What Drives Intraday Reversal? Illiquidity or Liquidity Oversupply?

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January 15, 2022

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Acknowledgement: The authors would like to thank Hui Chen, Xu Feng, Bin Guo, Xue-Zhong He, Conghui Hu (discussant), Jianfeng Yu, Wei Zhang and seminar participants at Tianjin University, Sun Yat-sen University, 2019 Chinese Finance Annual Meeting, 2019 China Financial Research Conference for helpful comments and discussions. Part of this work is done by Shen Lin when he is a post-doctoral researcher in PBC School of Finance, Tsinghua University. This work is supported by the National Natural Science Foundation of China (No.71903107, No.71790594) and China Postdoctoral Science Foundation (No.2019T120075). Shen Lin gratefully acknowledges a research grant from Research Centre for Asset Management at PBC School of Finance of Tsinghua University.

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Abstract

Previous studies of the U.S. market regard short-term reversal as compensation for liquidity provision. However, we find that intraday reversal has no significant dependence on stock liquidity in the Chinese market. Hence, based on a stylized framework, we propose an alternative explanation: irrational uninformed liquidity providers, who underestimate the information component in the equilibrium price due to physiological anchoring, trade against previous price movement, which generates an opposing price pressure. The empirical results confirm this explanation of liquidity oversupply (from irrational uninformed liquidity providers). The negative correlation between previous intraday returns and future returns in the Chinese market is reversed once we extend the holding period. This indicates that reversal is a pricing error due to excessive liquidity provision from uninformed retail traders instead of a price correction from a temporary price concession due to a lack of liquidity.

Keywords: Intraday reversal; liquidity; Chinese market

JEL: D82, G12, G14; G41

1 Introduction

Numerous studies have shown that short-term return reversal is both robust and economically significant.[1] An illiquidity-based explanation that a price reversal serves as risk compensation for investors who provide liquidity has received considerable attention in the literature.[2] Indeed, in the U.S. market, we find that the returns of illiquid stocks[3] are more likely to reverse than those with greater liquidity. For instance, when sorting all stocks into equal-weighted portfolios based on previous intraday return (PIR) and market capitalization, the difference between the sequential intraday return spread (returns of the high PIR portfolio minus those of the low PIR portfolio) for the most liquid stocks and that for the most illiquid stocks is 39.9 basis points (BPs) per day, with a t-statistic equal to 15.6. Our results are therefore complementary to the findings in Avramov et al. (2006), Nagel (2012), Da et al. (2014) and suggest that liquidity shocks are particularly

[1] See Jegadeesh (1990) and Lehmann (1990), for example. Numerous studies have found that stocks that are winners in a given short-term period tend to significantly underperform stocks that are losers in that same period using various different time frequencies and being considered in both the time-series and cross-section. As shown in Jegadeesh (1990), a zero-position strategy long on the bottom decile and short on the top decile of last month's return can earn a 2.49% monthly return. Since this seminal work, financial economists have extended research on reversal to various short horizons, such as weekly (Lehmann (1990), Avramov et al. (2006)) or daily (Cox and Peterson (1994), Bremer and Sweeney (1991)).

[2] Avramov et al. (2006) find that profits from the standard reversal strategy profits mainly derive from positions in small, low-turnover, and illiquid stocks; Da et al. (2014) report that the reversal profit is attributable to liquidity shocks on the long side because fire sales are more likely to demand liquidity, and Pástor and Stambaugh (2003) suggest directly measuring the degree of illiquidity by the occurrence of an initial price change and subsequent reversal.

[3] Measured by market capitalization, share turnover, or the Amihud (2002) illiquidity measure.

relevant to cross-sectional intraday return reversal.

Although the U.S. market has some of the world's largest stock exchanges and most liquid stocks, the adequate provision of liquidity is concentrated among the largest and most liquid firms (see Figure 3 for further details). Unlike the classical institutional investor-dominated structure in Western countries, the Chinese stock market is characterized by a majority of retail traders, most of whom trade frequently and lack sophisticated financial education backgrounds.[4] However, the market liquidity for small, high turnover and illiquid stocks in the U.S., from which standard reversal strategy profits mainly derive, is lower than that in the Chinese market. Hence, this paper attempts to provide insight into the following questions: Is there intraday reversal in the Chinese market considering the above observations indicating excessive liquidity supply? What drives this intraday reversal if intraday reversal does not depend on stock liquidity?

To start the analysis, Section 2 presents a stylized framework showing how a return reversal can occur as the result of either a lack of liquidity or excessive liquidity provision (from irrational uninformed liquidity providers).[5] The baseline framework provides

[4]For instance, by applying data from October 2003 to March 2004, Bailey et al. (2009) find that individual investors accounted for 92% of the trading volume in 198 large Chinese stocks. Moreover, according to the China Security Industry Development Report (2012), by the end of 2012, the trading of retail investors accounted for more than 99.63% of total trading volume. Those retail traders, who on average were over 50 years old and had a low level of education, are vulnerable to behavioral biases and often differ in their beliefs about a stock's fundamental value, resulting in excessive trading (e.g., Seasholes and Wu (2007), Mei et al. (2005), Xiong and Yu (2011), Pan et al. (2016)).

[5]We want to emphasize that we refer liquidity provision from irrational uninformed traders when mentioning liquidity oversupply. In an extreme case without frictions in the market, there should be no liquidity concerns, but one may not argue there is oversupplied liquidity. Of cause, there is no reversal in that situation.

insight into the illiquidity-based explanation and focuses on two market participants: 1) an informed speculator who demands liquidity with exogenous intensity and 2) a market maker who provides liquidity based on the aggregate order flow and his or her own risk attitude. Informed trades lead to a temporary price concession that, when absorbed by market maker, results in a reversal in price that serves as compensation for liquidity provision. In contrast, the extended stylized framework focuses on the liquidity oversupply explanation and introduces a new type of trader: irrational uninformed liquidity providers, such as retailed investors in the Chinese market, who underestimate the information component in the equilibrium price due to physiological anchoring. These additional traders irrationally trade against the previous price movement, which creates opposing price pressure at the intraday level and forms a return reversal pattern.[6]

A natural question follows: do illiquidity-based and liquidity oversupply explanations play different roles in driving intraday return reversal? We recognize that under each explanation, the reversal plays a different role in the return dynamics, either the correction of a temporary price concession due to a lack of liquidity (illiquidity-based explanation) or a pricing error due to excessive liquidity from irrational uninformed retail traders who underreact to news (liquidity oversupply explanation). Hence, future returns should also respond differently based on these two explanations. Within the liquidity oversupply

[6]The irrational uninformed liquidity providers play the similar role as that of contrarians in the heterogeneous agent models (HAMs). For example, He and Li (2015) study the interactions of fundamentalists, momentum traders, and contrarians in a nonlinear HAM. With bounded rationality, contrarians trade against previous price movement, and the resultant price pressure can lead to return reversal. However, the economic channels are different: our paper explores an information channel that endogenously causes liquidity providers to trade against prices, while the trading behaviors are directly determined by contrarian expectations in He and Li (2015) who highlight the expectations feedback.

framework, we would expect the negative correlation between previous intraday returns and future returns to subsequently reverse. Instead, if the reversal is a correction of a temporary price concession from a lack of liquidity, there is no economic reason for a resilience pattern to exist after the reversal period.

Next, we combine several common datasets from the literature, described in Section 3, to test the model predictions and draw further conclusions on the forces driving intraday reversal. First, we find that a significant cross-sectional intraday reversal pattern exists in the Chinese market, i.e., subsequent intraday returns (i.e., SIR) are negatively predicted by PIR. For instance, at the representative timing of 10:00 a.m. each day, an equal-weighted standard reversal strategy earns a return of 44 BPs in China after controlling for a basic possible bid-ask bounce and extreme liquidity shock. As a robustness check, by applying the Fama-MacBeth (1973) regression, the intraday predictive ability of PIR persists when we control for several famous return predictors.

Second, our empirical results for the Chinese market speak against illiquidity-based explanations. We sort all stocks into portfolios based on PIR and each of three liquidity measures (market capitalization, share turnover and the illiquidity measurement of Amihud (2002)) featured in the literature. Compared to U.S. market, liquidity has a much smaller impact on intraday reversal in the Chinese market. The difference between the SIR spread for the most liquid stocks and that for the most illiquid stocks is only 10.2, 3.4 and 9.8 BPs for the three different liquidity measures. This departure mainly derives from the SIR spreads for the most liquid group. In particular, for the most liquid group, the spreads are still above 24 BPs (-25.5, -31 and -34.3 BPs, respectively), which are much higher than those in the U.S. market. These observations indicate that the automatic application of illiquidity-based explanations should be viewed with suspicion.

Third, we investigate how the return spread between PIR portfolios responds across different holding periods for holding periods of up to 20 days. Indeed, consistent with the prediction from the liquidity oversupply explanation, for the Chinese market, the negative correlation between the PIR and the future daily return is reversed after the intraday period. For instance, for equal-weighted portfolios in the Chinese market, high-PIR stocks outperform low-PIR stocks by 26.1 BPs on the first day after reversal, with a t-statistic equal to 8.5. Thereafter, the high-PIR stocks continuously outperform the low-PIR stocks from the second day until the fourth day by 4.3, 8.3, and 5.5 BPs, respectively. As a robustness check, we also provide the results for the U.S. market, which show that only a nonsignificant negative correlation between PIR and the future return exists following the intraday period. For instance, in U.S. market for equal-weighted portfolios, high-PIR stocks underperform low-PIR stocks by 2.2 BPs on the second day after reversal, with a t-statistic equal to -1.5. Thereafter, the high-PIR stocks continuously underperform low-PIR stocks for up to 10 days. These results speak for the illiquidity-based explanation.

To summarize, the paper analyzes the cross-sectional intraday return patterns between the Chinese and U.S. markets and further studies the driving forces of each of them. Several recent studies focus on a similar intraday return pattern or highlight similar results. It is worth emphasizing that the underlying mechanisms are different, thus leading to contrasting testable implications:

1) Through the lens of institutional investors behavior, Baltussen et al. (2021) and Gao et al. (2018) document intraday momentum price patterns and address the driving forces behind them. Although resulting from different reasons (i.e., speculative trading or hedging trading), the market swings are both due to institutional trading

in these two papers. Baltussen et al. (2021) note that market makers for products with gamma exposure, such as options and leveraged ETFs, are commonly net short these products. Consequently, they have to buy additional securities when prices are rising and sell when prices are falling to ensure that their positions are delta-neutral. Instead, Gao et al. (2018) show that, under the infrequent rebalancing explanation, some institutional investors effectively choose to rebalance their portfolios in the first half hour while others do so in the last half hour. Rebalancing in the same direction can thus generate intraday momentum. Our paper focuses on the trading behavior of uninformed retail investors, which leads to intraday reversal pattern.

2) By contrast, Berkman et al. (2012) and Qiao and Dam (2020) study the intraday reversal pattern from the perspective of retail trading. Berkman et al. (2012) argue that retail investors tend to buy stocks that attracted their attention at the open. Hence, this buying pressure results in high overnight returns followed by intraday reversals. Qiao and Dam (2020) propose the "T+1" rule as the reason for the systematic differences in the overnight returns between the U.S. and Chinese markets. T+1 trading prohibits traders from selling shares they bought on the same day. This restriction leads to a discount on daily opening prices. However, Berkman et al. (2012) can only provide an explanation for the short-side reversal profit while Qiao and Dam (2020) only provides insight for the long-side reversal profit. Our paper instead documents significant returns for both the long and short sides of reversal strategy.

3) Although the focuses are different, the results of both Lou et al. (2019) and Hendershott et al. (2020) could generate an intraday return for both the long and short sides. Lou et al. (2019) show that firm-level intraday (overnight) returns positively

predict future intraday (overnight) returns but negatively predict future overnight (intraday) returns. They link this "tug of war" between overnight and intraday returns to institutions trading at the end of the day and retail investors trading at the beginning of the day. Hendershott et al. (2020) show that stock returns are positively related to beta overnight, whereas returns are negatively related to beta during the trading day. However, neither paper documents the "reversal of the reversal" that we demonstrate in this study. Hence, we provide novel evidence that reversal in the Chinese market is a pricing error due to excessive liquidity provision by uninformed retail traders instead of a price correction from a temporary price concession due to lack of liquidity.

Ultimately, we offer a fresh perspective on intraday return reversal. In the process, we make several contributions. First, we provide the first study comparing cross-sectional intraday reversals in the U.S. and Chinese markets, offering a unique contribution to the expansive literature on intraday price patterns (Jegadeesh (1990), Lehmann (1990), Bremer and Sweeney (1991), Cox and Peterson (1994), Avramov et al. (2006)). Second, in addition to the illiquidity-based explanation, this paper proposes an alternative mechanism, that is, liquidity oversupply, thereby providing new insights into intraday reversal. While numerous studies have explored the profitability of such contrarian strategies (Avramov et al. (2006), Nagel (2012), Da et al. (2014)), a complete understanding of what drives reversal profits remains unclear. We hence shed some new light on the economic drivers of intraday reversal profits. Finally, this paper offers the novel discovery that liquidity oversupply is the driving force for intraday reversal in the Chinese market. Many aspects of the Chinese economy are shared by other developing and developed countries, and thus, the insights from papers on China may be applicable to them.

The reminder of the paper is organized as follows. Section 2 presents a stylized framework. Section 3 describes the data sources and summary statistics. Section 4 discusses our main result on intraday reversal and several possible driving elements. Section 5 concludes the paper.

2 Conceptual Framework

In this section, we describe the economic foundation for our work. First, we analyze how illiquidity yields a reversal pattern as suggested by the majority of the literature. Second, we extend the baseline framework by introducing an additional layer of liquidity provision from uninformed liquidity providers. We show that this alternative mechanism could also lead to return reversal. Note that we do not provide a full theoretical model but instead illustrate the key elements bolstering our empirical tests. This stylized framework helps us to identify two different mechanisms that could lead to intraday reversal forces.[7]

2.1 Baseline Stylized Framework: Illiquidity-Based Explanation

Asset and agents: There is a risky asset and a risk-free numéraire. At the end of the game, each unit of the risky asset will pay off v units of the numéraire. Unconditionally, v is normally distributed with mean p_0 and variance $1/\tau(>0)$. Liquidity takers, informed traders and exogenous liquidity consumers, and the liquidity provider, the market maker, trade at time $t = 1$.

[7]This conceptual framework is self-contained and is designed to capture important trading details and to guide the empirical analysis. It is not intended to exactly generate all the specific empirical specifications or to provide comprehensive pricing implications for intraday reversal.

Liquidity takers: There is a unity continuum of speculators, indexed by $i \in [0, 1]$, who are informed traders. They are born with a noisy signal s_i about the fundamental with fixed precision $\tau_\epsilon : s_i = v + \epsilon_i$, where ϵ_i are *i.i.d.* normal with zero mean and variance $1/\tau_\epsilon (> 0)$. Informed traders submit market orders—that is, they cannot condition their demand on the price in the current trading round, similar to Kyle (1985). As a result, the demand function of the representative informed trader is [8]

$$y_i = \beta s_i \tag{1}$$

where β is increasing in the aggregate risk-bearing capacity of informed traders and decreasing in the level of risk they perceive and the price impact that they expect to have in aggregate. Here, the parameter β is exogenously given.[9] In addition to the informed traders, there are also exogenous liquidity consumers demanding liquidity with z_1, which is *i.i.d.* normal with zero mean and variance $1/\tau_z (> 0)$. Hence, the aggregate market order imbalance is:

$$w_1 = \int_0^1 \beta s_i di + z_1 = \beta v + z_1 \tag{2}$$

Liquidity provider: There is a representative liquidity provider who trades a share m of risky asset to maximize his or her expected payoffs subject to quadratic trading costs,

[8]It it very difficult to explicitly incorporate trading cost for liquidity takers in our model. Even though trading cost is widely considered as an important factor for short term reversal, our focuses are on liquidity oversupply and we did not investigate the effects of liquidity takers' trading costs. However, for the liquidity providers, we actually take these costs into consideration as indicated by the equation (3) and discussions afterwards.

[9]This can be justified, as the informed traders are passive funds or have a predesigned trading strategy. The model is self-contained and is designed to capture important trading details and to guide the empirical analysis. It is not intended to exactly generate all the specific empirical specifications or to provide comprehensive pricing implications for intraday reversal.

as in Banerjee et al. (2018),

$$\max_{m} E[m(v - p_1)|\mathcal{M}] - \frac{1}{2\gamma}m^2 \tag{3}$$

where $\mathcal{M}$ denotes the market maker's information set, which includes prices and order imbalances. To distinguish this actor from the uninformed liquidity providers introduced in next subsection, we call this liquidity provider the market maker. Hence, the liquidity provider's demand function can be described as

$$m = \gamma_m(E[v|\mathcal{M}] - p_1). \tag{4}$$

The slope of demand, γ_m, captures the aggressiveness with which the market maker supplies liquidity. One the one hand, the parameter γ_m reflects the risk attitude of the liquidity supplier. With a lower γ_m, the liquidity supplier has a higher perception of risk. This could be increasing in the risk-bearing capacity of the market-making and decreasing in the level of risk.[10] On the other hand, more directly, the parameter γ_m reflects the trading cost for the liquidity providers. As indicated by equation (3), a lower γ_m means a higher cost for supplying liquidity. We relate the influence of trading costs to intraday reversal in Online Appendix 5.

[Insert Figure 1 here]

Timeline: There are three dates in the model: $t \in [0, 1, 2]$, illustrated in the upper panel of Figure 1. At $t = 0$, the equilibrium asset price is the prior p_0 of the fundamental asset. At $t = 1$, all informed speculators arrive together, and they independently submit

[10] More generally, margin constraints, as in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009), or risk management constraints, as in Adrian and Shin (2010), effectively induce risk-averse behavior.

demand schedules y_i to trade the risky asset against the market maker based on his or her information set. At $t = 2$, the fundamental is realized, and the price is set as $p_2 = v$.

Proposition 1 *Given any informed trader's trading strategy β, the equilibrium trading price at time $t = 1$ is:*

$$p_1 = \frac{\tau}{\tau + \beta^2 \tau_z} p_0 + \left(\frac{1}{\gamma_m} + \frac{\beta \tau_z}{\beta^2 \tau_z + \tau} \right) w_1.$$

Following Kyle (1985), let parameter λ measure the illiquidity, and it is defined as

$$\lambda = \frac{\partial p_1}{\partial z_1}.$$

Holding the other parameters unchanged, when the parameter λ satisfies

$$\lambda > \hat{\lambda} = \frac{\beta \tau_z}{\beta^2 \tau_z + \tau}. \tag{5}$$

there exists a price reversal, i.e., $cov(p_1 - p_0)(v - p_1) < 0$. Furthermore, the reversal is more significant given a more illiquid market, i.e.,

$$\frac{\partial \left[cov(p_1 - p_0)(v - p_1) \right]}{\partial \lambda} < 0.$$

.

The intuition behind Proposition 1 is straightforward. Due to adverse selection costs, informed trades lead to a temporary price concession. When absorbed by market maker, this results in a reversal in price that serves as compensation for those who provide liquidity. We label this the illiquidity-based explanation and illustrate the intuition in the upper panel of Figure 2. As indicated by Proposition 1, the reversal is more significant in a more illiquid market. This is because that it is more costly to provide liquidity in an illiquid market. One the one hand, the price impact of liquidity takers is higher in the illiquid market; on the other hand, it is more difficult for the market maker to infer fundamental information from the price. Hence, the market maker demands higher compensation, which leads to a more significant reversal pattern.

[Insert Figure 2 here]

2.2 Stylized Framework with Liquidity Oversupply

We extend the baseline framework by introducing an additional layer of uninformed liquidity supply. The framework is similar to that described in Subsection 2.1. Next, we focus on the important departures from the previous discussion. Specifically, in addition to market maker, there is also a μ unity continuum of 'uninformed' liquidity providers. First, they are uninformed because we assume that they do not learn information from concurrent asset prices but instead infer information from previous equilibrium prices. This is because either rapidly obtaining price information is costly or filtering noise in price information is time consuming.[11] Second, as a young and fast-growing market, the Chinese stock market is characterized by a dominance of retail investors, a large amount of trading, relatively binding shortselling constraints, and changing regulations. Hence, we assume that these uninformed liquidity traders trade with a relatively high turnover rate. We next focus on the specific settings for the extended framework.

Timeline: There are four dates in the model, $t \in [0, 1, 1^+, 2]$, illustrated in the bottom panel of Figure 1. At $t = 0$, the equilibrium asset price is the prior p_0 of the fundamental

[11] We do not provide microfoundation for this setup. However, the related evidence can be found, for example in Easley et al. (2016),Kendall (2018) and Dugast and Foucault (2018). Easley et al. (2016) study the differential access to the price information while citekendall2018time and Dugast and Foucault (2018) consider a setup where filtering out noise in information is time-consuming.

asset. At $t = 1$, all liquidity takers arrive together, and they independently submit demand schedules. Informed traders submit $y_i = \beta s_i$ to trade the risky asset based on their information set. Exogenous liquidity consumers submit z_1 units of market orders. Additionally, the market maker submits $m = \gamma_m(E[v|\mathcal{M}] - p_1)$ and uninformed liquidity providers submit $x_{i,1}$. To reflect the large amount of trading and extremely high turnover, we add the time $t = 1^+$. At $t = 1^+$, only uninformed liquidity providers arrive, and they independently submit demand schedules $x_{i,1^+}$ to trade the risky asset based on their information set.

Liquidity oversupply: Similar to the market maker, uninformed liquidity provider trades to maximize his or her expected payoffs subject to quadratic trading costs, as in Banerjee et al. (2018). Hence, the uninformed liquidity providers' demand function at time t is

$$x_{i,t} = \gamma_U(E[v|I_{i,t}] - p_t). \tag{6}$$

where the parameter γ_U reflects the risk attitude of the liquidity suppliers. With a lower γ_U, the liquidity suppliers have a higher perception of risk. The first-period trading provides new information for uninformed liquidity providers. Because we consider an REE-type framework, observing the equilibrium prices is equivalent to knowing the aggregate order flow. When an uninformed liquidity provider can perfectly interpret the price information, he or she forms expectations about fundamentals as

$$E[v|I_{i,1^+}] = \frac{\tau p_0 + \beta \tau_z w_1}{\tau + \beta^2 \tau_z}. \tag{7}$$

However, the Chinese stock market is dominated by irrational retail trading.[12] Using

[12] China has two stock exchanges, both founded in 1990: the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). The market grew quickly, becoming the second-largest equity market in terms of market capitalization at the end of 2011, after only the U.S. Driven by the substantial growth

comprehensive account-level data from SHSE, An et al. (2021) found that the bottom 85% of small retail investors in China lost 30% of their initial equity wealth during the 2014-15 bubble-crash episode. Moreover, with a similar data set, Jones et al. (2021) found that order imbalance of retail investors negatively predicts the future return at the stock level. The combined evidence shows that the trading behaviors of Chinese retail investors is irrational on average. Therefore, we assume that among all the uninformed liquidity providers, a fraction θ of them has a psychological anchor that makes them underreact to new information when inferring equilibrium prices. Specifically, irrational liquidity providers might update their expectations about asset prices based on a representative anchor and, hence, underreact to new information. Based on the new information, the irrational liquidity providers form expectations about fundamentals.

$$E[v|I_{i,1^+}] = \frac{(1+\alpha)\tau p_0 + (1-\alpha)\beta\tau_z w_1}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z}. \tag{8}$$

Within the intraday setup, the previous day's closing price p_0 could be a physiological anchor for investors such that they underestimate the information component in the previous price movement. The parameter α reflects the magnitude of the anchoring effect and, hence, the level of underreaction. In sum, at time $t = 1^+$, the market clearing condition is:

$$\int_0^{\theta\mu} \gamma_U(E[v|I_{i,1^+}] - p_{1^+})di + \int_{\theta\mu}^{\mu} \gamma_U(E[v|I_{i,1^+}] - p_{1^+})di = 0.$$

Based on the above discussion, we have the following Proposition 2.

Proposition 2 *Given any informed traders' trading strategy β, the equilibrium trading*

of Chinese economy, the Chinese stock market experienced dramatic growth during the twenty-first century, especially after the Split-share Structure Reform in 2005.

price at time t = 1 is:

$$p_1 = \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m \tau}{\tau + \beta^2\tau_z} + \mu\gamma_U\right) p_0 + \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m \beta\tau_z}{\beta^2\tau_z + \tau} + 1\right) w_1.$$

The equilibrium trading price at time $t = 1^+$ is:

$$p_{1^+} = \left[\frac{\theta(1+\alpha)\tau}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\tau}{\tau + \beta^2\tau_z}\right] p_0 + \left[\frac{\theta(1-\alpha)\beta\tau_z}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\beta\tau_z w_1}{\tau + \beta^2\tau_z}\right] w_1.$$

When the parameter θ satisfies,

$$\theta > \hat{\theta} = \frac{(\tau + \beta^2\tau_z)(\Phi(\alpha)\tau + \beta^2\tau_z)}{(\Phi(\alpha) - 1))\tau}\left[\frac{\mu\gamma_U}{\tau + \beta^2\tau_z} - \frac{1}{(\gamma_m + \mu\gamma_U)\beta\tau_z}\right]. \tag{9}$$

there exists a price reversal, i.e., $cov(p_1 - p_0)(p_{1^+} - p_1) < 0$ and parameter Φ satisfies $\Phi(\alpha) = (1+\alpha)/(1-\alpha)$. Furthermore, the following predictions i) - iii) hold.

i) Intraday reversal and fraction of irrational traders: the intraday reversal is stronger with more irrational uninformed liquidity suppliers (higher θ).

ii) Intraday reversal and underreaction: the intraday reversal is stronger when irrational traders have a higher level of underreaction (higher α).

iii) Intraday reversal and fundamental risk: the intraday reversal is stronger with higher fundamental risk (lower τ/τ_z).

Furthermore, when conditions (5) and (9) both hold, there is a reversal of the reversal, i.e., $cov(p_{1^+} - p_1)(p_2 - p_{1^+}) < 0$. The following prediction iv) holds.

iv) Under the illiquidity explanation, the PIR should have no predictive power over the subsequent trading days. Under the liquidity oversupply explanation, the PIR should positively predict the subsequent trading days.

Prices in Proposition 2 share a similar structure with those in Proposition 1. However, comparing the equilibrium prices in Proposition 1 and Proposition 2, due to the abundant liquidity supply, the price reacts less to the exogenous liquidity consumption when there are uninformed liquidity providers. This can be reflected as:

$$\frac{\partial p_1}{\partial z_1} = \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m \beta \tau_z}{\beta^2 \tau_z + \tau} + 1\right) = \frac{\gamma_m}{\gamma_m + \mu\gamma_U}\lambda.$$

Hence, the liquidity supply from uninformed liquidity providers improves market liquidity.

Proposition 2 further illustrates that intraday reversal could also occur when there is liquidity oversupply (from irrational uninformed liquidity providers), as indicated by condition (9). Due to the anchoring effect, irrational uninformed liquidity providers trade against previous price movements and create price pressure. When there is liquidity oversupply, i.e., sufficient irrational uninformed liquidity providers (θ is higher), this price pressure is strong enough, which forms an intraday reversal pattern until the anchor is reset when a new closing price is given. We label this second explanation the liquidity oversupply explanation and illustrate the intuition in the bottom panel of Figure 2. [13]

To distinguish these two different mechanisms, from the above analysis, we have empirical prediction iv). We recognize that under each explanation, the reversal plays a different role in the return dynamics, either the correction of temporary price concessions from a lack of liquidity or a pricing error due to excessive liquidity from irrational traders with anchored expectations. Hence, future returns should also respond differently under these two explanations. Specifically, Figure 1 illustrates these two explanations and the different impacts of intraday reversal on future return dynamics. If the reversal is a

[13] Notice that Proposition 2 also shows that with higher trading cost (lower value of γ_U), the intraday reversal should be stronger. This means that trading cost could also be an important impact factor for intraday reversal. We show the influence of trading cost in Chinese market in Online Appendix 5.

pricing error due to excessive liquidity, we would expect there to be a significant resilience pattern for the accumulated return after intraday reversal because mispricing does not persist forever. Hence, the PIR should positively predict returns over the subsequent trading days. Instead, if the reversal is the correction of a temporary price concession from a lack of liquidity, the PIR should either negatively predict returns or have no predictive power over the subsequent trading days.

3 Data and Summary Statistics

3.1 Data and Key Variables

The sample period spans from January 1, 2000, to December 31, 2019, for the Chinese stock market. We mainly use stocks' intraday price data from the Resset database to calculate returns and form portfolios. However, due to the extensive missing observations in Resset before 2002, we additionally use intraday price data from the Wind database. For the Chinese market, we consider all common stocks, the codes of which begin with '60', '30' and '00', traded on the Shanghai Stock Exchange and Shenzhen Stock Exchange as our sample stocks. For the U.S. stock market, stock intraday price data between January 1, 2000, and December 31, 2012, are obtained from the Trade and Quote (TAQ) database. For the U.S. market, our sample includes all common stocks, the share codes of which are '10' or '11' traded on NYSE, AMEX and NASDAQ. We merge intraday price data into 15-minute intervals.[14] Hence, there are 26 observations for every U.S. stock per day

[14]To merge the intraday data into 15 minute intervals, for a given time, we consider the price to be the price of the previous trade.

and 16 observations for every Chinese stock per day.[15]

Some basic requirements are considered for stocks to enter our portfolios, including 1) prices must be equal to or higher than 5 domestic dollars and 2) the stock must have at least 10 nonmissing daily stock returns within the most recent month and have appeared in the corresponding database for longer than 6 months. Although our main predictor is at the daily level, we filter our sample stocks at the beginning of every month based on the latest available data to ensure that our analysis is comparable with general empirical studies. We also exclude stocks that are on a dividend-paying day or on a share-split day. Our result is robust to the use of different filters or different sample updating.

Specifically, to examine the predictive power of the cross-sectional intraday return, for each stock per day, we calculate the first m-minute return using the previous day's closing price and the price after market opening for m-minutes. This gives us the main cross-sectional predictor, i.e., the previous intraday return (PIR) :

$$PIR^m_{i,t} = \frac{P^m_{i,t}}{P^c_{i,t-1}} \tag{10}$$

where $P^m_{i,t}$ is the price of stock i after market opening for m minutes on day t and $P^c_{i,t-1}$ is the previous day's closing price. We further investigate the subsequent return. To simplify the expression, we define the subsequent intraday return (SIR):

$$SIR^n_{i,t} = \frac{P^c_{i,t}}{P^n_{i,t-1}} \tag{11}$$

where $P^n_{i,t}$ is the price of stock i after market opening for n minutes on day t, and $P^c_{i,t}$ is the closing price on that day. Several other studies also consider this PIR predictor, but they mainly focus on time-series intraday return patterns.[16] Instead, we use PIR

[15]Trading hours in the Chinese stock market are from 9:30 to 15:00 with a 90-minute break from 11:30 to 13:00.

[16]For example, Zhang et al. (2016) found that the market-wide aggregation of directions of stock-level

as our main intraday return predictor to cross-sectionally investigate the intraday return pattern.[17]

In addition to PIR and SIR, some other well-known return predictors are considered as control variables, including market equity (ME), the book-to-market ratio (BM), return volatility ($Vola$), short-term reversal (Rev), long-term momentum (Mom), share turnover (TO) and illiquidity (Ami). ME is share price times total shares outstanding for the U.S. and total market value (obtained directly from CSMAR) for China. BM is the value of book equity divided by market equity. $Vola$ is the volatility of daily returns into the last calendar month. Rev is the return in the last month. Mom is the cumulative return over the past year with a one-month gap. TO is trading volume during the last calendar month divided by the total share number (shares outstanding for the U.S. and total tradable shares for China[18]) at the end of the last month. Ami is the average value of the absolute daily return divided by trading dollars times 10^6 over the last six calendar months. For the Chinese market, daily and monthly stock data are obtained from the CSMAR database (www.gtarsc.com), which is the only database in

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PIRs significantly predicts the following intraday market return, which is holding the market index (or index future) from time m to the current day's market close. In another intraday study, Gao et al. (2018) found that the first 30-minute ETF return, the definition of which is same as our PIR, predicts the last 30-minute ETF return.

[17]In the analysis in Section 3 and Section 4, we focus on the case of $m = 30$ and $n = 45$; however, we demonstrate in the Online Appendix that our results are robust to different choice of m and n.

[18]In the Chinese market, the outstanding shares of most listed companies contains some nontradable shares. These shares are often held by the state, a listed legal entity or a financial investment firm before an IPO, and often require a long lock-up period before they can be traded on the secondary market. Therefore, we only consider the tradable shares in the calculation of turnover rate to exclude the dilution effect of these nontradable shares.

China offering stock and financial statement data for Wharton Research Data Services. Data for financial statements are also from the CSMAR database. For the U.S. stock market, low-frequency stock data are from the Center for Research in Security Prices (CRSP) database, and data on financial statements are from the Compustat database.

3.2 One-Way Sort: Intraday Reversal

We begin the analysis by measuring intraday patterns in the cross-section of stock returns through one-way sort portfolio construction. Table 1 presents summary statistics when stocks are sorted on PIR. To control for extreme liquidity shocks, we exclude stocks with an absolute PIR larger than 5%. With representative $m = 30$, we sort stocks for each market into deciles based on their PIRs. In each decile, the SIR is calculated as the equal-weighted or value-weighted return of individual stocks with representative $n = 45$, i.e., from 45 minutes after market opening to close so that we can rule out the basic bid-ask bounce. Because of delayed holding, we require the absolute value of this fifteen-minute return to be smaller than 5% and at least one available trade to occur in this fifteen minute span.

For each decile, Table 1 reports the equal-weighted PIR, equal- and value-weighted SIR, and equal-weighted firm characteristics. For PIR and SIR, the t-statistics of all deciles and the difference between the highest and lowest PIR deciles are reported in parentheses. For firm characteristics, we only report t-statistics for the difference between the highest and lowest PIR deciles to save space. All t-statistics are based on the Newey-West (1987) standard errors with a lag of 120. We do not apply the heteroscedasticity-consistent standard errors of White (1980) because of the possible existence of periodic autocorrelation of returns at the daily (Campbell et al. (1993)) or intraday level (Heston et al. (2010)).

[Insert Table 1 here]

The results for the Chinese and U.S. stock markets are given in the upper and bottom panels of Table 1, respectively. Consistent with previous reversal studies, high-PIR portfolios (row 10) underperform low-PIR portfolios (row 1) for both the Chinese and U.S. markets, and the return differences are significant. For instance, the equal-weighted SIR spread between high- and low-PIR stocks is approximately -40 bps with a t-statistic of -15.5 for the Chinese market and approximately -27 bps with a t-statistic of -13.8 for the U.S. market per day. Similar results hold for the other filters for the portfolios. We wish to emphasize that, in Chinese market, the main profit of the arbitrage strategy is from the long leg. This result seems to be in contrast with the results in the U.S., where most abnormal returns stem mainly from the short leg, e.g., Stambaugh et al. (2012). Similar results can also be found in Han et al. (2020) who document that the profits of the betting against beta strategy stem mainly from the long leg of the portfolio in China but the short leg in the U.S. The findings in both our paper and Han et al. (2020) suggest stark differences between the U.S. and Chinese markets. This should imply different mechanisms in driving the intraday reversal in the U.S. and Chinese markets; thus, it provides further support for the two different theoretical mechanisms proposed in our paper.

The results in Table 1 show the significant cross-sectional intraday reversals in both the Chinese and U.S. markets. It is well known that short-term stock returns are negatively autocorrelated (e.g., Lehmann (1990) and Lo and MacKinlay (1990)). This phenomenon does not only occur in the U.S. market, as documented in Heston et al. (2010), it also appears in other developing markets, as illustrated in our study. Even with the limitation of daily price change, the equal-weighted SIR spread in the Chinese market is still higher than that in the U.S. market and is more stable, with slightly higher t-statistics. This result shows the importance of understanding cross-sectional intraday reversal in the Chinese market.[19]

[Insert Table 2 here]

A single-sorting portfolio demonstrates the existence of intraday reversal in both the Chinese and U.S. stock markets. To further exclude potential factors driven by other low-frequent return predictors, we employ the Fama and MacBeth (1973) cross-sectional regression. For every day, we run the cross-sectional regression of SIR with $n = 45$ on the PIR with $m = 30$. The control variables include monthly firm characteristics: the logarithm of market equity ($\log(ME)$), logarithm of book-to-market ratio ($\log(BM)$), short-term reversal (Rev), long-term momentum (Mom), share turnover (TO) and return volatility ($Vola$). The time-series average of regressed coefficients and their t-statistics based on Newey-West standard errors are reported in Table 2.

[19] Table 1 also reports firm characteristics for each portfolio. We are especially interested in liquidity measures because they identify different patterns for the Chinese and U.S. markets. For the U.S. market, the extreme PIRs (row 1 and row 10) are caused by liquidity. For instance, the Ami of stocks in the highest and lowest PIR is approximately three times higher than those in other quintiles. In contrast, liquidity is not a crucial factor for the determination of stocks' PIRs in China. There is no significant economic difference among different deciles. In addition, the average daily turnover of U.S. stocks is less than 10% and that of Chinese stocks is more than 40%. This is because the active participation of individual investors leads the turnover rate of tradable shares to be maintained above 100% per year for most Chinese stocks. Furthermore, it worth noting the existence of a U-shaped relationship between PIR and other firm characteristics. Extreme PIR mostly comes from highly volatile stocks, which tend to represent smaller sized firms and have high volatility of past daily returns and high turnover.

The results reported in Table 2 confirm the results of the single-sorting portfolio and the existence of intraday reversal in both markets. The regressions show a statistically significant coefficient of -0.081 for the U.S. market and -0.11 for the Chinese market after including the general return predictors. This implies that, on average, approximately 8.1% and 11% of price movements in the first 30-minute trading period of every day will reverse to the market average for the U.S. and China, respectively. There is no doubt that the intraday reversal is an economically important element for both academic pricing questions and industry timing of intraday or daily trading. The intraday reversal is robust even after controlling for monthly and daily return predictors, such as size, book-to-market, past returns and turnover. The result implies that intraday reversal cannot be explained by general asset pricing models or famous return predictors.

4 A Closer Examine of Intraday Reversal

In this section, we examine intraday reversal in greater detail. To proceed, double-sorting portfolio results are reported, indicating that illiquidity is not crucial in driving cross-sectional intraday reversal in the Chinese market. Next, we seek possible explanations for our documented nondependence of intraday reversal anomalies on stock liquidity in the Chinese market.

4.1 Double Sorts: The Role of Liquidity

As shown in the previous section, our PIR measure negatively predicts the rest-of-day intraday returns for both the Chinese and U.S. markets. For the U.S. market, a popular explanation is that a price reversal serves as risk compensation for investors who provide liquidity (i.e., the illiquidity-based explanation).[20] We now examine the extent to which these predictive patterns depend on stock liquidity measures. With a representative $m = 30$, we independently sort stocks into quintiles based on PIR and one of our three liquidity measures (market equity (ME), share turnover (TO) and illiquidity (Ami)). We next trace both equal- and value-weighted SIR with a representative $n = 45$.

[Insert Table 3 here]

Table 3 presents the double-sorting results based on our PIR and each of the three proxies for liquidity. Panel A and Panel B report the returns for the Chinese and U.S. markets, respectively. Because of the independent sorting, we have a similar spread for the PIR in the liquidity group and the illiquidity group. However, future returns exhibit distinct patterns in these two groups. We take market equity (ME) as an example. In the U.S. market of equal-weighted portfolios, for the most illiquid group, high-PIR stocks underperform low-PIR stocks by 41.7 BPs per day, with the t-statistic equal to -20. In contrast, for the most liquid group, the negative correlation between PIR and future returns is attenuated: the SIR spread (difference between the SIR of the portfolio with the highest and lowest PIRs, e.g. $PIR5$-$PIR1$) is only 1.8 BPs per day with nonsignificant t-statistics. By comparison, the unconditional SIR spread is approximately 27.4 BPs (in Table 1). Columns B-S report the difference between the SIR

[20]After first being discovered by Jegadeesh (1990) and Lehmann (1990) at the monthly and weekly level, illiquidity was always considered to be the most important reason for the reversal pattern in the short term. The idea is that some price movement is not information driven, and this temporary deviation from fundamental value would be sustained in the short-term due to the lack of liquidity. This is well tested in the cross-section by Avramov et al. (2006) who show a stronger short-term reversal with more illiquid stocks, and in the time-series by Nagel (2012), who find a higher reversal profit when liquidity has evaporated.

spread among the most liquid stocks and that among the most illiquid stocks. For ME, this difference-in-difference is 39.9 BPs per day, with a t-statistic equal to 15.6. The other two proxies display similar patterns. In particular, the difference-in-differences are 45.8 and 44.4 BPs per day for TO and Ami, indicating that intraday reversal is significantly stronger among illiquid stocks. In addition, this liquidity dependence pattern also holds for the value-weighted portfolio. In general, the double sorting results for the U.S. market are consistent with the illiquidity-based explanation.

In the Chinese market, we obtain similar results, but the impact of liquidity on the intraday reversal is weak. The difference-in-differences are 10.2, 3.4 and 9.8 BPs for the three different liquidity measures with equal-weighted returns. Note that these differences in the SIR spread are much smaller than those in the U.S. market. This is because, even for the most liquid group, the SIR spreads are still above 24 BPs (-25.5, -31 and -34.3), which is much higher than those in the U.S. market.[21]

[21]For a strategy with daily rebalancing, the trading cost should be a significant impact factor considering that it mechanically increases turnover. Therefore, we check the impact of transaction costs on return of intraday reversal. Result shown in the online appendix table A4 implies that the high arbitrary cost in Chinese market is another important driving force for intraday reversal. During periods with high stamp-tax, both the longing low-PIR stocks or the long-short portfolio cannot earn a positive return. On the other hand, in the low-fee periods, longing low-PIR stocks can still earn a marginally significant 5.6 BPs per day, which implies that the magnitude of intraday reversal cannot entirely explained by limitation of arbitrage. The high return spread between high and low PIR portfolios and its independency with liquidity seems to be a challenge to the market efficiency in China, especially the main profit of arbitrage strategy is from the long leg. Previous analysis shows that arbitrage cost could explain most of return. However, even investors cannot directly obtains an excess return, PIR signal could be used for investors with other transaction motive and help them decreasing the costs of trading by postpone the time of buying stocks with high PIR.

The double-sorting approach is simple and intuitive, but it cannot explicitly control for other variables that may influence returns. However, sorting on three or more variables is impractical. Thus, to examine other possible mechanisms, we perform a series of Fama and MacBeth (1973) cross-sectional regressions, which allow us to conveniently control for additional variables. The results in Table 2 help us to investigate the role of liquidity in the price reversal anomaly. Under each liquidity proxy, the regression has one additional independent variable compared to the benchmark regression in Subsection 3.2: an interaction term between the liquidity proxy and PIR. For Ami, the coefficient estimate of the interaction term is negative and significant, while it is positive and significant for ME and TO. These results suggest that intraday reversal is significantly stronger among illiquid stocks, confirming that our results based on double sorts still hold even after we control for other famous return predictors. It is noteworthy that the coefficient of PIR itself typically appears to be negative and significant, suggesting that low-PIR stocks have higher future returns than high-PIR stocks, especially when they are illiquid.

4.2 Liquidity in the U.S. and Chinese Markets

One might argue that the significant negative spread among the most liquid Chinese stocks could be the result of a lack of liquidity in the Chinese market. However, the high participation of individual investors in China creates an environment with exceptional liquidity by showing an average share turnover (approximately 50% per month) higher than that in the U.S. market. It is untenable to argue for an insufficient liquidity supply in China.

[Insert Figure 3 here]

Formally, we compare the liquidity in the U.S. and Chinese markets in Figure 3.

Although the U.S. market has some of the world's largest stock exchanges and most liquid stocks, the provision of liquidity is concentrated among the largest and most liquid firms. The distribution of stock liquidity, shown in Figure 3, is flat. The difference between the most liquid and most illiquid U.S. stocks is significant. For instance, the bottom 10% and bottom 1% of U.S. stocks are significantly more illiquid than are stocks of an average value.

Unlike the classical institutional investor dominated structure in Western countries, China has two stock exchanges, both founded in 1990: the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). The market grew quickly, becoming the second largest equity market in terms of market capitalization by the end of 2011, only after the U.S. As a young and fast-growing market, the Chinese stock market is characterized by the dominance of retail traders and a large amount of trading. Their trades are distributed across the whole market and do not only focus on specific large and liquid firms.

However, the market liquidity for small, low turnover and illiquid stocks in the U.S., from which the standard reversal strategy profits mainly derive, is lower than that of the Chinese market. In summary, the results indicate that limited liquidity cannot explain intraday reversal in the Chinese market.

4.3 Illiquidity vs. Liquidity Oversupply

Based on Corollary 3, we formally identify the channels for intraday reversal in the Chinese and U.S. markets by calculating the SIR spreads for high- and low-PIR stocks and their accumulative levels over the subsequent trading days. Specifically, we study the returns on relatively well-diversified (equal-weighted or value-weighted) long-short portfolios formed on the basis of PIR. Using the methodology of Jegadeesh and Titman (1995), we sort stocks into ten deciles based on their returns over the previous half-hour interval. We form portfolios of "losers" and "winners" and calculate equal-weighted or value-weighted returns on portfolios of stocks that have the lowest and highest 10% of returns for the first thirty trading minutes, respectively. When forming the portfolios, the same filters are applied as in Section 3. The column labeled "H-L" is the average return on a portfolio that is long on the winners portfolio and shorts the losers portfolio. T-statistics based on Newy-West standard errors are given in parentheses. The long-short average return and their accumulated level are reported in detail in Table 4 and are also plotted as a function of following trading days in Figure 4.[22]

[Insert Table 4 and Figure 4 here]

Consistent with the previous literature and the analysis in Section 2, the SIR-spread is negative and significant for both the Chinese and U.S. markets. However, the most striking patterns in Figure 4 and Table 4 are that, following the reversal period, the return spreads for high- and low-PIR stocks respond differently in the two markets. We still use the equal-weighted return spreads for illustration purposes. In the Chinese market, following the intraday reversal period, the negative correlation between PIR and future returns is reversed: high-PIR stocks outperform low-PIR stocks by 26.1 BPs on the first day after the reversal, with a t-statistic equal to 8.5. Thereafter, the high-PIR stocks

[22]Figure 4 also shows some details about the reversal that are unobservable in the previous tables. The reversal from m to n in the U.S. (approximately 23 basis points) is higher than that in the Chinese market (approximately 16 basis points), although the PIR spread is similar, at approximately 4.2%. The more rapid reversal confirms the major role of liquidity in the U.S. market because the price movement from the liquidity shock and corresponding reversal should be more sensitive and immediate after a high PIR.

continuously outperform the low-PIR stocks from the second day until the fourth day by 4.3, 8.3, and 5.5 BPs. Over this period, the smallest t-statistic at the daily frequency is 3.4. Except for the fifth day, which has negative return spreads, the difference remains positive and statistically significant for up to 20 days. It appears that there is a persistent and predictable pattern over the trading days following reversal: PIR positively predicts returns over the trading days following the reversal period. The value-weighted portfolios display similar patterns.

In the U.S. market, we obtain different results. For equal-weighted portfolios, following the intraday reversal period, there only exists an insignificant negative correlation between PIR and future returns: high-PIR stocks underperform low-PIR stocks by 2.2 BPs on the second day after reversal, with a t-statistic equal to -1.5. Subsequently, the high-PIR stocks continuously underperform low-PIR stocks for up to 10 days, while the largest t-statistic at the daily frequency is only -1.5. In addition, although the return spreads on the first day after reversal and over the eleventh to twentieth days are positive, this is not statistically significant (with t-statistics equal to 4.1 and 0.5, respectively). Hence, PIR either negatively predicts the returns or has no predictive power over the trading days following the reversal period. The value-weighted portfolios display similar patterns.

We then turn to accumulated return spreads. Figure 4 plots the results of the accumulated equal-weighted return of the long-short portfolios formed on the basis of PIR, as shown in Table 4.[23] For the Chinese market, after the reversal period, the equal-weighted

[23]Specifically, we first plot a bar for the actual PIR spread of H-L at the left-most end and mark its magnitude on the left Y-axis as a percentage. Then, we plot the accumulated return from 45 minutes up to following 60 trading days, and each dot represents the accumulated return from the n of day t to the end of a given day. The background of the PIR spread and return before n is set as gray, as a reminder that the return cannot be obtained for this part. We adjusted the line to make n as 0 which

accumulated return spread shrinks from -40.4 to -13.1 These accumulated spreads continue shrinking over the rest of the trading day and turn positive at the end of the tenth day (16.7 basis points with a t-statistic of 2.6).[24] In contrast, for the U.S. market, the accumulated equal-weighted return spread for the highest to lowest PIR remains stable, with the smallest and largest return spreads equal to -27.4 and -19.7, respectively. In summary, after the reversal period, the accumulated equal-weighted spread remains stable for the U.S. market, while it shows a pattern of a reversal of the intraday reversal for the Chinese market.

4.4 Other Predictions

After identifying the driving force of intraday reversal in the Chinese market, we test some other predictions for the theoretical framework, as illustrated in Proposition 2.

Intraday reversal and fundamental risks: Proposition 2 predicts that intraday reversal is stronger with higher fundamental risk. Due to the anchoring effect, irrational liquidity providers trade against previous price movements and create price pressure. When liquidity is oversupplied, this price pressure becomes strong enough, which causes intraday reversal. This anchoring effect tends to move the stock price back to the starting point. However, with higher fundamental risk, the stock price volatility and price

is the beginning of our portfolio holding. The accumulated returns are marked as basis points shown in the right Y-axis.

[24]The positive accumulated return ending at t+10 could be raised by the 15-minute gap between PIR and the holding timing or by the already existing reversal before time m. Considering the high liquidity in the Chinese market, the result implies that, due to the high participation of individual investors, intraday reversal in China is a mispricing phenomenon that should be stronger for individual investors. In addition, all the mispricing will be corrected in the subsequent days.

derivation, on average, are larger. Hence, we expect stronger price reversal. To test this prediction, we independently sort stocks into quintiles based on PIR and one of three fundamental risk measures (cash-flow volatility ($CASHVOL$), volatility of return on equity ($ROEVOL$) and volatility of return on asset ($ROAVOL$)). We next trace both the equal- and value-weighted portfolio returns from $n = m + 15$ to market close. Table 5 presents the results for double-sorted portfolios. We take the $ROEVOL$ as an example. For the equal-weighted portfolio, among the riskiest stocks, high-PIR stocks underperform low-PIR stocks by 36.4 BPs per day, with a t-statistic equal to -13.4. In contrast, for the least risky group, the negative relationship between PIR and SIR is weaker: the SIR spread is only 29 BPs per day, with a t-statistic equal to -11.7. Columns B-S report the difference in SIR spread which is 7.5 BPs per day for $ROEVOL$ with a t-statistic of 4.8. Similar patterns are displayed for the other two proxies and in the value-weighted return. This indicates that intraday reversal is stronger among stocks with higher fundamental risk.

[Insert Table 5 here]

Persistence of returns in intraday reversal strategy: Proposition 2 predicts that intraday reversal is stronger when irrational liquidity providers have a higher level of underreaction. It is difficult to directly identify traders' underreaction level, but we argue that the underreaction level does not easily vary. For example, inexperienced traders should be less able to infer fundamental information from stock prices, making them more underreaction. When the market experiences a large influx of inexperienced investors, the underreaction level will remain high for a long time, until they learn how to correctly infer information from prices. Therefore, the profitability of intraday reversal should exhibit persistence. Indeed, Table 6 provides evidence for the persistence of intraday reversal. We regress the daily return spread of the PIR portfolio on the average return spread of the same portfolio over the past 60 trading days ($AvgIR$). Both the value- and equal-weighted returns are considered. The coefficient is significantly positive, indicating that there is persistence in intraday reversal.

[Insert Table 6 here]

Retail investors as the source of liquidity oversupply: The previous subsection suggests the liquidity oversupply explanation for intraday reversal in the Chinese market. Hence, we now examine the extent to which these predictive patterns depend on the participation of retail investors to provide further evidence for this explanation. Since the trade size of retail investors is far smaller than that of institutional investors on average (Lee and Radhakrishna (2000)), several papers use the number or value of traded shares to identify retail trades(Barber et al. (2008), Han and Kumar (2013)). In this spirit, we employ the value per holder (VPH), the daily trading amount per transaction ($DAPT$) and the trading amount per transaction during holding ($HAPT$) to measure the proportion of retail investors in stock levels. VPH is the market cap scaled by the shareholder number, $DAPT$ is the daily dollar trading volume scaled by the number of transactions, and ($HAPT$) is the dollar trading volume scaled by the number of transactions during the holding period of PIR portfolios. We independently sort stocks into quintiles based on PIR and each of the retail trading measures and then trace both equal- and value-weighted portfolio returns from $n = m + 15$ to market close.

[Insert Table 7 here]

Table 7 presents the double-sorting results based on PIR and the other three proxies for the retail trading measures. Due to independent sorting, we have a similar spread for the PIR in the high retail trading group and the low retail trading group. However, future returns exhibit distinct patterns in these two groups. We take $HAPT$ as an example. For the equal-weighted portfolio, among the high retail trading stocks, high-PIR stocks underperform low-PIR stocks by 35 BPs per day, with a t-statistic equal to -16.8. In contrast, for the low retail trading group, the SIR spread is attenuated: high-PIR stocks underperform low-PIR stocks by only 14.7 BPs per day, with a t-statistic equal to -3.9. Columns B-S report the difference in the SIR spread between stocks with the highest and lowest participation by retail investors. For $HAPT$, this difference-in-difference is 20.2 BPs, with a t-statistic of 7.7. The other two proxies display similar patterns, indicating that intraday reversal is significantly stronger among stocks with higher participation by retail investors. In addition, this pattern also holds for the value-weighted portfolio. In summary, we provide further evidence that liquidity oversupply from retail investors causes intraday reversal in the Chinese market.

[Insert Table 8 here]

To examine other possible mechanisms, we also perform a series of Fama-MacBeth cross-sectional regressions, which allow us to conveniently control for additional variables. In all of the Fama-MacBeth regressions here, we control for the same return predictors as in Table 3. The results in Table 8 help us to investigate the role of retail investors in price reversal anomalies.

The benchmark regression in the first column shows that the coefficient of $PIR_{i,t}^{m=30}$ is significant and positive, suggesting that stocks with high PIR have low future returns, which confirms the intraday reversal findings. Next, we investigate the role of retail investor participation in intraday reversal. Under each fraction of the retail investor proxy, the regression has two more independent variables than the benchmark regression:

the retail investor participation proxy and an interaction term between the proxy and PIR. For all three proxies, the coefficient estimate of the interaction term is negative and significant. This suggests that stocks with more retail investor participation have more price reversal than stocks with less retail investor participation, confirming that our results based on double sorts still hold even after we control for other return predictors. It is noteworthy that the coefficient of PIR itself typically appears to be negative and significant, suggesting that stocks with low-PIR tend to have higher future returns than high-PIR stocks, especially when stocks have more retail investor participation.

[Insert Table 9 here]

Additional analysis: To provide further evidence on the impact of retail investors, we investigate how their participation influences the return dynamics over the trading days following the reversal period. Previous analysis shows that, for the Chinese market, high-PIR stocks underperform low-PIR stocks over intraday returns; however, the return spreads turn positive afterwards. Hence, if the reversal period can be treated as a pricing error due to excessive liquidity from irrational traders with anchoring expectations, higher participation by retail investors not only leads to more significant reversal but also more significant resilience after the reversal period. Indeed, Table 9 shows this result.

The results in Table 9 further help us to investigate the role of retail investor participation in price reversal anomalies. The benchmark regression in the first column shows that the coefficient of $PIR_{i,t}^{m=30}$ is significant and positive, while the coefficient of $SIR_{i,t}^{n=45}$ is significant and negative, suggesting that the PIR positively predicts the returns over the subsequent trading days, while the SIR negatively predicts them. This confirms that intraday reversal in the Chinese market is caused by liquidity oversupply, as illustrated in Figure 1. Next, we show evidence of the influence of retail traders. Under each retail investor participation proxy, the regression has two more independent variables than the benchmark regression: the retail investor participation proxy and an interaction term between the proxy and SIR. For all three proxies, the coefficient estimate of the interaction term is negative and significant. This means that after the reversal, resilience is more significant for stocks with higher retail investor participation. This suggests that the participation of retail investors has a significant impact on intraday reversal, confirming that our results based on double sorts still hold even after we control for size, book-to-market, past returns, stock return volatility, and share turnover.

4.5 Robustness Check and Further Analysis

Our main empirical findings hold up well in a variety of robustness checks, and we present the details in the Online Appendix. First, for the Chinese market, different timings for forming the portfolios are tested. The results indicate that for most portfolio formation times, high-PIR stocks significantly underperform low-PIR stocks and that the evidence for intraday reversal is significantly stronger and more robust among stocks with high retail trading. Second, we show that the cumulative wealth growth of unconditional PIR hedge portfolios slowed down after 2015, with serious stock market tsunamis. This is consistent with the decreasing activity level of individual investors, confirming an important role that retail investors play in reversal anomalies. Third, the results of the dual listing stocks on the Mainland and Hong Kong markets help to rule out the influence of different fundamentals. The difference between return spreads for high- and low-PIR stocks for the two markets is statistically significant, emphasizing the influence of retail investors after the fundamentals are controlled for in this section . Finally, we provide the cross-sectional versions of the results of Gao et al. (2018) and compare them to ours to further demonstrate the robustness of intraday reversal. In summary, these tests demonstrate that the explanation of intraday reversal and its mechanism in our paper are quite robust.

5 Conclusion

In this paper, we explore the role of liquidity in the intraday return reversal anomaly. Due to the documented nondependence of intraday reversal anomalies on stock liquidity in the Chinese market, the illiquidity-based explanation, which has long been documented in U.S. data, should not be automatically applied. Hence, based on the theoretical framework, we have proposed an alternative explanation, i.e., the explanation of liquidity oversupply (from irrational uninformed liquidity providers). We show that there is a significant resilience pattern for accumulated returns after intraday reversal: the negative correlation between previous intraday returns and future returns in the Chinese market is subsequently reversed. This suggests that the reversal in the Chinese market tends to be a pricing error due to excessive liquidity provision from irrational uninformed retail traders.

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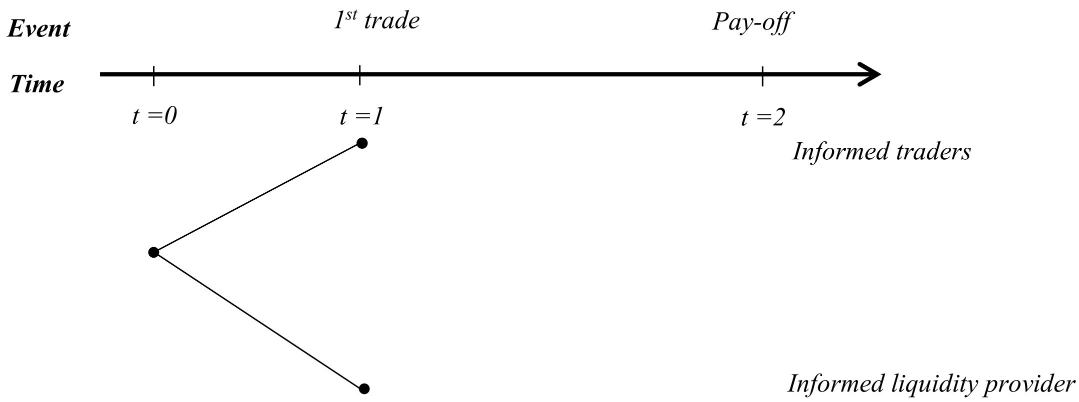
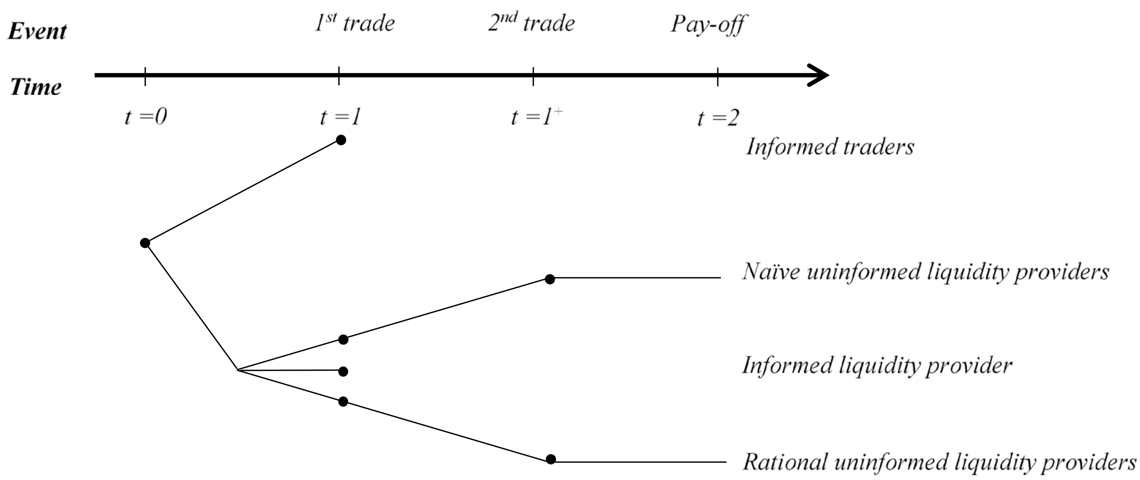
Figure 1: Timeline for Conceptual Framework

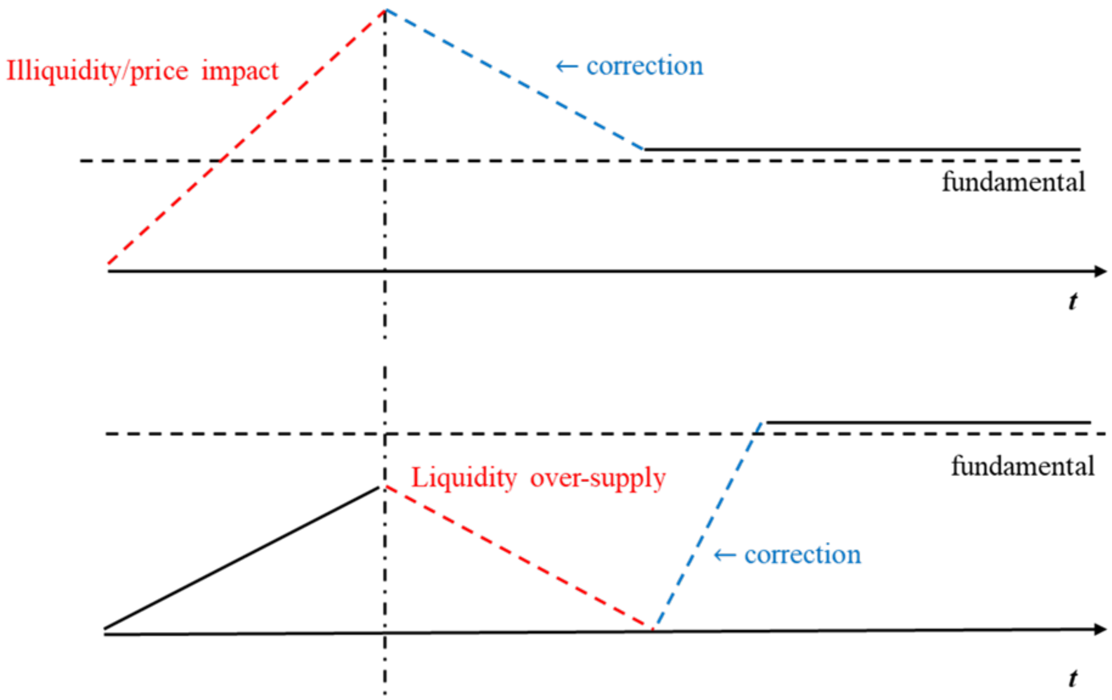


Panel A: Baseline stylized framework



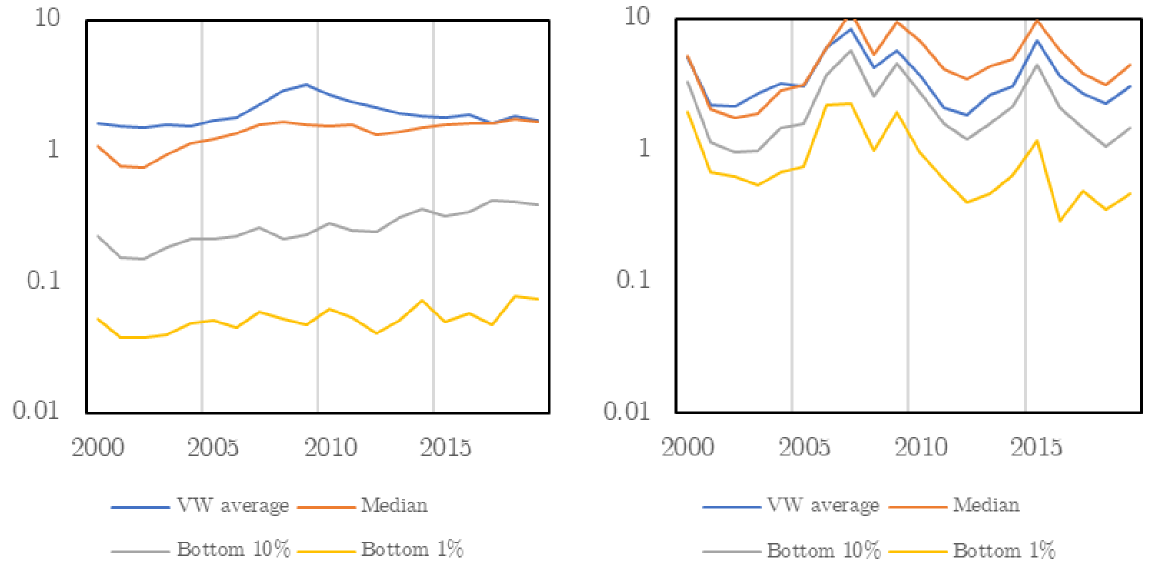
Panel B: Stylized framework with liquidity oversupply

Figure 2: Illiquidity Channel and Liquidity Oversupply Channel for Intraday Reversal

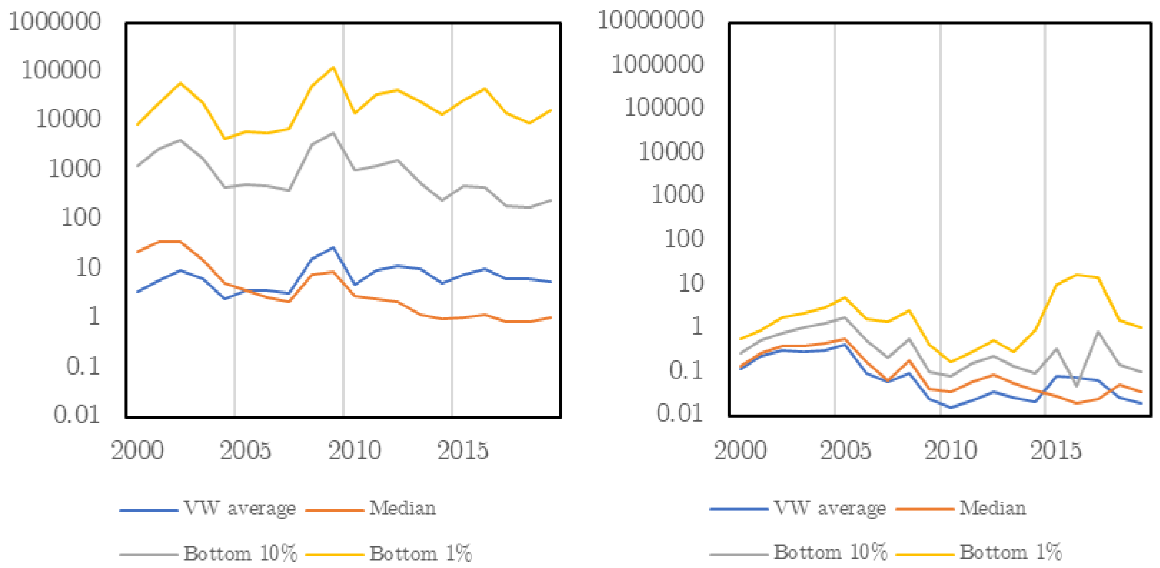


This figure plots two different channels resulting in intraday reversal. The first is the illiquidity channel through which intraday reversal occurs during the correction stage due to the illiquidity or price impact. The second is the liquidity oversupply channel through which intraday reversal occurs due to noise trading from excessive liquidity supply. The price correction will ultimately push the price back to the correct level.

Figure 3: Liquidity in the Chinese and U.S. Stock Markets

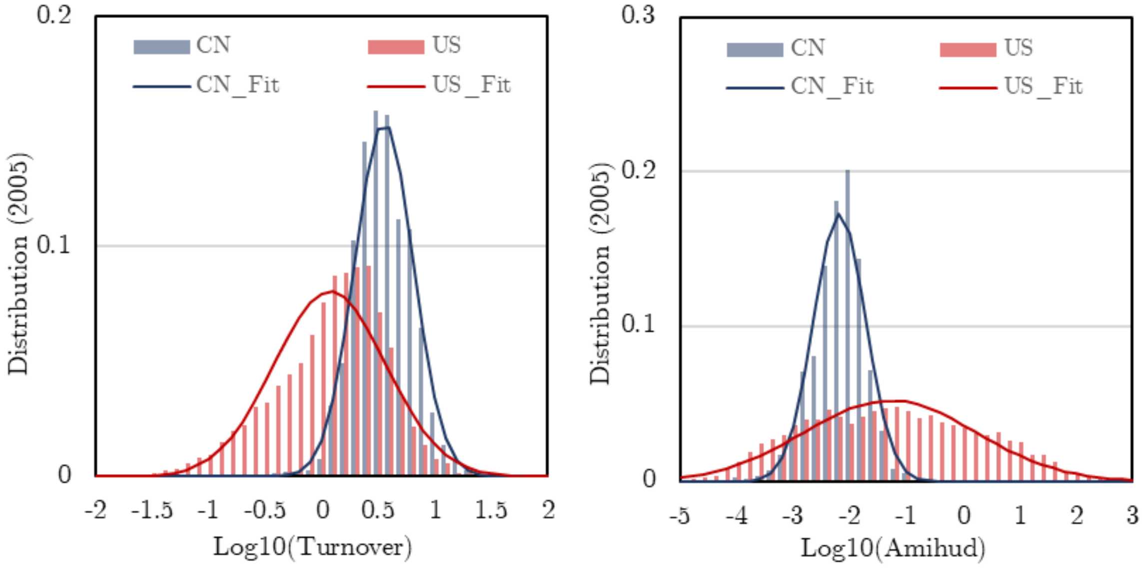


Panel A. Share Turnover



Panel B. Amihud measure

Figure 3: Continued

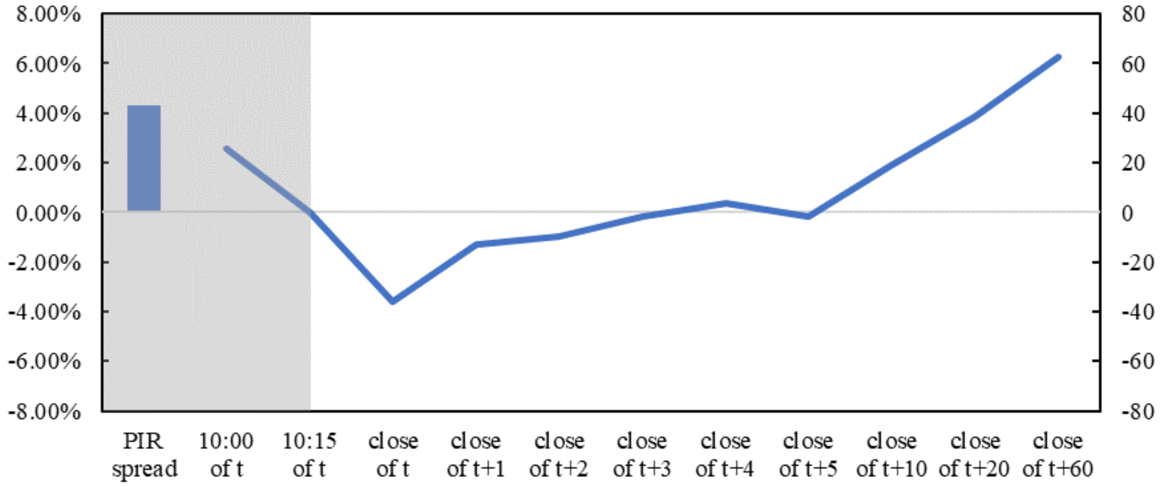


Panel C. Liquidity distributions of China and U.S. Market in 2005

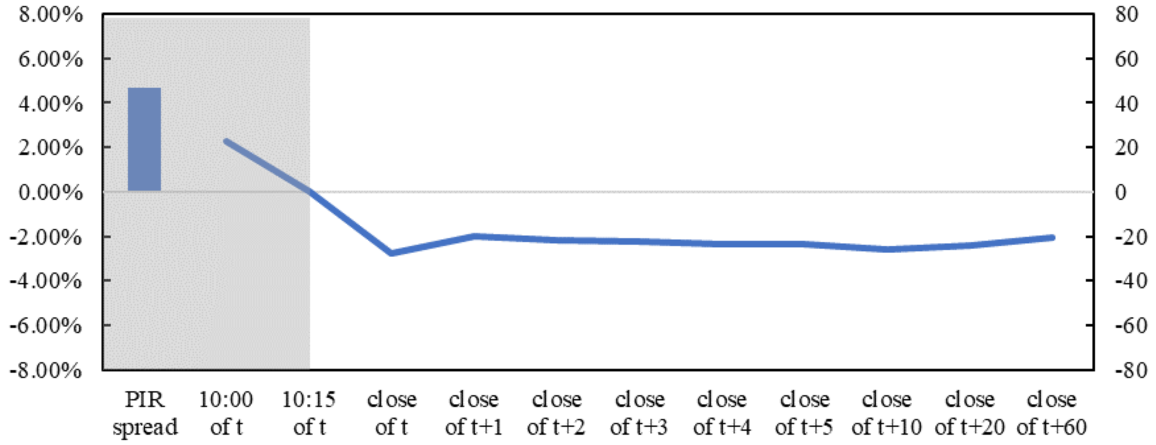
For each year, we calculate two liquidity measures for all common stocks listed in both markets and then report the market-level statistics in this figure. Those measures are 1) annual share turnover, which is the average monthly share turnover times 12, and 2) the Amihud measure, which is the average value of the daily return (in percentage) divided by the daily domestic-dollar trading volume times 10^6. For each market-year, we report the value-weighted average, median, bottom 10% cutoff and bottom 1% cutoff value of the liquidity measure. Panel A shows the results for share turnover, and panel B shows those for the Amihud measure. In each panel, the left figure shows the results for the U.S. market and the right panel shows those for the Chinese market.

Additionally, we depict the liquidity distributions of both markets in 2005 as a representative year in panel C for a clear comparison. The bars show the density of firms in each interval and the lines show the fitted normal distribution. The left and right figures show the distributions of share turnover and the Amihud measure respectively, in which the red bars and lines show the results for the U.S. market, and blue bars and lines show the results for China.

Figure 4: Accumulated Return of Long-Short strategy on PIR with Timing $m = 10:00$.



Panel A. Accumulated Equal-weighted Spread of H-L PIR portfolio in C.N.



Panel B. Accumulated Equal-weighted Spread of H-L PIR portfolio in U.S.

This figure plots the accumulated return of investing in long-short portfolio based on PIR up to 60 trading days for both Chinese and U.S. market. The timing m of PIR is 10:00 and the hedge portfolio is longing on stocks with top decile of PIR and shorting on the counterpart with bottom decile of PIR.Similar filters for stocks as in table 1 are considered. We also plot the average PIR spread between long and short portfolios and the average return of 15-minutes gap between the time of single observation and holding in the left within grey background. The accumulated holding returns and 15-minute gap return are given in basis-points shown in the right Y-axis. The PIR spread is reported in percentage in the left Y-axis. Panel A shows the result of Chinese market and Panel B shows the one of U.S.

Table 1: Summary Statistics

This table reports the time-series average of daily equal-weighted PIR, subsequent intraday returns (SIR) and equal-weighted firm characteristics for the decile portfolios sorted by PIR with $m = 10:00$ in U.S. and Chinese stock markets. Portfolios are sorted by PIR, which is return from the previous day's closing price to price of the last trade before m. At time m each day, we sort all common stocks into deciles based on the ranked value of PIR. For the U.S. stock market, we consider the stocks traded on NYSE/AMEX/NASDAQ and that have sharecodes of '10' or '11' as our sample stocks. For China, common stocks are the stocks traded on the Shanghai Stock Exchange and Shenzhen Stock Exchange and with sharecodes beginning with '0', '3' or '6'. SIR is the value-weighted (VW) or equal-weighted (EW) return from $n = 10:15$ to current day's closing price. TO is share turnover, which is the trading volume in the last calendar month divided by the share outstanding at the end of the last month. Ami is the measurement of illiquidity, which is the average value of the absolute daily return divided by trading dollars times 10^6 over the last six calendar months. Ret is daily close-to-close return. $Log(ME)$ is the logarithm of a firm's market equity. BM is the book value of equity divided by market value at the end of the last month with the latest available data. $Vola$ is the volatility of the daily return in the last calendar month. Rev is the short-term reversal which is the return in the last month. Mom is the cumulative return over the past year with a one-month gap.

The portfolio is rebalanced every day. To enter our portfolio, we require our a stocks' price to be equal to or higher than 5 domestic dollars. We also require our stocks to have at least 10 nonmissing daily stock returns in previous calendar month and 120 nonmissing daily stock returns in previous calendar year, to be listed on the exchange for longer than 6 months and to have an absolute PIR smaller than 5%. The summary statistics for the Chinese market are reported in the upper panel and those for the U.S. market are in the bottom panel. We report the PIR in percentage and SIR in BPs with their t-statistics based on Newey-West standard errors with 120 lags given in parentheses. The difference between the bottom and top decile portfolio (high-low) is given in the last rows, and the t-statistics are also shown in parentheses.

Table 1: Continued

	PIR (in %)		SIR (in BPs)				Liquidity(in %)		Other Firm Characteristics				
	EW	t(EW)	EW	t(EW)	VW	t(VW)	TO	Ami	log(ME)	BM	Vola	Rev	Mom
Panel A. CN													
Low	-2.11	(-35.5)	28.39	(11.2)	21.28	(8.8)	57.15	0.35	9.61	0.33	2.95	3.80	29.61
2	-1.18	(-27.1)	19.83	(7.6)	13.34	(5.9)	49.61	0.26	9.62	0.36	2.76	2.04	23.48
3	-0.79	(-24.0)	15.59	(5.9)	10.69	(4.6)	46.29	0.24	9.62	0.38	2.67	1.40	20.40
4	-0.51	(-20.9)	13.26	(4.9)	9.83	(4.1)	44.56	0.23	9.61	0.39	2.61	1.06	18.58
5	-0.27	(-15.7)	10.93	(4.2)	8.79	(3.5)	43.73	0.23	9.61	0.40	2.58	0.91	17.69
6	-0.04	(-2.8)	8.81	(3.7)	6.12	(3.3)	43.57	0.23	9.61	0.40	2.58	0.95	17.81
7	0.22	(12.8)	5.37	(2.4)	4.27	(2.1)	43.95	0.24	9.62	0.39	2.59	1.03	18.34
8	0.55	(18.1)	1.85	(0.9)	1.03	(0.6)	45.18	0.24	9.62	0.38	2.64	1.30	20.04
9	1.04	(20.5)	-4.23	(-2.0)	-3.86	(-2.0)	47.69	0.25	9.64	0.37	2.71	1.83	22.58
High	2.30	(29.9)	-12.05	(-5.9)	-11.06	(-5.2)	52.34	0.29	9.64	0.34	2.85	2.79	26.88
High-Low	4.42	(33.8)	-40.44	(-15.5)	-32.34	(-12.3)	-4.82	-0.07	0.03	0.02	-0.10	-1.01	-2.73
							(-7.8)	(-2.6)	(7.5)	(10.0)	(-8.8)	(-7.5)	(-3.6)
Panel B. US													
Low	-2.32	(-26.6)	22.81	(9.1)	3.55	(1.4)	11.84	29.30	8.80	0.62	3.46	2.31	28.54
2	-1.17	(-19.0)	11.67	(5.5)	2.98	(1.5)	10.03	14.79	8.98	0.60	2.96	1.78	21.98
3	-0.72	(-17.4)	8.40	(4.4)	2.74	(1.6)	9.06	10.20	9.05	0.60	2.72	1.70	19.70
4	-0.41	(-15.2)	6.70	(3.9)	2.16	(1.4)	8.52	9.62	9.09	0.60	2.59	1.71	18.75
5	-0.15	(-9.5)	5.41	(3.2)	1.83	(1.1)	8.24	10.27	9.10	0.60	2.54	1.69	18.63
6	0.09	(9.7)	4.56	(2.6)	0.91	(0.6)	8.30	8.66	9.11	0.60	2.53	1.71	19.41
7	0.35	(23.9)	3.00	(1.8)	0.12	(0.1)	8.55	9.33	9.10	0.60	2.58	1.69	19.73
8	0.66	(23.4)	1.83	(1.0)	0.83	(0.5)	9.15	10.87	9.07	0.61	2.69	1.66	20.91
9	1.13	(23.3)	0.78	(0.4)	0.78	(0.5)	10.21	14.48	9.00	0.61	2.92	1.71	23.82
High	2.33	(32.5)	-4.57	(-2.0)	-2.12	(-0.8)	12.22	26.61	8.83	0.64	3.41	2.06	30.92
High-Low	4.65	(29.7)	-27.38	(-13.8)	-5.67	(-2.0)	0.38	-2.69	0.03	0.01	-0.05	-0.25	2.37
							(2.1)	(-3.2)	(5.8)	(1.5)	(-3.1)	(-1.9)	(4.1)

Table 2: Intraday Reversal and Liquidity—Fama-MacBeth Regression

For each day, we run a cross-sectional regression of SIR to market close on the PIR with $m = 10:00$ and its interaction with liquidity measurements for both the Chinese and U.S stock markets:

$$SIR_{i,t}^{m+15} = a_t + \beta_{1,t} PIR_{i,t}^{m} + \beta_{2,t} PIR_{i,t}^{m} Liquidity_{i,t} + \beta_{3,t} Liquidity_{i,t} + \sum \beta_{c,t} Controls_{i,t}^{c}$$

We control for the firm characteristics listed in Table 1 in the regression, and the time-series average of regression coefficients is reported. The filters for stocks to enter our sample are same as those in Table 1. The sample period is from January 2000 to December 2012 for the U.S. and January 2000 to December 2019 for China. The t-statistics are in parentheses and calculated based on Newey-West standard errors with 120 lags.

	C.N						U.S.					
PIR	-0.095	-0.110	-0.100	-0.287	-0.110	-0.262	-0.114	-0.081	-0.043	-1.013	-0.155	-0.715
	(-19.0)	(-22.2)	(-19.5)	(-12.3)	(-20.3)	(-10.1)	(-4.34)	(-3.26)	(-1.50)	(-3.68)	(-3.41)	(-2.42)
PIR* Ami			-0.456			-0.169			-0.440			-0.328
			(-4.58)			(-1.22)			(-2.09)			(-1.38)
PIR* ME				0.027		0.023				0.071		0.049
				(7.49)		(6.01)				(3.16)		(1.92)
PIR* TO					0.691	1.274					7.111	1.612
					(1.85)	(2.94)					(1.76)	(0.36)
ME		-0.001	-0.001	-0.001	-0.001	-0.001		0.001	0.001	0.000	0.001	0.000
		(-9.83)	(-9.81)	(-10.1)	(-9.77)	(-9.90)		(1.34)	(1.30)	(1.08)	(1.34)	(0.99)
BM		0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000
		(0.47)	(0.59)	(0.54)	(0.47)	(0.62)		(0.12)	(0.12)	(0.14)	(0.12)	(0.15)
Rev		-0.004	-0.004	-0.004	-0.004	-0.004		0.017	0.017	0.017	0.017	0.017
		(-1.27)	(-1.28)	(-1.27)	(-1.29)	(-1.25)		(1.55)	(1.56)	(1.55)	(1.56)	(1.56)
Mom		0.000	0.000	0.000	0.000	0.000		0.002	0.002	0.002	0.002	0.002
		(-1.07)	(-1.09)	(-1.10)	(-1.08)	(-1.08)		(1.23)	(1.21)	(1.23)	(1.25)	(1.23)
TO		0.001	0.001	0.001	0.001	0.001		-0.236	-0.239	-0.239	-0.194	-0.177
		(4.38)	(4.38)	(4.37)	(4.39)	(4.38)		(-1.81)	(-1.82)	(-1.83)	(-1.56)	(-1.41)
Vola		-0.039	-0.039	-0.039	-0.034	-0.035		-0.083	-0.082	-0.085	-0.083	-0.086
		(-7.61)	(-7.60)	(-7.60)	(-6.43)	(-6.51)		(-1.65)	(-1.65)	(-1.65)	(-1.64)	(-1.64)
Ami		0.004	0.006	0.004	0.004	0.005		2.182	2.093	2.079	2.225	1.891
		(1.33)	(1.58)	(1.42)	(1.36)	(1.35)		(1.15)	(1.21)	(1.10)	(1.18)	(1.14)

Table 3: Intraday Reversal and Liquidity

At time $m = 10:00$ each day, we sort all stocks into five-times-five portfolios independently based on PIR with timing m and liquidity measures. Then, we hold the portfolios from $n = m + 15$ minutes to the market close on the current day. Equal-weighted and value-weighted return, spreads and t-statistics of the spreads are reported. We only report the lowest, median and highest portfolios to save space. Returns are reported in BPs and t-statistics are based on Newey-West standard errors with 120 lags. Three liquidity measurements are considered: market equity (ME), share turnover (TO) and illiquidity (Ami). Their descriptions are same as those in Table 1.

	Market Equity				Turnover				Illiquidity			
	S	M	B	B-S	S	M	B	B-S	S	M	B	B-S
Panel A. C.N.												
Equal-weighted Return												
PIR 1	30.3	23.7	17.1		27.5	23.8	22.2		16.3	24.4	28.3	
PIR 3	13.8	9.5	5.6		10.6	9.2	7.9		5.8	10.4	11.6	
PIR 5	-5.3	-8.2	-8.3		-7.0	-7.4	-8.8		-8.1	-8.1	-6.0	
5 - 1	-35.6	-31.9	-25.4	10.2	-34.4	-31.2	-31.0	3.4	-24.4	-32.5	-34.2	-9.8
	(-17.8)	(-13.9)	(-11.0)	(7.0)	(-15.5)	(-13.7)	(-12.7)	(2.7)	(-10.5)	(-15.0)	(-17.0)	(-7.2)
Value-weighted Return												
PIR 1	29.8	23.6	13.7		19.7	18.6	18.5		13.1	23.4	26.7	
PIR 3	13.6	9.4	5.4		7.2	7.0	5.7		5.2	10.0	10.5	
PIR 5	-5.4	-8.5	-6.8		-6.3	-8.2	-8.5		-6.8	-8.4	-6.5	
5 - 1	-35.2	-32.1	-20.5	14.7	-26.0	-26.7	-27.0	-1.0	-19.9	-31.9	-33.1	-13.2
	(-18.0)	(-13.9)	(-8.9)	(8.6)	(-10.4)	(-11.0)	(-10.2)	(-0.5)	(-8.3)	(-14.2)	(-16.7)	(-8.4)
Panel B. U.S.												
Equal-weighted Return												
PIR 1	33.3	13.0	3.8		38.1	16.9	0.7		2.7	10.7	36.4	
PIR 3	7.8	5.2	3.2		8.6	5.4	-0.6		3.0	5.1	9.0	
PIR 5	-8.4	0.4	2.1		-9.1	1.5	-0.6		2.1	1.4	-9.6	
5 - 1	-41.7	-12.6	-1.8	39.9	-47.1	-15.4	-1.3	45.8	-0.7	-9.3	-46.0	-45.4
	(-20.0)	(-6.6)	(-0.9)	(15.6)	(-19.5)	(-6.7)	(-0.7)	(18.3)	(-0.3)	(-3.7)	(-18.2)	(-14.5)
Value-weighted Return												
PIR 1	31.6	13.0	0.9		19.0	4.5	-4.1		0.6	11.9	36.5	
PIR 3	7.8	5.1	0.9		4.7	1.2	-3.2		0.8	5.3	8.7	
PIR 5	-8.4	0.4	-0.6		-9.0	0.9	0.7		-0.5	0.4	-11.9	
5 - 1	-39.9	-12.7	-1.4	38.5	-28.0	-3.6	4.8	32.8	-1.1	-11.5	-48.4	-47.3
	(-18.7)	(-6.5)	(-0.6)	(12.7)	(-6.0)	(-1.6)	(2.3)	(7.4)	(-0.4)	(-5.3)	(-22.8)	(-14.7)

Table 4: Return over Subsequent Days.

We sort all common stocks in the Chinese and U.S. markets into decile portfolios based on PIR. In addition to the SIR within same day, we investigate the return of portfolios over the following trading days. The same filters as in Table 1 for both the Chinese and U.S. stock markets are considered. We report the equal-weighted and value-weighted return over the following 20 trading days for each market. We also report the accumulated return from the holding time, which is 10:15 on day $t + 0$, to the end of a given day. T-statistics are calculated based on Newy-West standard errors with 120 lags.

Panel A. C.N.

	EW Return		VW Return		EW Ac. Return		VW Ac. Return	
	H-L	t(H-L)	H-L	t(H-L)	H-L	t(H-L)	H-L	t(H-L)
t+0	-40.4	(-15.5)	-32.3	(-12.3)	-40.4	(-15.5)	-32.3	(-12.3)
t+1	26.1	(8.5)	30.0	(8.7)	-13.1	(-4.3)	-1.5	(-0.5)
t+2	4.3	(3.4)	5.1	(3.1)	-9.3	(-2.5)	3.3	(0.8)
t+3	8.3	(6.1)	5.5	(3.3)	-1.5	(-0.4)	8.4	(1.8)
t+4	5.5	(4.7)	4.0	(2.7)	3.4	(0.7)	11.6	(2.4)
t+5	-5.6	(-5.7)	-4.9	(-3.3)	-3.1	(-0.6)	5.5	(1.1)
6 to 10	19.3	(6.7)	14.9	(4.0)	16.7	(2.6)	21.8	(3.2)
11 to 20	19.9	(4.7)	20.1	(2.9)	35.7	(4.5)	41.5	(4.1)

Panel B. U. S.

	EW Return		VW Return		EW Ac. Return		VW Ac. Return	
	H-L	t(H-L)	H-L	t(H-L)	H-L	t(H-L)	H-L	t(H-L)
t+0	-27.4	(-14.1)	-5.6	(-2.0)	-27.4	(-14.1)	-5.6	(-2.0)
t+1	7.7	(4.1)	12.5	(3.9)	-19.7	(-8.4)	6.8	(1.6)
t+2	-2.2	(-1.5)	-4.6	(-1.5)	-21.7	(-8.3)	2.6	(0.7)
t+3	-0.8	(-0.4)	-5.5	(-1.9)	-22.5	(-6.7)	-2.9	(-0.6)
t+4	-0.6	(-0.4)	-3.3	(-1.2)	-23.2	(-6.6)	-6.1	(-1.0)
t+5	-0.8	(-0.5)	-2.7	(-1.1)	-23.6	(-6.9)	-8.2	(-1.4)
6 to 10	-2.1	(-0.7)	-6.6	(-1.2)	-26.1	(-5.8)	-14.9	(-1.7)
11 to 20	1.8	(0.5)	-3.7	(-0.5)	-24.4	(-4.1)	-18.4	(-1.6)

Table 5: Intraday Reversal and Fundamental Risks

At time $m = 10:00$ each day, we sort all stocks into five-times-five portfolios independently based on PIR and each of the measures of fundamental risk. Then, we hold the portfolios from $n = m+15$ minutes to the market close. Equal-weighted and value-weighted return, spreads and t-statistics of the spreads are reported. We only report the bottom, middle and top quintiles to save space. Returns are reported in basis points, and t-statistics are based on Newey-West standard errors with 120 lags.

Three measures of fundamental risk are considered: cash-flow volatility ($CASHVOL$), the volatility of the return on equity ($ROEVOL$) and the volatility of the return on assets ($ROAVOL$). $CASHVOL$ is measured by the standard deviation of the ratio of annual operating cash flows to sales during the past 5 years (a minimum of 3 nonmissing years). $ROEVOL$ and $ROAVOL$ are measured by the standard deviation of quarterly ROE and ROA, respectively, during the past 5 years (a minimum of 12 nonmissing quarters of data). Quarterly ROE is equal to earnings before extraordinary items divided by one-quarter-lagged common shareholders' equity. Quarterly ROA is equal to earnings before extraordinary items divided by one-quarter-lagged total assets. To control for seasonality effects, we demean the ROE/ROA at the quarterly level within last 5 years when calculating $ROEVOL/ROAVOL$.

	CASHVOL				ROEVOLA				ROAVOLA			
	S	M	B	B-S	S	M	B	B-S	S	M	B	B-S
Equal-weighted Return												
PIR 1	22.2	23.2	25.0		21.8	22.9	27.4		21.8	23.3	27.5	
PIR 3	8.7	8.6	9.9		9.2	8.8	12.1		9.2	9.1	12.3	
PIR 5	-7.4	-8.7	-8.5		-7.1	-7.8	-9.1		-7.1	-7.6	-9.2	
5 - 1	-29.6	-31.9	-33.6	-4.0	-29.0	-30.7	-36.4	-7.5	-29.0	-30.9	-36.7	-7.7
	(-11.6)	(-12.6)	(-14.8)	(-3.6)	(-11.7)	(-11.4)	(-13.4)	(-4.8)	(-11.5)	(-11.2)	(-13.4)	(-5.5)
Value-weighted Return												
PIR 1	17.1	18.1	19.8		15.5	17.4	21.1		15.3	18.5	20.5	
PIR 3	7.5	5.8	6.8		8.0	5.9	9.2		7.7	6.6	9.6	
PIR 5	-6.5	-9.5	-8.0		-5.6	-8.1	-9.3		-6.1	-7.1	-9.1	
5 - 1	-23.6	-27.6	-27.8	-4.1	-21.1	-25.4	-30.5	-9.4	-21.4	-25.6	-29.6	-8.2
	(-8.4)	(-10.6)	(-11.3)	(-2.3)	(-7.8)	(-7.8)	(-11.9)	(-4.4)	(-7.7)	(-7.6)	(-12.5)	(-3.8)

Table 6: Persistence of Intraday Reversal

We regress the daily return spread of the PIR portfolio on the average return spread of the same portfolio over the past 60 trading days ($AvgIR$). The spread is the return difference from 10:15 to the daily close between stocks with top- and bottom-decile PIRs at 10:00. Both the value- and equal-weighted return are considered. As a robustness check, we also control for two other components: 1) fundamental risk using the average VIX over past 60 trading days ($AvgVIX$) and market volatility using the standard deviation of the market factor ($MKTVOLA$) of Liu et al. (2019) and 2) trading activity by abnormal market volume ($ABVOL$), which is the average daily dollar volume of all common shares over the past 60 trading days divided by that over the past 240 trading days. VIX data are the CBOE China ETF volatility index from FRED Economic Data which is only available since March, 16, 2011.

Y=PIR Spread	Value-weighted			Equal-weighted		
AvgPIRs	0.594	0.401	0.407	0.679	0.397	0.427
	(7.732)	(4.163)	(2.791)	(10.382)	(3.782)	(2.319)
MKTVOLA		-12.347			-13.919	
		(-4.747)			(-4.960)	
AvgVIX			-0.787			-0.967
			(-1.853)			(-2.057)
ABVOL		5.202	2.979		3.632	-2.641
		(1.308)	(0.377)		(0.994)	(-0.441)
Constant	-12.867	-6.471	3.278	-12.965	-7.953	8.237
	(-4.519)	(-1.259)	(0.242)	(-4.481)	(-1.983)	(0.725)
Sample N	4662	4482	2035	4662	4482	2035
R2	0.014	0.019	0.012	0.026	0.035	0.022

Table 7: Intraday Reversal and Retail Investors in China

At time $m = 10:00$ each day, we sort all stocks into five-times-five portfolios independently based on PIR with timing m and each one of measures of the activity of retail investors. Then, we hold the portfolios from $m + 15$ minutes to the market close. For both markets, filter 3) mentioned in Table 2 is considered. Equal-weighted and value-weighted return, spreads and t-statistics of the spreads are reported. We only report the lowest, median and highest portfolios to save space. Returns are reported in basis points, and t-statistics are based on Newey-West standard errors with 120 lags. Three measures for retail investors are considered: value per holder (VPH), daily amount per trade ($DAPT$) and amount per trade during the holding ($HAPT$). VPH is market equity divided by the number of shareholders. $DAPT$ and $HAPT$ are the trading amount divided by the number of trades during the whole day and the holding period respectively. Because of data limitations, the VPH portfolios span from May 2002 to December 2019 and the $DAPT$ portfolios span from January 2012 to December 2019. The $HAPT$ portfolios also span from January 2012 to December 2019 but only contains the stocks listed in the Shenzhen Stock Exchange with sharecodes beginning with '0' and '3'.

	VPH				DAPT				HAPT			
	S	M	B	B-S	S	M	B	B-S	S	M	B	B-S
Equal-weighted Return												
PIR 1	27.1	23.2	25.4		2.0	14.6	33.8		-0.4	13.6	37.5	
PIR 3	12.9	9.6	10.6		-7.3	6.4	24.8		-8.9	5.2	26.7	
PIR 5	-7.2	-8.5	-5.3		-30.5	-12.1	16.2		-35.4	-14.0	22.8	
5 - 1	-34.3	-31.8	-30.7	3.6	-32.5	-26.7	-17.6	14.9	-35.0	-27.6	-14.7	20.2
	(-13.5)	(-12.1)	(-11.5)	(3.4)	(-15.6)	(-12.5)	(-5.5)	(8.7)	(-16.8)	(-13.2)	(-3.9)	(7.7)
Value-weighted Return												
PIR 1	23.6	17.9	16.3		-0.1	8.7	15.4		-1.2	7.3	19.9	
PIR 3	10.4	7.5	8.4		-9.1	-0.3	13.1		-10.8	-1.6	14.3	
PIR 5	-6.0	-10.2	-4.8		-31.1	-15.5	6.2		-37.2	-21.0	9.6	
5 - 1	-29.6	-28.1	-21.1	8.5	-31.0	-24.2	-9.2	21.8	-36.0	-28.3	-10.3	25.7
	(-14.1)	(-10.8)	(-7.9)	(5.0)	(-16.6)	(-11.4)	(-3.6)	(11.0)	(-18.4)	(-13.3)	(-3.3)	(11.0)

Table 8: Intraday Reversal and Retail Investors—Fama-MacBeth Regression

Each day, we run a cross-sectional regression of SIR to market close on the PIR with $m = 10:00$ and its interaction with measures for the activity of retail investors (RI) for Chinese stock market:

$$SIR_{i,t}^{m+15} = a_t + \beta_{1,t}PIR_{i,t}^m + \beta_{2,t}PIR_{i,t}^m RI_{i,t} + \beta_{3,t}RI_{i,t} + \sum \beta_{c,t}Controls_{i,t}^c$$

We control for the firm characteristics listed in Table 1 and interaction terms between PIR and liquidity in the regression, and the time-series average of regression coefficients is reported. We consider three measures for RI: $-VPH$, $-DAPT$ and $-HAPT$ as defined in Table 7. The filters for stocks to enter our sample are the same as in Table 1. Because of data limitations, the sample period for the regression with VPH spans from May 2002 to December 2019 and that with $DAPT$ spans from January 2012 to December 2019. The $HAPT$ sample also span from January 2012 to December 2019 but only contains the stocks listed on the Shenzhen Stock Exchange with sharecodes beginning with '0' and '3'.

RI=		-VHP	-DAPT	-HAPT
PIR	-0.262	-0.291	-0.145	-0.053
	(-10.17)	(-10.55)	(-3.07)	(-1.01)
PIR*RI		-0.001	-0.033	-0.053
		(-2.80)	(-5.93)	(-6.57)
RI		0.000	-0.003	-0.003
		(3.11)	(-15.79)	(-14.12)
PIR* Ami	-0.169	-0.126	-0.231	-0.530
	(-1.22)	(-0.81)	(-0.80)	(-1.99)
PIR* ME	0.023	0.028	-0.001	-0.019
	(6.01)	(6.86)	(-0.14)	(-2.47)
PIR* TO	1.274	1.118	0.102	0.130
	(2.94)	(2.49)	(0.62)	(0.64)
ME	-0.001	-0.001	-0.003	-0.003
	(-9.90)	(-10.23)	(-16.06)	(-11.89)
BM	0.000	0.000	0.002	0.002
	(0.62)	(3.55)	(6.75)	(6.72)
Rev	-0.004	-0.002	-0.002	-0.004
	(-1.25)	(-0.62)	(-0.42)	(-0.81)
Mom	0.000	0.000	-0.003	-0.003
	(-1.08)	(-1.33)	(-8.78)	(-9.78)
TO	0.001	0.000	0.000	0.000
	(4.38)	(1.85)	(-2.05)	(-2.69)
Vola	-0.035	-0.028	-0.032	-0.034
	(-6.51)	(-5.08)	(-6.29)	(-7.01)
Ami	0.005	0.011	0.002	-0.002
	(1.35)	(2.97)	(0.30)	(-0.42)

Table 9: Retail Investors and Reversal of Intraday Reversal—Fama-MacBeth Regression

For each day, we run a cross-sectional regression of the following 20-days' return on the PIR, SIR, RI and their interaction-terms for the Chinese stock market:

$$Ret_{i,t}^{t+1,t+20} = a_t + \beta_{1,t} PIR_{i,t}^{m} + \beta_{2,t} SIR_{i,t}^{m+15} + \beta_{3,t} SIR_{i,t}^{m+15} RI_{i,t} + \beta_{4,t} RI_{i,t} + \sum \beta_{c,t} Controls_{i,t}^{c}$$

We control for the firm characteristics listed in Table 1 and interaction terms between SIR and liquidity in the regression, and the time-series average of regression coefficients is reported. We consider three measures for RI: $-VPH$, $-DAPT$ and $-HAPT$ as defined in Table 7. The filters for stocks to enter our sample are the same as in Table 1. Because of data limitations, the sample period for the regression with VPH spans from May 2002 to December 2019 and that with $DAPT$ spans from January 2012 to December 2019. The $HAPT$ sample also spans from January 2012 to December 2019 but only contains the stocks listed on the Shenzhen Stock Exchange with sharecodes beginning with '0' and '3'.

RI=		-VPH	- DAPT	- HAPT
PIR	0.121	0.145	0.171	0.167
	(7.83)	(11.07)	(14.45)	(13.42)
SIR	-0.206	-0.594	-1.289	-1.380
	(-15.53)	(-4.95)	(-8.61)	(-8.91)
SIR*RI		-0.002	-0.097	-0.114
		(-1.38)	(-8.84)	(-10.47)
RI		0.000	0.001	0.002
		(-0.07)	(0.73)	(1.33)
SIR * Ami		-2.045	-0.984	-0.708
		(-3.94)	(-1.32)	(-0.87)
SIR * ME		0.059	0.178	0.197
		(3.53)	(8.46)	(8.58)
SIR * TO		0.827	-0.234	0.117
		(0.90)	(-0.34)	(0.19)
ME	-0.010	-0.009	-0.011	-0.015
	(-3.19)	(-2.78)	(-2.39)	(-2.70)
BM	0.009	0.007	0.004	0.003
	(2.87)	(2.60)	(0.90)	(0.64)
Rev	-0.343	-0.326	-0.282	-0.245
	(-5.42)	(-4.85)	(-3.64)	(-2.81)
Mom	-0.021	-0.020	-0.015	-0.018
	(-3.90)	(-3.65)	(-2.33)	(-2.70)
TO	0.008	0.006	0.007	0.006
	(2.85)	(1.93)	(2.27)	(2.18)
Vola	-0.424	-0.323	-0.410	-0.426
	(-6.22)	(-5.12)	(-6.10)	(-6.86)
Ami	0.057	0.078	0.138	0.084
	(0.97)	(1.15)	(1.00)	(0.66)

Appendix A Proofs

We provide the proofs for the main propositions mentioned in the paper.

Appendix A.1 Baseline Stylized Framework

We first calculate the equilibrium for the baseline framework. Due to the exogenous strategy of the informed traders, we only need to derive the trading strategy for the market maker.

$$E[v|\mathcal{M}] = \frac{\beta\tau_z w_1 + \tau p_0}{\beta^2\tau_z + \tau}.$$

The market clearing condition requires that market maker absorb all the market orders on the market, which means that

$$\gamma_m(E[v|\mathcal{M}] - p_1) + w_1 = 0.$$

This yields the equilibrium price at time $t = 1$

$$p_1 = \frac{\tau}{\tau + \beta^2\tau_z} p_0 + \left(\frac{1}{\gamma_m} + \frac{\beta\tau_z}{\beta^2\tau_z + \tau}\right) w_1.$$

Moreover, following the classical definition of liquidity, we let

$$\lambda = \frac{\partial p_1}{\partial z_1} = \frac{1}{\gamma_m} + \frac{\beta\tau_z}{\beta^2\tau_z + \tau}.$$

Hence, we can compute the correlation between first period price movement and second period price movement as:

$$\begin{aligned} cov(p_1 - p_0, v - p_1) &= \lambda\left(\frac{\beta(1-\lambda\beta)}{\tau} - \frac{\lambda}{\tau_z}\right) = \lambda\left(\frac{\beta}{\tau} - \left(\frac{\beta^2}{\tau} + \frac{1}{\tau_z}\right)\lambda\right) \\ &= -\left(\frac{\beta^2}{\tau} + \frac{1}{\tau_z}\right)\lambda^2 + \frac{\beta}{\tau}\lambda. \end{aligned}$$

Hence, based on the basic properties of the quadratic equation, when the market becomes more illiquid, there is a reversal and reversal increases with illiquidity.

Appendix A.2 Stylized Framework with Liquidity Oversupply

The equilibrium price at time $t = 1$ is similar to what we observed previously, except that now there are additional liquidity supplies (beyond the market maker) in the market. Hence, the market clearing condition at time $t = 1$ condition becomes

$$\gamma_m(E[v|\mathcal{M}] - p_1) + \mu\gamma_U(E[v|I_1] - p_1) + w_1 = 0.$$

For brevity, we assume that uninformed traders do not learn information from concurrent asset prices but that they can infer information from previous equilibrium prices. Hence, at this moment, the expectation is:

$$E[v|I_1] = p_0.$$

Plugging this into the market clearing condition, we have:

$$\gamma_m\left(\frac{\beta\tau_z w_1 + \tau p_0}{\beta^2\tau_z + \tau} - p_1\right) + \mu\gamma_U(p_0 - p_1) + w_1 = 0.$$

Hence, we can solve the equilibrium price at time $t = 1$ as

$$p_1 = \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m\tau}{\tau + \beta^2\tau_z} + \mu\gamma_U\right)p_0 + \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m\beta\tau_z}{\beta^2\tau_z + \tau} + 1\right)w_1.$$

On the other hand, at $t = 1^+$, only uninformed traders arrive, and they independently submit demand schedules $x_{i,1^+} = \gamma_U(E[v|I_{i,1^+}] - p_{1^+})$ to trade the risky asset based on their information set. The market clearing condition yields:

$$\int_0^{\theta\mu}\gamma_U(E[v|I_{i,1^+}] - p_{1^+})di + \int_{\theta\mu}^{\mu}\gamma_U(E[v|I_{i,1^+}] - p_{1^+})di = 0.$$

By Simplifying the above equation, we have

$$\theta\mu\gamma_U\left(\frac{(1+\alpha)\tau p_0 + (1-\alpha)\beta\tau_z w_1}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} - p_{1^+}\right) + (1-\theta)\mu\gamma_U\left(\frac{\tau p_0 + \beta\tau_z w_1}{\tau + \beta^2\tau_z} - p_{1^+}\right) = 0.$$

Hence, the equilibrium price at time $t = 1^+$ equals

$$p_{1^+} = \left[\frac{\theta(1+\alpha)\tau}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\tau}{\tau + \beta^2\tau_z}\right] p_0 + \left[\frac{\theta(1-\alpha)\beta\tau_z}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\beta\tau_z}{\tau + \beta^2\tau_z}\right] w_1.$$

Finally, we come to the price reversal as

$$\begin{aligned} cov(p_1 - p_0, p_{1^+} - p_1) &= cov\left(\lambda_l w_1, \left(\frac{\theta(1-\alpha)\beta\tau_z}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\beta\tau_z}{\tau + \beta^2\tau_z} - \lambda_l\right) w_1\right) \\ &= \lambda_l \left(\frac{\theta(1-\alpha)\beta\tau_z}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\beta\tau_z}{\tau + \beta^2\tau_z} - \lambda_l\right)\left(\frac{\beta^2}{\tau} + \frac{1}{\tau_z}\right). \end{aligned}$$

where the parameter λ_l is defined as

$$\lambda_l = \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m\beta\tau_z}{\beta^2\tau_z + \tau} + 1\right).$$

To have the price reversal, we have the following condition:

$$\frac{\theta(1-\alpha)\beta\tau_z}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\beta\tau_z}{\tau + \beta^2\tau_z} < \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m\beta\tau_z}{\beta^2\tau_z + \tau} + 1\right).$$

By simplifying the above condition, we have

$$\frac{(\Phi(\alpha) - 1))\tau}{(\tau + \beta^2\tau_z)(\Phi(\alpha)\tau + \beta^2\tau_z)}\theta > \frac{1}{\tau + \beta^2\tau_z} - \frac{1}{\gamma_m + \mu\gamma_U}\left(\frac{\gamma_m}{\beta^2\tau_z + \tau} + \frac{1}{\beta\tau_z}\right) = \frac{\mu\gamma_U}{\tau + \beta^2\tau_z} - \frac{1}{(\gamma_m + \mu\gamma_U)\beta\tau_z}.$$

We next turn to the price correlation for the second period.

$$cov(p_{1^+} - p_1, v - p_{1^+}) = cov\left((K - \lambda_l)w_1, v - Kw_1\right) = (K - \lambda_l)\beta(1 - K\beta)\frac{1}{\tau} - (K - \lambda_l)K\frac{1}{\tau_z}.$$

where the parameter K is represented as

$$K = \frac{\theta(1-\alpha)\beta\tau_z}{(1+\alpha)\tau + (1-\alpha)\beta^2\tau_z} + \frac{(1-\theta)\beta\tau_z}{\tau + \beta^2\tau_z}.$$

When condition (11) holds, $K < \lambda_l$. Furthermore, it is easy to show that

$$\beta(1 - K\beta)\tau_z > K\tau.$$

once condition (9) holds. We have thus provided all the proofs.

Internet Appendix:

What Drives Intraday Reversal? Illiquidity or Liquidity Oversupply?

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January 15, 2022

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A.1 Different Timing of Intraday Reversal

The very first concern of intraday reversal might be the timing for forming the portfolios. Specifically, one might argue that the result could be data-snooped, which only exist for the specific timing 10:00 as shown in the tables of manuscript. To inspect the robustness of intraday reversal, we try to form the portfolios based on PIR with different ms, and show the SIR-spread for single sorting on PIR and double sorting with $DAPT$. We only report the difference between highest and lowest decile for single sorting results and difference-in-difference (as PIR 5-1 and $DAPT$ B-S) for double-sorting portfolios in Table A1.[1] Equal-weighted and value-weighted return for Chinese market are shown respectively. T-statistics given in the parentheses are based on Newey-West (1987) standard errors with 120-lag.

[Insert Table A1 here]

Firstly, Table A1 demonstrates that negative relationships between PIR and following intraday return are robust for different timing choices. For all six different time stamps (from 10:00 till 14:00), the high-PIR stocks significantly underperform low-PIR over intraday return. Besides, the spreads between high- and low-PIR stocks weakly decrease with later time for forming the portfolios. For instance, considering the equal-weighted

[1] For single-sorted portfolio as Table 1, we sort all common stocks into decile portfolios based on a stock's PIR at the end of every half hour and holding the portfolios from 15-minute later to the today's close. For each time m, time-series average differences between highest and lowest (H-L) is reported. We do not report every single decile for easy observation. For double-sorted portfolio as in Table 7, we independently sort all common stocks into five times five portfolios based on quintiles of their PIR and $DAPT$ at the end of every half hour and calculates the portfolios return from 15-minute later to the today's close. We only report the difference-in-difference of double-sorting portfolios in Table 7.

portfolio, high-PIR stocks significantly underperform low-PIR by 40.4 BPs with a of -15.5 with $m = 30$; however, the SIR-spread decreases to 3.97 BPs with $m = 180$. The value-weighted spreads are consistent with the equal-weighted one. The gradual decreasing of intraday reversal with later forming time implies that, in Chinese market, it is not mainly driven by portfolio rebalance from institutional investors, whose transactions are mostly completed at the last 30 minutes of daily trading hours. The result provides additional evidence for our story of over-liquidity.

Secondly, for the role of retail investors, intraday reversal is more pronounced among stocks with more participation of retail investors, especially in the morning. The return difference among stocks with highest and lowest $DAPT$ is about one third of unconditional reversal spread for the timing m before 11:30. This phenomenon almost disappeared in the afternoon. For instance, considering the equal-weighted portfolio, the columns B-S report the difference between SIR-spread among the least-retailed-trading and those among the most-retailed-trading. For $m = 30$, this difference-in-difference is 14.87 BPs per day, with a t-statistic of 8.7. For $m = 180$, the difference-in-difference is only 1.1 BPs per day. This result confirms our previous analysis that participant of retailed investors had huge impact on the intraday reversal anomaly.

A.2 Period Dependency

Due to serious loss during the 2014-2015 stock market tsunami, the activeness of individual investors and the proportion of them in the market might be gradually decreasing after 2015. Hence, another concern, that whether our results are period-dependent, naturally raised. To investigate the period dependency of intraday reversal, we calculate and present the accumulated wealth of intraday reversal strategy in Figure A1. Specifically, upper panel shows accumulated wealth investing in different deciles of PIR portfolio and bottom panel shows the SIR-spreads with different level of participant of retailed investors.[2]

[Insert Figure A1 here]

The result shows that, in general, intraday reversal anomaly is not period-dependent. The wealth accumulations of reversal strategies are stable and smooth. This implies that intraday reversal exists in the most time during our sample period. However, it can also be observed that, after 2017, the cumulative wealth growth of unconditional PIR hedge portfolio has slowed down, which is consistent with decreasing activeness of individual investors. But if we look closely at the PIR hedge portfolio conditional on $DAPT$ by turning into bottom panel, we observe that the disappearance of intraday reversal is mainly because of stocks with high $DAPT$ (represented by grey line). On the other hand, low $DAPT$ stocks still retain a significant pattern, making the difference-in-difference maintain a steady upward trend. This suggests that the retailed investors still have huge impacts on intraday reversal anomaly in Chinese market, However, the unconditional intraday reversal is getting weaker only due to less participation of retailed investors. To sum up, all the result implies that intraday reversal is a long-live phenomenon in Chinese stock market and the activeness of retails investors play an important role in this phenomenon.

[2]For PIR portfolio, we only plot the portfolios with highest, forth, seventh and lowest deciles of PIR along with the long-short portfolio for easy observation. For the same purpose, only the SIR-spreads with high, median and low $DAPT$ and the difference-in-difference are reported for double-sorted portfolio.

A.3 Dual Listing for Mainland and Hong Kong Market

The firms simultaneously listed in the exchanges of Chinese mainland market (Shanghai Stock Exchange or Shenzhen Stock Exchange, so-called A-share) and Hong Kong market (Hong Kong Exchanges and Clearing Limited, so-called H-share) provide us an opportunity to test the impact of individual investors on intraday reversal after controlling the fundamental movements of sample assets.[3] The data of these multi-listed firms is acquired from 'Wind' data-base including firms' name, their share codes in A-share and H-share, and their IPO date in both markets. And then, we obtain the intraday and daily price in Hong Kong market from TRTH based on their share code. Because of limited number of multi-list firms and the availability of Hong Kong data, the sample period is from January 2005 to December 2017. At $m = 30$ of everyday, we sort all sample stocks, which is simultaneously listed in mainland and Hong Kong markets, into three portfolios based on their corresponding PIRs for both markets respectively. We hold the portfolios from $n = 45$ to the today's close and calculate the equal-weighted portfolio return. To enter portfolios, the stocks must be listed on both markets longer than six months. In a given day, we require at least 30 stocks in our sample to form the portfolio which implies at least 10 stocks for each group. Portfolio returns of simultaneously listed firms

[3]The previous evidence shows that the driving force on intraday reversal is very different between China and the United States. Although we argue that the reason for the difference is the liquidity over-supply of individual investors, the existence of difference in underlying assets cannot guarantee the correctness of this statement. If changes in asset fundamentals are usually in opposite directions during the daytime and overnight, the intraday reversal could be induced by seasonally changes of asset fundamentals.

are given in the top panel of Table A2. Besides of listing, we also require the stocks are simultaneously traded on both markets to enter portfolios as an additional test and result is given in the bottom panel. We also report the SIR-spread along with its difference between mainland and Hong Kong market.

[Insert Table A2 here]

If the activities of individual investors are the cause of China's liquidity over-liquidity, then the following two channels could lead a significant difference between the intraday pattern of the Chinese and Hong Kong markets: 1) the proportion of individual investors in the Hong Kong market is significantly lower than the mainland market; 2) The price limitation, which is applied in mainland market but not in the Hong Kong exchange, may amplify the behavioral bias of individual investors, by reducing possible losses of trading against PIR in intraday. The result shown in Table A2 implies that component of individual investors and price limitation play a crucial role in intraday reversal. Stocks with identical fundamental variation show diverse intraday patterns in two different markets. In mainland market, return spread between stocks with highest and lowest PIR is -22.4 BPs daily meanwhile the one in Hong Kong is only -2.3 with an insignificant statistic. The disappearance of reversal in Hong Kong market with these sample stocks may be caused by their characteristics of high market value which qualifies them to list in both markets. High market value, which indicates the high liquidity, correspond to insignificant intraday price reversal as discussed in illiquid based explanation. The difference between two markets is statistically significant 20 BPs. Result remains the same after additional requirement of simultaneously trading.

A.4 First Thirty-minute PIR and Last Thirty-minute Return.

Gao et al. (2018) argue that infrequently rebalances of institutional investors are based on similar information signal. They tend to trade at the opening and closing time of the market, which lead to a pattern of intraday momentum. With a variety of ETF data, they found that the first thirty-minute intraday return positively predicts the last thirty-minute intraday return in time-series level. We now provide the cross-sectional version results of Gao et al. (2018), and compare our results with theirs to demonstrate the cross-sectional intraday reversal.

To this end, we sort all sample stocks into decile portfolios based on a stock's PIR at timing m = 30 and investigating the return over last thirty minutes of trading hours in both Chinese and U.S. stock market. Similar filters as in Table 1 are considered which require the absolute value of stocks' PIR is smaller than 5% and at least one available trade between first and last thirty minutes. Equal-weighted and value-weighted returns of every deciles and the return spreads between highest to lowest decile are calculated and reported in Table A3. Their t-statistics based on Newey-West standard error with 120-lag are given in the parentheses.

[Insert Table A3 here]

Result of both Chinese and U.S. stock market shows that, in cross-section, first thirty-minute intraday return negatively predicts last thirty-minute intraday return which is inconsistent with result in time-series, especially for U.S. market. In U.S. market, stocks in bottom PIR-decile earn about 10 BPs equal-weighted return in the last 30-minutes which is significantly higher than other deciles. The return spread between highest and lowest decile are about -8.3 BPs with t-statistics of -11.4. The negative value and the overall trend of result support the existence of intraday reversal among those two periods with high institutional participations.

In general, the pattern in China is similar with U.S. stock market. Both equal-weighted and value-weighted return spreads are negative and also statistically significant. The magnitude of spread, which is -1.4 and -2.2 BPs for equal-weighted and value-weighted respectively, is smaller than the ones of U.S. market. Another noteworthy feature of result in China is that the last 30 minutes return of PIR-portfolio shows an inverted U-shaped as PIR of first 30-minute increases. A possible explanation is stocks with extreme PIR values tend to have a greater overnight risk, resulting a strong selling pressure before market close. This phenomenon is more pronounced in small-cap stocks, so the inverted U-shape is relatively small in the value-weighted portfolio. Although this phenomenon seems to dominate in China, the significantly negative H-L spread proves that the intraday reversal is stable even in the case of the first to last 30-minute prediction.

A.5 Transaction Cost

The high return spread between high and low PIR portfolios seems to be a challenge to the market efficiency in China, especially the main profit of arbitrage strategy is from the long leg. Meanwhile, intraday reversal strategy needs daily rebalance, which mechanically increases turnover. Hence, trading cost should be a significant impact factor. Considering that, as a developing market, the transaction cost of China stock market is quite high, which could seriously damage the profit of PIR portfolio considering the execution is at a daily frequency. Therefore, we check the impact of transaction costs on intraday reversal.

We firstly collect and report the data of the transaction cost in Chinese market in the panel A of table A4. Two types of fee are charged during the trading: stamp-tax charged by the government, and commission fee charged by brokers. Commission fee is varied with different brokers and different types of investors, generally is between 1 to 10 BPs for retail investors, but could be lower than 1 BPs for institutional investors especially for the quantitative hedge fund. Without losing generality, we set the commission as 1 BP per trade. Stamp-tax is much larger than commission fee, which is above 10 BPs per trade and changed frequently before 2008. After the last change at 19^{th} September, 2008, the stamp-tax maintain at 10 BPs per trade.

With the transaction cost, we then calculate and report the after-fee-return of PIR portfolio in panel B. Only portfolios in top (H) and bottom (L) deciles of PIR and the long-short portfolio (longing at bottom and shorting at top, L-H) are reported in table A4. For L and H, net return is the raw return minus the stamp-tax and commission. For L-H, return is the difference between L and H, minus twice the stamp-tax and commission.

Result shows that PIR-porfolios cannot obtain a significant positive return during the overall sample period. After adjustment of fees, both the longing at L and long-short portfolio earn a negative return. The implication is that the market is quite efficient, and investors cannot directly obtain a significant positive return by investing in low-PIR stocks if they do not have other trading motivation. Another observation in the panel A is that, after 2008, the stamp-tax is maintained at a relatively low level. Maybe PIR-portfolio could survive in those low-fee periods. We then separate the whole sample period into two sub-sample: ones with a high stamp-tax (> 20 BPs) and ones with a low stamp-tax (≤ 20 BPs). Result shows that the long-leg of PIR portfolio can earns a marginal significant 5.6 BPs per trade in the low-fee period. The result implies that transaction cost significantly decreases the profitability of intraday strategy in China stock market, such as our PIR portfolio. Even investors cannot directly obtains an excess return, PIR signal could be used for investors with other transaction motive and help them decreasing the costs of trading by postpone the time of buying stocks with high PIR.

In summary, result shown in the online appendix table A4 implies that the high arbitrary cost, i.e., trading cost, in Chinese market is another important driving force for intraday reversal. During periods with high stamp-tax, both the longing low-PIR stocks or the long-short portfolio cannot earn a positive return. On the other hand, in the low-fee periods, longing low-PIR stocks can still earn a marginally significant 5.6 BPs per day, which implies that the magnitude of intraday reversal cannot entirely explained by limitation of arbitrage.

References

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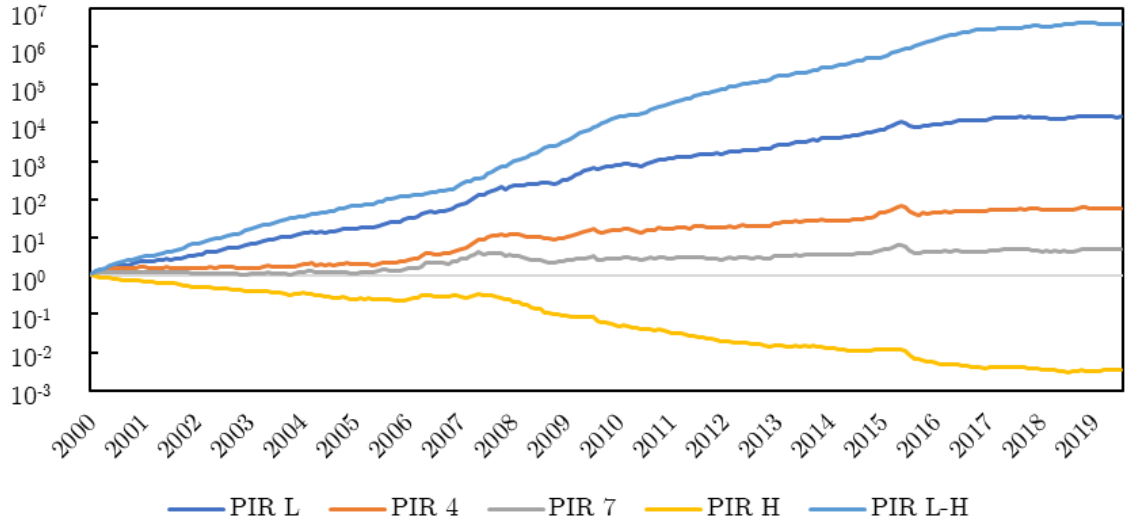
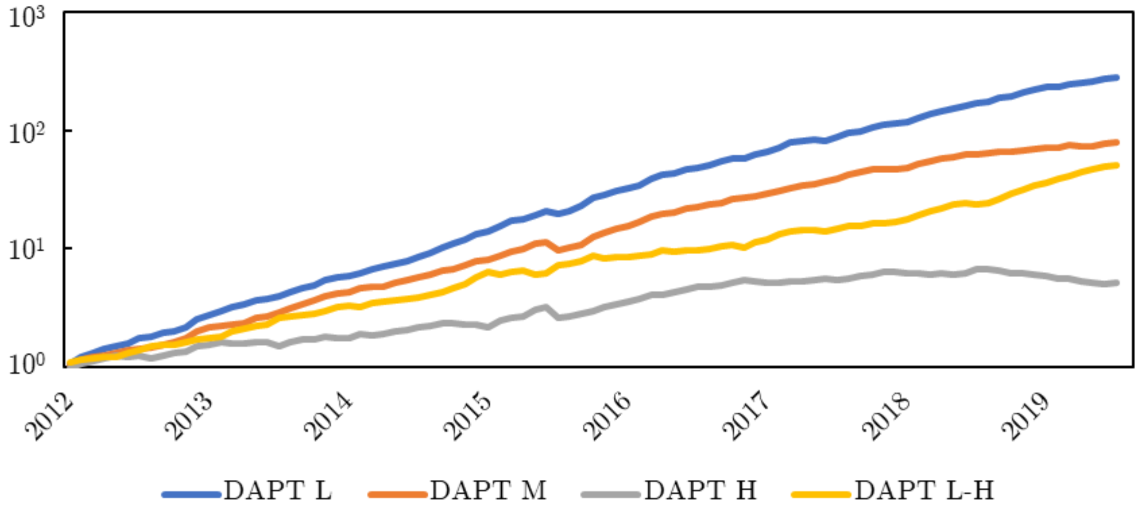
Newey, W. K. and West, K. D. (1987), 'Hypothesis testing with efficient method of moments estimation', *International Economic Review* pp. 777–787.

Figure A1: Accumulated Wealth of Intraday Reversal





This figure plots the accumulated wealth of portfolios based on PIR. Panel A reports result of single-sorted portfolios based on PIR as in table 1 and panel B reports the one conditional on the activities of retails investors ($DAPT$) as in table 7. For single-sorted portfolios, we only report the wealth of highest, 4th, 7th and lowest decile PIR and the one of the differences between lowest and highest for easily observation. For double-sorted portfolios, the reversal spreads, which is the return difference between lowest and highest quintiles PIR, with lowest ($DAPT$ L), median ($DAPT$ M) and highest ($DAPT$ H) are shown in panel B along with the difference between lowest and highest $DAPT$.

Table A1: Different timing for PIR portfolios

Single-sorting portfolios based on PIR as in table 1 and double-sorting portfolios based on PIR and $DAPT$ as in table 1 are constructed at different timing m for China stock market. For each m, the portfolio is held from $m + 15$ to same day close and similar filters as in table 1 are applied. For saving place, this table only reports the 'High-Low' spreads of single-sorting and the difference-in-difference of double-sorting portfolios for each timing m. Returns are reported in BPs and the Newey-West t-statistics with 120 lags are given in the parentheses.

Equal-Weighted				
	Single sorting on PIR		Double-sorting with DAPT	
m	H-L	t(H-L)	B-S of H-L	t(B-S of H-L)
10:00	-40.44	(-15.5)	14.87	(8.7)
10:30	-30.80	(-15.0)	9.63	(4.3)
11:00	-23.91	(-14.2)	7.18	(3.2)
11:30	-23.57	(-14.9)	1.01	(0.5)
13:30	-13.27	(-9.5)	0.92	(0.4)
14:00	-3.97	(-3.4)	1.10	(0.5)
Value-Weighted				
	Single sorting on PIR		Double-sorting with DAPT	
m	H-L	t(H-L)	B-S of H-L	t(B-S of H-L)
10:00	-32.34	(-12.3)	21.80	(11.0)
10:30	-24.41	(-11.5)	14.75	(7.3)
11:00	-20.44	(-12.4)	9.52	(4.5)
11:30	-21.77	(-13.4)	2.97	(1.4)
13:30	-12.73	(-9.2)	2.34	(1.0)
14:00	-5.62	(-4.7)	2.92	(1.6)

Table A2: Intraday reversal of firms simultaneously listed and traded in Hongkong and Mainland exchange

Every day, we group stocks, which are simultaneously listed in the Chinese mainland stock exchange (Shanghai Stock Exchange and Shenzhen Stock Exchange, A share) and Hong Kong Exchanges and Clearing Limited (H share), into three portfolios based on their PIR in the corresponding market of both stock market respectively. The timing m of both PIR is 10:00. Table reports the equal-weighted return of each portfolio from 10:15 to the market close. To enter our portfolio, the stocks must be listed in both markets longer than 6 months. The upper panel only requires stocks are simultaneously listed and the bottom panel additionally requires stocks are simultaneously traded in given day. Returns are reported in basis-points and t-statistics based on Newey-West standard error with 120 lags are given in parentheses. Because of the availability of Hong Kong data, the sample period is from January 2005 to December 2017.

	L	M	H	H-L
Simultaneously listed				
Mainland	18.4	10.5	-4.1	-22.4
	(6.4)	(4.2)	(-1.8)	(-9.3)
Hongkong	1.9	-3.3	-0.4	-2.3
	(0.7)	(-1.5)	(-0.2)	(-1.0)
M - H				-20.1
				(-4.9)
Simultaneously listed and traded				
Mainland	21.3	11.5	-5.5	-26.7
	(5.5)	(3.6)	(-2.0)	(-7.4)
Hongkong	-2.3	-5.3	-6.1	-3.8
	(-0.6)	(-2.2)	(-1.8)	(-0.9)
M - H				-22.7
				(-4.1)

Table A3: PIR of first 30 minutes and last 30 minutes intraday return

This table reports the return spread of holding the PIR-based portfolio during the last 30 minutes of trading day which is from 15:30 to 16:00 for U.S and from 14:30 to 15:00. The timing m of PIR is 10:00 which is the end of first 30 minutes of trading day. Both equal-weighted and value-weighted return are reported in basis-points. The t-statistics given in the parentheses are based on Newey-West standard error with 120 lags.

	L	2	3	4	5	6	7	8	9	H	H-L
China											
EW	4.3	5.3	5.5	5.5	5.9	5.9	5.9	5.4	5.2	2.8	-1.5
	(3.7)	(5.6)	(6.3)	(5.9)	(6.4)	(6.9)	(6.5)	(6.3)	(5.7)	(3.6)	(-2.2)
VW	5.4	4.9	5.1	5.1	5.5	5.2	5.6	4.6	5.0	3.6	-1.7
	(4.5)	(5.0)	(5.7)	(5.4)	(5.8)	(6.0)	(6.4)	(5.8)	(6.6)	(4.4)	(-1.9)
United States											
EW	10.3	6.1	5.0	4.3	3.7	3.7	3.6	3.6	3.3	2.0	-8.3
	(9.1)	(6.7)	(6.4)	(6.1)	(5.4)	(5.5)	(5.3)	(5.3)	(5.2)	(2.7)	(-11.4)
VW	4.2	2.4	2.1	1.6	1.4	1.0	0.6	0.0	-0.2	-3.8	-8.0
	(5.1)	(3.8)	(3.2)	(2.4)	(2.5)	(1.7)	(1.1)	(-0.0)	(-0.3)	(-3.2)	(-6.7)

Table A4: PIR-portfolio: after transaction costs

This table reports the return spread of PIR-based portfolio after considering the transaction cost. Panel A report the time-variation of transaction cost, including the stamp-taxes for the government and the representative commission for the broker. Panel B report the value-weighted return of PIR-portfolios within the lowest (L) decile, highest (H) decile and the long-short (L-H) portfolio as in table 1. For L and H portfolios, return is the raw return minus the stamp-tax and commission. For L-H, return is the difference between L and H, minus twice the stamp-tax and commission.

Panel A. Transaction fee		
Anouncement date	stamp-tax (%)	commission(%)
before 20001116	0.6	0.01
20001116	0.4	0.01
20050124	0.2	0.01
20070530	0.6	0.01
20080424	0.2	0.01
20080919	0.1	0.01
Panel B1. All sample		
L	H	L - H
-3.1	-34.6	-16.6
(-1.25)	(-13.11)	(-4.65)
Panel B2. Sample with high fee (stamp-tax > 0.2%)		
L	H	L - H
-28.3	-81.1	-71.2
(-4.13)	(-14.66)	(-11.76)
Panel B3. Sample with low fee (stamp-tax ≤ 0.2%)		
L	H	L - H
5.6	-23.3	1.0
(2.11)	(-11.03)	(0.36)