** Under the “+ trading rule”, when \( g \lambda > 1 \), the strategic trader has two optimal trading strategies. The first one is:

\[ X' = \frac{1}{2} X_0 - \frac{(g \lambda + 3) X}{4}, \]  

and the second one is:

\[ X' = \frac{1}{2} X_0 + \frac{(g \lambda + 3) X}{4} \]

When \( g \lambda < 1 \), the first-order condition yields

\[ X' = -\frac{2}{g \lambda + 7} X_0. \]  

(19)

When \( g \lambda > 1 \), the objective function (19) is convex; it is maximized at either \(-\infty\) or \(+\infty\). In order to ensure a bounded solution, we make the following assumption:

\[ |X| \leq k X_0, \quad k > 0. \]  

(21)

The above constraint means that the quantity the strategic trader buys or sells cannot be more than \( k X_0 \) in the first period. It is a mechanical assumption to obtain an interior solution. We further assume that \( k \geq 1 \), and \( k \) can be understood as an investor’s funding ability. \( ^7 \) Comparing the utilities from \( X = k X_0 \) and \( X = -k X_0 \), we find that the objective function (19) is maximized at the right boundary:

\[ X' = k X_0. \]  

(22)

Substituting (22) into Eq. (18), the strategic trader's optimal trading quantity in period 3 is given by

\[ X' = -\frac{1}{2} X_0 - \frac{(g \lambda + 3) k X_0}{4} \]

when \( 0 < g \lambda < 1 \), the strategic trader's optimal trading quantities are:

\[ X' = k X_0 \]

and

\[ X' = -\frac{1}{2} X_0 - \frac{(g \lambda + 3) k X_0}{4} \]

when \( 0 < g \lambda < 1 \), the strategic trader's optimal trading quantities are:

\[ X' = k X_0 \]

The interpretation of the optimal trading strategies in Proposition 3 is the same as in Proposition 2, except that the solution is unique when \( g \lambda > 1 \). This is due to the fact that we impose a bound for the first-period trading under the “+” scenario, which makes the model asymmetric.

**5. Comparison of “+” and “+” trading rules**

In this section, we compare the equilibrium properties for these two trading mechanisms. First, in Table 1, we summarize the strategic trader’s optimal trading strategies, described in the previous two sections.

Next, we compare the equilibrium properties, including total trading volumes, price volatilities, and investors’ welfare.

**5.1. Equilibrium volumes**

We use \( V_{(t+1)} \) and \( V_{(t+0)} \) to denote total trading volumes under the “+” and “+” trading rules, respectively.

Under the “+” trading rule:

\[ V_{(t+1)} = |X'| + |Y'| + |X'| + |Y'| \]

\[ = \frac{g \lambda + 1}{4} X_0 + \frac{(g \lambda + 3) k X_0}{4} X_0 + X_0 + g \lambda X_0 \]

\[ = \frac{g \lambda^2 + 6 g \lambda + 5}{4} X_0. \]

Under the “+” trading rule:

\[ V_{(t+0)} = |X'| + |Y'| + |X'| + |Y'| \]

\[ = k X_0 + g \lambda k X_0 + \left( \frac{1}{2} X_0 + \frac{(g \lambda + 3) k X_0}{4} \right) (g \lambda + 1) \]

\[ = \frac{1}{4} (k (g \lambda + 7) + 2) (g \lambda + 1) X_0. \]

Comparing \( V_{(t+1)} \) with \( V_{(t+0)} \) yields:

\[ V_{(t+1)} - V_{(t+1)} = \left( \frac{1}{4} g \lambda^2 (k - 1) + g \lambda (2 k - 1) + \frac{7}{4} k - \frac{3}{4} \right) X_0. \]

It is easy to note that when \( k > \frac{3 + \sqrt{41}}{4} \), \( V_{(t+1)} - V_{(t+1)} > 0 \). Since \( k \geq 1 \), adopting the “+ trading rule” tends to reduce the total trading volume. Intuitively, the “+ trading rule” imposes an upper-limit for the strategic trader to manipulate the price, thus inducing less trading.
5.2. Price volatilities

We use \( P_{\text{max}} - P_{\text{min}} \) to measure the price volatility, where \( P_{\text{max}} \) and \( P_{\text{min}} \) are the maximum and minimum prices in day 1, respectively.

Under the “\( T+1 \) trading rule”, the strategic trader has two equilibrium trading strategies. It is easy to check that these two strategies actually yield the same price volatility measured by \( P_{\text{max}} - P_{\text{min}} \). Without loss of generality, we consider only the case where \( g \lambda > 1 \). Under this scenario, the price rises in periods 1 and 2 and falls in periods 3 and 4. The maximum price must be \( P_2 \) and the minimum price can be \( D_0 \) or \( P_4 \). We have \( P_2 = D_0 + \lambda (\frac{g \lambda + 1}{2}) X_0 \) and \( P_4 = D_0 + \lambda (\frac{g \lambda + 1}{2}) X_0 \), when \( g \lambda > 3 \), \( P_4 > D_0 \), \( \min(D_0, P_4) = D_0 \).

\[
\sigma(T+1) = |P_2 - D_0| = \frac{\lambda (g \lambda + 1)^2}{4} X_0.
\]

When \( g \lambda < 3 \), we have \( P_2 < D_0 \), \( \min(D_0, P_4) = P_4 \).

\[
\sigma(T+1) = |P_2 - P_4| = \lambda X_0(1 + g \lambda).
\]

Under the “\( T+0 \) trading rule”, \( P_2 = D_0 + \lambda (g \lambda + 1) X_0 \), \( P_4 = D_0 + \lambda (\frac{1}{2} + \frac{1}{4} g \lambda) (1 + g \lambda) X_0 < D_0 \), so the price volatility is:

\[
\sigma(T+0) = |P_2 - P_4| = \lambda (g \lambda + 1) X_0 - \lambda \left( \frac{1}{2} + \frac{1}{4} g \lambda \right) (1 + g \lambda) X_0
\]

\[
= \lambda \left( \frac{1}{2} + \frac{3}{4} g \lambda \right) (1 + g \lambda) X_0.
\]

Simple calculation yields that:

when \( g \lambda > 3 \),

\[
\sigma(T+0) - \sigma(T+1) = \frac{1}{4} \lambda (g \lambda + 1) (g \lambda - g \lambda + 3 k + 1) X_0 > 0;
\]

and, when \( g \lambda < 3 \),

\[
\sigma(T+0) - \sigma(T+1) = \frac{1}{4} \lambda (g \lambda + 1) (g \lambda - 2 + 3 k) X_0 > 0.
\]

Therefore, we find that the “\( T+1 \) trading rule” reduces the price volatility relative to the “\( T+0 \)” rule when the strength of trend-following is strong.

5.3. Welfare

In this section, we compare both the strategic trader and trend chasers’ welfare under two trading rules. Given the results presented in Tables 1 and A.1 in Appendix A, it is easy to see that when \( 0 < g \lambda < 1 \) the strategic trader’s expected utilities under the two scenarios are the same. We next consider the case that \( g \lambda > 1 \), where

\[
U_{(T+1)} - U_{(T+0)} = \frac{(g \lambda)^2 + 2g \lambda - 7}{8} X_0^2
\]

\[
- k(g \lambda - 1)(g \lambda + 7 k + 4) - 4 \frac{X_0^2}{8}
\]

\[
= -\frac{1}{8} (g \lambda - 1)(g \lambda + 7 k - g \lambda - 3) X_0^2.
\]

When \( k \gg 1 \), we have:

\[
U_{(T+1)} < U_{(T+0)}.
\]

Thus the strategic trader is better off under the “\( T+0 \) trading rule” when \( k \gg 1 \). Intuitively, the strategic trader can manipulate prices to a larger extent without constraints on the maximum quantities she can sell.

With regard to trend chasers, we measure their welfare by their expected trading profit. Under the “\( T+1 \) trading rule”, the trend chasers’ welfare is given by:

\[
W_{(T+1)} = E(D - P_2) \left( \frac{g \lambda + 1}{4} \right) X_0 + (P_4 - D_0) g \lambda X_0
\]

\[
= -\lambda \left( \frac{g \lambda + 1}{4} \right) X_0 \left( \frac{g \lambda + 1}{4} \right) X_0 + \lambda \frac{g \lambda^2}{4} - 2 g \lambda - 3 \frac{X_0 g \lambda X_0}{4}
\]

\[
= -\frac{1}{16} g \lambda (1 + g \lambda) (g \lambda^2 - 2 g \lambda + 13) X_0^2.
\]

Under the “\( T+0 \) trading rule”, the trend chasers’ welfare is given by:

\[
W_{(T+0)} = (D_0 - P_2) g \lambda k X_0 + (P_4 - D_0) \left( \frac{1}{2} X_0 + \frac{(g \lambda + 3) X_0}{4} \right) g \lambda
\]

\[
= -\frac{1}{16} g \lambda^2 (1 + g \lambda) (g \lambda^2 - 3 g \lambda + 4 k + 13 k^2 + 4) X_0^2.
\]

The difference between trend chasers’ welfare under the “\( T+1 \)” and “\( T+0 \)” mechanisms is given by:

\[
W_{(T+0)} - W_{(T+1)} = -\frac{1}{16} g \lambda^2 (1 + g \lambda) (g \lambda^2 - 3 g \lambda + 4 k + 13 k^2 + 4) X_0^2
\]

\[
+ 2 k g \lambda + 2 g \lambda + 13 k - 9 < 0.
\]

This shows that trend chasers are better off under the “\( T+1 \) trading rule”. In summary, we show that compared with the “\( T+0 \) trading rule”, adopting the “\( T+1 \) trading rule” reduces the total trading volume and the price volatility, and protects the welfare of trend chasers. Intuitively, the “\( T+1 \) trading rule” imposes an upper-bound on the magnitude to which the strategic trader can manipulate prices. As a result, total trading volume, as well as price volatility, decreases and trend chasers benefit from a smaller amount of negative profit from trading under “\( T+1 \)”. The results are summarized in the following proposition.

**Proposition 4.** Compared with the “\( T+0 \) trading rule”, the “\( T+1 \) trading rule” leads to smaller total trading volume, lower price volatility, and higher welfare for trend chasers.

6. Empirical test

In this section, we test the model’s predictions that, when trend-chasing is strong, introducing the “\( T+1 \) trading rule” will reduce both price volatility and total trading volume. In China’s stock market, price manipulation and trend-chasing behavior are very common. Therefore, we expect that the above hypothesis holds. The Chinese stock market is separated into an A-share market and a B-share market. In the A-share market, listed stocks are traded in Chinese currency RMB, while all stock transactions listed in the B-share market are carried out in foreign currencies. The A-share market was introduced in December, 1990 and included only eight stocks. The B-share market was introduced in February 1992.

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8. The volatility measurement with high price minus low price has been widely used by financial professionals. It is also explored in the academic literature, e.g., Garman and Klass (1980).

9. When \( g \lambda < 1 \), these two price volatilities, based on Table 1.
Initially, both markets adopted the "T + 0 trading rule". In January 1995, however, the A-share market abandoned the "T + 0 trading rule" and replaced it with the "T + 1 trading rule". The B-share market adopted the "T + 1 trading rule" in December 2001. We test the predictions in Proposition 4 with data from the B-share market. We understand that we can obtain richer data from the A-share market, but that market switched its trading rule at a time when the Chinese stock market was still quite immature and we are concerned with the quality of the data, so we believe that using data from the B-share market could be the better choice.

For comparison, we include two years of data before and after the switch from the "T + 0 trading rule" to the "T + 1 trading rule", to test our hypotheses. More specifically, our sample consists of daily data of 109 B-share stocks listed on China's B-share market from December 1999 to November 2003. There are 955 trading days included: 479 trading days are under the "T + 0 trading rule" and 476 trading days are under the "T + 1 trading rule". We use $i$ to denote the stock, $i \in [1, 109]$, and $t$ to denote the trading day, $t \in [1, 955]$. Let $V_i(t)$ denote the daily volume of stock $i$ in the number of shares at day $t$. Following our theory, we use $\ln \left( \frac{P_c(t)}{P_c(t-1)} \right)$ as a measure of daily price volatility of stock $i$ on day $t$, where $P_{c,i}$ and $P_{c,i-1}$ are the highest and lowest prices of stock $i$ on day $t$, respectively. Under the "T + 0 trading rule", the average daily trading volume and price volatility for stock $i$ are given by:

$$V_{(T+0)} = \frac{479}{t=1} V_i(t) \quad \text{and} \quad \sigma_{(T+0)}^{\text{high-low}} = \frac{479}{t=1} \sigma_{(T+0)}^{\text{high-low}},$$

where $\sigma_{(T+0)}^{\text{high-low}}$ is stock $i$'s volatility on day $t$, which denotes volatility calculated from $P_{c,i}$ and $P_{c,i-1}$. Similarly, under the "T + 1 trading rule", the average daily trading volume and price volatility for stock $i$ are:

$$V_{(T+1)} = \frac{476}{t=480} V_i(t) \quad \text{and} \quad \sigma_{(T+1)}^{\text{high-low}} = \frac{476}{t=480} \sigma_{(T+1)}^{\text{high-low}}.$$

For robustness, we also use the standard deviation of close-to-close log return series for each stock, to measure the stock's volatility. The return series $r_i(t) = \ln \left( \frac{P_{c,i}(t)}{P_{c,i}(t-1)} \right)$, where $P_{c,i}$ and $P_{c,i-1}$ are stock $i$'s close prices on day $t$ and day $t - 1$, respectively. The volatility under the "T + 0 trading rule" is defined by the sample standard deviation of the return series: $\sigma_{(T+0)}^\text{std} = \sqrt{\frac{1}{t-1} \sum_{t=1}^{479} (r_i(t) - \bar{r}_i)^2}$, where $\bar{r}_i$ is the average of the return series. The volatility under the "T + 1 trading rule" can be defined in a similar way and we denote it as $\sigma_{(T+1)}^\text{std}$.

Denote the differences in trading volume and price volatilities due to the change of trading rule by $\Delta V_i = V_{(T+0)} - V_{(T+1)}$, $\Delta \sigma_{(T+0)}^{\text{high-low}} = \sigma_{(T+0)}^{\text{high-low}} - \sigma_{(T+1)}^{\text{high-low}}$ and $\Delta \sigma_{(T+0)}^{\text{std}} = \sigma_{(T+0)}^{\text{std}} - \sigma_{(T+1)}^{\text{std}}$, respectively. Table 2 presents the summary statistics of $\Delta V_i$, $\Delta \sigma_{i}^{(T+0)}$ and $\Delta \sigma_{i}^{(T+1)}$ for 109 B-share stocks.

### Table 2

<table>
<thead>
<tr>
<th>$\Delta V_i$/shares</th>
<th>$\Delta \sigma_{i}^{(T+0)}$</th>
<th>$\Delta \sigma_{i}^{(T+1)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1,076,723</td>
<td>0.0171</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>1,062,113</td>
<td>0.0038</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.6487</td>
<td>-0.4847</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>6.2444</td>
<td>3.8327</td>
</tr>
<tr>
<td>Min</td>
<td>-2,701,784</td>
<td>0.0045</td>
</tr>
<tr>
<td>5% Qntl.</td>
<td>111,190</td>
<td>0.0105</td>
</tr>
<tr>
<td>25% Qntl.</td>
<td>462,714</td>
<td>0.0146</td>
</tr>
<tr>
<td>50% Qntl.</td>
<td>871,951</td>
<td>0.0177</td>
</tr>
<tr>
<td>75% Qntl.</td>
<td>1,521,220</td>
<td>0.0194</td>
</tr>
<tr>
<td>95% Qntl.</td>
<td>3,224,088</td>
<td>0.0222</td>
</tr>
<tr>
<td>Max</td>
<td>5,254,964</td>
<td>0.0268</td>
</tr>
</tbody>
</table>

10 Wilcoxon Signed Rank test is a nonparametric test, commonly used to compare two sample medians without the assumption of the distribution.
Denote $V_{T+1,T:0} = \ln \left( \frac{VT}{T0} \right)$. We further decompose $V_{T+1,T:0}$ into the part which can be explained by the change in the trading rule and explained by the increase in the number of shareholders, $NS_{T+1,T:0} = \frac{NST_{+1}}{NST_{0}}$, which is a proxy variable for the “Opening-up” policy. This decomposition is in line with the spirit of our above empirical analysis and separates the effects of the change of trading rule and the “Opening-up” policy. Following this logic, we conduct the following regression:

$$V_{T+1,T:0} = \alpha + \beta NS_{T+1,T:0}. \quad (23)$$

Note that $V_{T+1,T:0}$ is the logarithm of $\frac{VT}{T0}$, thus if we can reject the null hypothesis of “$H_0: \beta = 0$”, then we can conclude that volume under the “$T+1$ trading rule” is smaller. Thus the constant $\alpha$ measures the effect of the change from “$T+0$” to “$T+1$” and $\beta$ measures the effect of the “Opening-up” policy. Similarly, we define

$$\sigma_{\text{high-low}}^{T+1,T:0} = \ln \left( \frac{\sigma_{\text{high-low}}^{T+1}}{\sigma_{\text{high-low}}^{T+0}} \right) \quad \text{and} \quad \sigma_{\text{std}}^{T+1,T:0} = \ln \left( \frac{\sigma_{\text{std}}^{T+1}}{\sigma_{\text{std}}^{T+0}} \right).$$

We have the following two regressions:

$$\sigma_{\text{high-low}}^{T+1,T:0} = \alpha + \beta NS_{T+1,T:0}, \quad (24)$$

$$\sigma_{\text{std}}^{T+1,T:0} = \alpha + \beta NS_{T+1,T:0}. \quad (25)$$

To further check the robustness, we also carry out our regression for different time horizons. We estimate our models using samples within one-year and two-year observations, and before and after the switching of trading rules, respectively. We present the results in Table 6.

Table 6 shows that the constant terms are significant at the 5% significance level. A one-sided t-test can reject the null hypothesis of “$H_0: \beta \geq 0$” at the 5% significance level. Thus we can confirm that volumes and volatilities are all smaller under the “$T+1$ trading rule” than under the “$T+0$ trading rule” after controlling for the effect of the “Opening-up” policy.

It is worth noting that in Table 6, the coefficient of $NS_{T+1,T:0}$ is negative but not significantly different from zero. This coefficient measures the contribution of the “Opening-up” policy to volume and volatility, which is driven by two offsetting effects. On the one hand, the “Opening-up” policy brings more rational investors to the B-share market. Competition among rational investors makes intentional manipulation less effective. As a result, the trading volume and price volatility tend to decrease. The reduction in trading volume and volatility is consistent with the argument that more rational speculators stabilize asset prices, which dates back to Friedman (1953).11 Tirole (1982) also shows that price bubbles rely on the myopia of traders and that they disappear if traders are all rational. On the other hand, the “Opening-up” policy introduces more irrational trend chasers to the B-share market as well, which leads to stronger trend-chasing (a larger $g$). As shown in Sections 5.1 and 5.2, both trading volume and price volatility are positively related to $g$. Hence, volume and volatility tend to increase. Our empirical results indicate that in China’s B-share market, these two effects roughly offset each other, though the first effect is weakly stronger than the second one. As the coefficient is not significantly different from zero, this negative coefficient should not be overly emphasized.

7. Conclusion

China’s stock market adopts a unique “$T+1$ trading rule”: an investor is only allowed to sell stocks he bought at least one day prior, and is forbidden to sell stocks he bought during the same day. In this paper, we develop a dynamic price manipulation model to analyze the effects of the “$T+1$ trading rule” in terms of trading

11 See also Shleifer and Vishny (1997).
Table 3
Results of Wilcoxon Signed Rank test.

<table>
<thead>
<tr>
<th>Sample periods</th>
<th>Trading volume ((V))</th>
<th>Price volatility ((\sigma_{\text{high-low}}))</th>
<th>Price volatility ((\sigma_{\text{imp}}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 year 2 years</td>
<td>1 year 2 years</td>
<td>1 year 2 years</td>
</tr>
<tr>
<td>Test statistics</td>
<td>8.84 8.42</td>
<td>9.06 7.85</td>
<td>8.83 8.83</td>
</tr>
<tr>
<td>P-value</td>
<td>2.2e−16 2.2e−16</td>
<td>2.2e−16 2.2e−15</td>
<td>2.2e−16 2.2e−16</td>
</tr>
</tbody>
</table>

Table 4
Results of test for the sample after “Opening-up” policy.

<table>
<thead>
<tr>
<th>Sample periods</th>
<th>Trading volume ((V))</th>
<th>Price volatility ((\sigma_{\text{high-low}}))</th>
<th>Price volatility ((\sigma_{\text{imp}}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sample 1 Sample 2</td>
<td>Sample 1 Sample 2</td>
<td>Sample 1 Sample 2</td>
</tr>
<tr>
<td>Test statistics</td>
<td>8.26 8.88</td>
<td>8.71 9.06</td>
<td>7.98 8.81</td>
</tr>
<tr>
<td>P-value</td>
<td>2.2e−16 2.2e−16</td>
<td>2.2e−16 2.2e−15</td>
<td>2.2e−15 2.2e−16</td>
</tr>
</tbody>
</table>

Table 5
Summary statistics for \(N_{570-9}\) and \(N_{571+}\).

<table>
<thead>
<tr>
<th>Sample periods</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average number of shareholders under “(T + 0)’’</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 years</td>
<td>4.67e+4</td>
<td>4.65e+4</td>
<td>4.88e+3</td>
<td>2.61e+5</td>
</tr>
<tr>
<td>1 year</td>
<td>5.09e+4</td>
<td>4.95e+4</td>
<td>5.13e+3</td>
<td>2.69e+5</td>
</tr>
<tr>
<td>Average number of shareholders under “(T + 1)’’</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 years</td>
<td>5.67e+4</td>
<td>4.78e+4</td>
<td>1.06e+4</td>
<td>2.65e+5</td>
</tr>
<tr>
<td>1 year</td>
<td>5.77e+4</td>
<td>4.90e+4</td>
<td>1.01e+4</td>
<td>2.73e+5</td>
</tr>
</tbody>
</table>

Table 6
Estimation results.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>2 years</th>
<th>1 year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression (23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>−0.6566**</td>
<td>−1.1131**</td>
</tr>
<tr>
<td>(\beta)</td>
<td>−0.2810</td>
<td>−0.2540</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.0512</td>
<td>0.0260</td>
</tr>
<tr>
<td>Regression (24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>−0.4378**</td>
<td>−0.3149**</td>
</tr>
<tr>
<td>(\beta)</td>
<td>−0.0404</td>
<td>−0.0730</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.0194</td>
<td>0.0206</td>
</tr>
<tr>
<td>Regression (25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>−0.4589**</td>
<td>−0.3672*</td>
</tr>
<tr>
<td>(\beta)</td>
<td>−0.0275</td>
<td>−0.0594</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.0031</td>
<td>0.0095</td>
</tr>
</tbody>
</table>

* We have tested our models for heteroskedasticity by using White test at the 1% level of significance. In regression (23), we find the evidence of heteroskedasticity during the 2-year sample period. For volatilities, we find that there is no heteroskedasticity in regression (24) and there is heteroskedasticity in regression (25) during both sample periods. For the cases when there is heteroskedasticity, we use the HC3 estimator (Huber, 1967 and White, 1980) for efficient estimation of coefficients’ covariance matrix. For all of the models under both sample periods, we can reject the null hypothesis of “\(H_0: \alpha = 0\)” at the 5% level of significance by a one-sided t-test.

** 5% Level of significance.

* 1% Level of significance.

volume, price volatility, and investors’ welfare. We compare it with the usual “\(T + 0\) trading rule” adopted by all other equity markets, with respect to the above three aspects.

We show that the “\(T + 1\) trading rule” can effectively reduce the total trading volume and price volatility, and improves the trend chasers’ welfare compared with the “\(T + 0\) trading rule”; when the strength of trend-chasing is strong. An empirical test with data from China’s B-share market strongly supports our theory.

Acknowledgements

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Appendix A. Proof of Proposition 2

Step 1. We first consider the case where \(-X_0 \geq \bar{X}\). In this case, we have a boundary solution, i.e., \(\bar{X} = \max\{-X_0, \bar{X}\} = -X_0\). Since \(-X_0 - \bar{X} = -\frac{1}{2}X_0 + \frac{1}{2}X + \frac{1}{4}X \geq 0\), we thus have \(X \geq \frac{2}{3}X_0\).

Substituting \(\bar{X} = -X_0\) into (17) yields:

\[
\max \left\{ -2X^2 + \left(\bar{X} + 1\right)X \right\} = \left(\bar{X} + 1\right)X \\
\left(\bar{X} + 1\right)X \geq -X_0. \quad (26)
\]

The first-order condition gives:

\[
X^* = \frac{\bar{X} + 1}{4}X_0. \quad (27)
\]

Similar to the period 3 problem, we have the period 1 solution \(X^* = \max\{X, \frac{1}{2}X_0^2\}\).

We then solve the case where \(-X_0 \leq \bar{X}\). In this case, we obtain:

\[
\bar{X} = \max\{-X_0, \bar{X}\} = \bar{X} = \frac{1}{2}X_0 - \frac{1}{4}X + \frac{1}{4}. \quad (28)
\]

Plugging Eq. (28) into (17) yields:

\[
\max X \left\{ \frac{1}{2}(\bar{X} + 7)(\bar{X} - 1)X^2 + \frac{1}{2}(\bar{X} - 1)X_0X - \frac{1}{2}X_0^2 \right\} \\
\left(\bar{X} + 1\right)X \geq -X_0. \quad (29)
\]

The first-order condition gives:

\[
X = -\frac{2}{3}X_0. \quad (30)
\]
Whether (30) is optimal depends on the sign of the second-order derivative, i.e., the sign of $SO_X = \frac{1}{2} (g \lambda + 7)/(g \lambda - 1)$. Plugging Eq. (28) into $-X_0 < X$ yields:

$$-X_0 - \frac{2}{\lambda} X_0 + \frac{(g \lambda + 3) X_0}{4} < 0.$$ 

Rearrangement gives:

$$X \leq \frac{2}{g \lambda + 3} X_0. \quad (31)$$

For the case where $-X_0 \leq X$, we also need to consider two subcases as well. The first subcase is $g \lambda < 1$. Since $SO_X < 0$, the object function (29) is quadratic and concave. Because $-X_0 \leq \frac{-2}{g \lambda + 3} X_0 \leq \frac{2}{g \lambda + 3} X_0$, the optimal solution is $X^* = -\frac{2}{g \lambda + 3} X_0$. For the second subcase where $g \lambda > 1$, the object function is quadratic and convex. Thus, it is maximized at either $-X_0$ or $\frac{2}{g \lambda + 3} X_0$. Plugging $-X_0$ or $\frac{2}{g \lambda + 3} X_0$ into Eq. (29) shows that $X^* = -X_0$ is the optimal solution. Therefore, we can summarize the above results obtained in Step 1 in the following lemma.

**Lemma 1.** If $-X_0 \geq X$, then $X^* = \max \left\{ \frac{g \lambda - 1}{g \lambda + 3} X_0, -\frac{2}{g \lambda + 3} X_0 \right\}$; if $-X_0 < X$ and $g \lambda < 1$, then $X^* = -\frac{2}{g \lambda + 3} X_0$.

**Step 2.** Lemma 1 gives only intermediate results for the strategic trader’s optimal trading strategy. We next obtain the equilibrium results by comparing the expected utility of wealth for the strategic trader in the cases of $-X_0 < X$ and $-X_0 \geq X$. Simple calculation leads to the following summary table.

**Table A.1** presents the strategic trader’s optimal trading quantities in periods 1 and 3 and the corresponding expected utilities in two cases. From this table, it is easy to derive the final equilibrium trading strategy for the strategic trader. When $g \lambda > 1$, the expected utilities for the cases $X > -X_0$ and $X \geq -X_0$ are the same. Therefore, the optimal trading quantity of the strategic trader in period 1 is not unique. It is given by either $X^* = -\frac{2}{g \lambda + 3} X_0$ or $X^* = -X_0$. Correspondingly, her optimal trading quantity in period 3 is given by either $X^* = -X_0$ or $X^* = -\frac{2}{g \lambda + 3} X_0$. When $0 < g \lambda < 1$, comparing the expected utilities between the two cases yields:

$$\frac{-(g \lambda + 3) X_0}{g \lambda + 7} - \frac{(g^2 \lambda^2 + 2 g \lambda - 11) X_0^2}{(g \lambda + 3)^2} = -\frac{2}{g \lambda+1} \frac{(1 - \lambda^2)(5 + \lambda \lambda)}{(g \lambda + 3)^3} > 0.$$ 

Therefore, the strategic trader’s optimal trading quantities in periods 1 and 3 are given by:

$$X^* = X_0 = \frac{-2X_0}{g \lambda + 7}.$$

### Table A.1

<table>
<thead>
<tr>
<th>$g \lambda &gt; 1$</th>
<th>$g \lambda &lt; 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X^* \geq X$</td>
<td>$X^* = -X_0$</td>
</tr>
<tr>
<td>$X_0$</td>
<td>$-\frac{2}{g \lambda + 3} X_0$</td>
</tr>
<tr>
<td>$EU_1$</td>
<td>$-\frac{2}{g \lambda + 3} X_0$</td>
</tr>
</tbody>
</table>

Note: $EU_1$ is the expected utility in period 1.

### References


