# Essays in Overnight Returns, Intraday Reversals, and Short-Selling Constraints in Chinese Stock Market

*by*

**Jiayan Qiu**

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Supervisors:

Ying Jiang

Wei Huang

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# Contents

# List of Figures

# List of Tables

# List of Appendices

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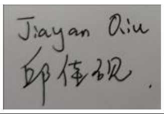
# Declaration

I declare that the material contained in the thesis has not been previously submitted, either in whole or in part, for a degree or qualification in this or any other institution. I further declare that the working paper titled “Overnight and Intraday Returns in Chinese Stock Market” drawn from Chapter 2 of this thesis is co-authored with Ying Jiang. The working paper titled “A Closer Look at Intraday Return Reversals in China: The Role of Retail Investors” drawn from Chapter 3 is co-authored with Ying Jiang and Wei Huang. The working paper titled “Short Selling, Margin Buying, and Stock Return Predictability” drawn from Chapter 4 is co-authored with Ying Jiang.

Signed: 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## Abstract

This thesis examines cross-sectional stock returns in the Chinese stock market, which has a unique setting of the T+1 rule arrangement and short-sales regulation policy.

The first essay, *Overnight and Intraday Returns in Chinese Stock Market*, documents strong persistence and a reversal pattern of overnight and intraday returns across a trading day based on an analysis of high-frequency trading data of the Chinese stock market from 2009 to 2021. A decomposition of the abnormal returns of 11 trading strategies over intraday intervals reveals a U-shape pattern of anomalous profits, which mainly exist at the opening and closing of the market, especially for the variables of trading friction. To the best of our knowledge, these findings are unique and novel. We attribute the different pattern to the trading behavior of heterogenous investors in China, who prefer to trade at different times compared with those in the US market. The unique T+1 trading rule may be causing institutions to trade actively at market open. Our results are robust for the different measures of institutional investors.

The second essay, *A Closer Look at Intraday Return Reversals in China: The Role of Retail Investors*, investigates the relationship between the intensity of intraday return reversals and future stock returns in the Chinese stock market. The abnormal frequency of positive overnight returns, followed by negative daytime returns, positively predicts the one-month ahead returns. Additional evidence supports our conjecture that daytime noise traders trade against high opening prices to an extent below firms' fundamentals. As a result, higher price errors are generated during a prolonged, intense tug of war, yielding a strong return prediction.

The third essay, *Short Selling, Margin Buying, and Stock Return Predictability*, explores whether information from short selling and margin buying predicts future stock returns in the Chinese stock market. The result shows that, before August 2015, short selling had negative predictive power on stock returns in the following month, although this predictability was not long lasting. In contrast, margin buying predicted significant positive future returns in the following week/month, but the sign of the

prediction reversed after China Securities Regulatory Commission imposed a tight policy in August 2015. According to our rationale, the T+1 shorting ban drove out many informed leveraged traders, leaving mostly irrational ones in the market.

# Chapter 1

# Introduction

This thesis comprises three essays on empirical asset pricing. We focus on investigating cross-sectional stock returns in the Chinese stock market, which has the second-largest economy scale and market capitalization in the world.

Many variables are known to predict the cross-section of stock returns. Standard finance theory fails to explain these variables and there is little consensus on the sources of the predictability of anomalous returns. Scholars attribute the better performance of some stocks at specific times of the day to investor heterogeneity (see Berkman et al., 2012; Lou et al., 2019; Hendershott et al., 2020). However, there are vast differences in investor composition as well as regulatory rules between the Chinese stock market and other countries, for instance, the United States (US) market. For example, investors are prohibited from selling stock shares on the same day of their purchases (i.e., T+1 rule) in China, whereas no such restrictions exist in most other countries. Likewise, the short-sale constraint that prevents short sellers from paying back shares they have borrowed on the same day was implemented since August 2015. In this regard, Chapter 2 deals with literature on intraday return patterns across daily trading cycles. Chapter 3 examines the asset pricing implication of the intensity of intraday return reversals. Chapter 4 explores the literature on the informational roles of leverage traders in the equity market. In the following sections, we elaborate on the focus of each chapter.

In Chapter 2, we make an early attempt to apply the investor heterogeneity assumption to explain the recurring intraday pattern and the difference in return pattern from the US market. Existing studies on the US explain return continuations over the same interval and return reversals over the cross-period interval of a day as different investor clienteles trading at different times of a trading day (Lou et al., 2019; Berkman et al., 2012). There is also a well-established presence of positive overnight stock premiums and zero or even negative intraday premiums in the US and most other markets (Cliff et al., 2008; Kelly and Clark, 2010; Berkman et al., 2012).

China is a good setting for studying this intraday phenomenon using the investor heterogeneity assumption. First, according to the 2017 Shanghai Stock Exchange Yearbook, institutional investors only contribute less than 20% of the daily trading volume in China, but to 90% in the US market. Therefore, whether institutional investors play an important role in creating intraday return reversals is a question of interest. Second, institutional investors cannot balance their portfolios at the same day of purchasing owing to the unique T+1 trading rule. It is worth exploring when the most active trading for institutional investors is, and how their trading behavior affects the intraday return pattern.

We document an overall negative overnight return of -1.58% per month, followed by return reversals shortly after market open. This return pattern is the complete opposite of what we observe in the US market. Our findings of a strong same-period intraday return continuation and a cross-period reversal effect suggest that two groups of clienteles with different preferences may dominate trades at different times during a day. Using two measures to identify different groups of investors, we evidence that the clientele trading timing is also different to the US market: institutions tend to trade more actively near market open and close, whereas retail investors tend to trade more during the rest of the daytime.

Given investor preference may be tied to different firm characteristics, we relate component returns to a series of commonly used anomalies. We document a pronounced U-shape pattern of long–short profits over a trading day, especially for trading-related variables, meaning that the long-short strategy mainly makes profits through overnight and the last half-hour session. Contrariwise, the most effective anomalies in the US market earn their premiums at intraday (Lou et al., 2019; Bogousslavsky, 2021). Our results reveal a relatively important role played by institutions, compared with retail investors, for the opening and closing periods, as stock prices move in the same direction as institutions' trades. We provide supportive evidence for the intentions of institutions' early trades—that is, seeking mispricing profits that are probably induced by the unique T+1 rule and a sequence of overnight news.

Chapter 2 contributes to the literature in several aspects. First, to the best of our knowledge, this study is an early attempt to link the heterogeneity of investors to intraday return patterns in the Chinese stock market. We shed light on this area by comprehensively investigating heterogeneous investors' trading times over a daily trading cycle and their preferences. Second, we explore possible reasons for the differences in return patterns between the Chinese and US markets by considering the investor composition and trading rules that are unique to China. Finally, we add to the emerging work on the impacts of institution and/or retail trades on stock returns by relating the U-shape anomalous return pattern to investors' trade directions.

In Chapter 3, we build upon and contribute to the literature that explores the asset pricing implication of intraday return reversals. Akbas et al. (2022) reports a positive relationship between the intensity of the intraday return reversal that is characterized by high opening prices and future stock returns. Given the interpretation that heterogeneous investor clienteles may persistently dominate the respective overnight and daytime sessions, Akbas et al. (2022) explain it as daytime arbitrageurs overcorrecting a sequence of positive overnight returns by overweighting the role of noise traders.

China's intraday return pattern has negative overnight returns and positive daytime returns, opposite to the US and most other markets. The unique T+1 rule may account for the difference in this pattern (Qiao and Dam, 2020; Bai, 2020; Zhang, 2020). Kang et al. (2022) also explain the intraday return reversal as pricing errors caused by daytime irrational investors excessively trading against previous price movements. There being differences in the potential driving force of intraday return reversals between the US and Chinese market is intriguing; we thus investigate whether the return predictability of the intensity of intraday return reversals that Akbas et al. (2022) document works in China as well as the mechanism thereof.

Our univariate sorting scheme empirically shows that stocks with a high abnormal frequency of positive overnight returns, followed by negative daytime returns (ABNR), outperform stocks with a low level of ABNR by a value-weighted monthly portfolio spread of 0.49% (*t=4.34*). This result is robust after controlling a set of firm characteristics and various risk factors, as well as using the equal-weighting scheme. It also survives transaction costs, as Han et al. (2016) report.

We further explore the potential mechanism behind the positive predictability of ABNR. Based on the findings in Chapter 2—that institutions tend to trade more at market open, whereas retail investors are likely to initiate trades during the daytime session—we explain the positive relationship between ABNR and future returns as the tendency of daytime retail traders to over trade against the high opening price that essentially contains firms' fundamentals by overweighting their own information-processing skills or the precision of their private information (Odean, 1998; Barber and Odean, 2000). A host of findings are reported to support this argument.

Chapter 3 has several implications. On the one hand, we document a firm characteristic that not only provides incremental information beyond other firm characteristics, but also, it delivers hedge portfolio returns that are statistically significant and robust to transaction costs. On the other hand, this essay complements to the existing literature by providing additional evidence for the role of retail investors on stock prices in China.

In Chapter 4, we explore the literature on the informational role of leverage traders, namely, short sellers and margin buyers. It is well established that short sellers play an important role in preventing overpricing and the formation of price bubbles in financial markets (Miller, 1977). Indeed, the negative relationship between shorting volume and future returns is indicative of the prevalence of informed short selling (see Boehmer et al., 2008, 2020, 2021; Christopher et al., 2004, 2010; Engelberg et al., 2012). On the contrary, the evidence on the return predictability of margin buying is mixed (Hirose et al., 2009; Chang et al., 2014; Lee and Ko, 2016). One argument for the negative relationship between short-selling activities and future stock returns is the high shorting costs that would make uninformed short sellers abstain while leaving informed short sellers more active (Diamond and Verrecchia, 1987). However, thin trading and heavy restrictions on short selling in China may deteriorate the informativeness of short sales.

Empirically, we investigate the predictive power of short-selling and margin-buying activities for future returns using the daily frequency data in the Chinese market for the period of 2011–2019. We compare the return predictability of short selling and margin buying before and after the policy change stipulated by the Chinese Security Regulatory Commission in August 2015—that is, the T+1 rule that prevents short sellers paying back stocks borrowed on the same day.

Our study reveals a host of interesting findings based on empirical evidence. First, before August 2015, short selling had negative predictive power for future stock returns and margin trading had positive predictive power for returns in the following month. After August 2015, short selling had no predictive power for future stock returns and the sign of the predicted return of margin buying reversed to negative. Second, short sellers took advantage of forthcoming earnings surprises before 2015 and have superior skills to process negative firm-specific information, but not for second sub-period. As for margin buyers, the wrongly predicted sign of their trades on future price movements after the policy change can be attributed to their inferiority in anticipating and dealing with information contained in publicly available media news, especially with those that arise price increase around news releases. Third, the trading behaviors of short sellers and margin buyers varied over two different sample periods. We rationalize that the heavy shorting restriction drives out most informed traders, and the irrational ones mainly exist in the short-selling and margin-buying market.

These findings have several notable implications. First, whether short selling and/or margin buying has predictive power on future returns has been a concern for both investors and regulators since its launch. Second, our findings that the short sale restriction will reduce the predictive power of short selling and margin buying offer valuable evidence for policymakers involved in implementing a new regulation.

# Chapter 2

# Overnight and Intraday Returns in Chinese Stock Market

## 2.1 Introduction

A growing body of literature has documented periodical return patterns across the daily trading cycle. Studies focusing on the US market find that the overnight return premium is significantly positive, whereas the intraday return premium is mostly close to zero and sometimes negative (Cliff et al., 2008; Branch & Ma, 2012; Berkman et al., 2012). In addition, a well-documented tendency for return continuation over the same interval within a trading day broadly exists in different countries (Heston et al., 2010; Lou et al., 2019).

Lou et al. (2019) attribute this recurring intraday pattern to different investor clienteles trading at different times of the day. More specifically, there is evidence that retail investors are inclined to trade at or near the morning open, whereas institutional investors trade more actively at approaching market close for portfolio rebalancing purposes. Price pressures induced by excessive demands from these two clienteles owing to different preferences may pull prices in opposite directions and thus create a *tug of war* that leads to a recurring cross-period reversal effect.

This chapter builds upon and contributes to these strands of literature by examining whether there is an intraday interval return difference and continuation in the Chinese stock market. We adopt the investor heterogeneity assumption of Lou et al. (2019) to explain the intraday return pattern. Existing literature documents an opposite intraday return pattern in the Chinese stock market to that of the US, that is, negative overnight returns followed by positive intraday returns. They attribute the difference to the unique T+1 trading arrangement in China (Qiao et al., 2020; Bai, 2020; Zhang, 2020) as they argue that the one-day selling lockup will lead to open price discounts. This study looks into this issue from an alternative perspective, that is, the trading behavior of two clienteles, to explain the pattern and the difference to that of the US market. In particular, we investigate when the institutional and retail investors trade more actively, why they like to trade at a certain time, and what kind of stocks they trade. By decomposing 11 trading strategy profits during the day, this chapter comprehensively analyzes the component return pattern in the Chinese stock market.

China provides a special setting for investigating this intraday/overnight phenomenon. First, China's stock market has different investor composition than developed countries. According to the Shanghai Stock Exchange (SSE), retail trading accounts for at least 80% of total trading volume in China, whereas this figure only amounts to 10% in the US market. [1] The extensive literature on retail investors' behaviors, such as Barber and Odean (2000; 2008), Barber et al. (2009), and Daniel and Hirshleifer (2015), show that retail investors are less sophisticated and more likely to be overconfident. Chinese retail investors normally predict the wrong sign of future returns (Jones et al., 2021).[2] Under this condition, whether the institutional investors still play an important role in creating *tug of war* return patterns documented in Lou et al. (2019) in China is a question of interest.

Second, China has a unique trading mechanism, namely, the T+1 trading rule. The T+1 rule prohibits traders from selling stocks they have bought on the same day. It is documented that arbitrageurs are incentivized to reduce their positions at the end of the day to avoid overnight risk, that is, extreme illiquidity and large price moves (Bogousslavsky, 2021). The implication is that a large proportion of trading volume at the end of market is contributed by institutions that balance their accounts. In China, however, institutional investors cannot balance their portfolios on the same day of purchasing. Hence questions like when the most active trading time is for institutional investors and how it affects the intraday/overnight return pattern in China are worth

[1] The retail investors trading, however, could be heterogenous (Jones et al., 2021) and the large trades may move in the same direction with future price movements.
[2] By contrast, as institutions are commonly regarded as sophisticated and informed (Chan and Lakonishok, 1993), they tend to move prices in the direction of the trade.

exploring.

Our sample consists of common A-share stocks from January 2009 through March 2021. We decompose the standard daily close-to-close return into overnight and eight intraday interval components and aggregate them into monthly returns for each interval. Our result shows that the average overnight return is -1.58% per month, followed by return reversals shortly after market open. We also find a relatively large and significant return in the last half hour of the trading period.[3] This result differs from the US market and is consistent with most prior literature on China.

We find return continuation documented by Lou et al. (2019) that stocks with high intraday interval returns over the last month tend to continue to have high corresponding intraday interval returns over the next month. Similar patterns are found for low overnight returns. Under the interpretation that overnight and intraday components of returns may reflect specific demands by institutions and retail investors, our results suggest that these two groups of investors tend to dominate trades at different times of the day.

To examine when institutions and retail investors trade, we use two different measures to distinguish trading by institutions and individual investors. First, we define small orders (below 40,000 Chinese Yuan (CNY)) as trades submitted by retail investors and large orders (above CNY500,000) as those submitted by institutions (Lee and Radhakrishna, 2000). Our results show that institutions tend to trade actively near market open and market close, whereas retail investors tend to trade more during the daytime. We also find that over one-quarter of trading volume from institutions is concentrated in the initial 5 minutes in the first half-hour after market open. We also find supportive evidence when using an alternative measure, the change of institutional ownership (IO) (see Lou et al., 2019).

We then decompose component returns by a list of commonly studied firm characteristics and further analyze the return pattern as persistent investor preference

[3] We report return series using sample period from August 2005 to March 2021 in Appendix 2.2. The results are qualitatively similar.

may be tied to different firm characteristics. We find that the returns to portfolios sorted by high/low firm characteristics show similar patterns to the component returns. For both high and low quintile portfolios sorted by these firm characteristics, the overnight returns are generally significant and negative, whereas there is a reversal during the intraday. It indicates that the intraday return pattern in China is not due to the firm characteristics. In addition, the significant spread between the high and low portfolios results in an anomaly profit. The profit of a firm's characteristics, based long-short portfolio, tends to be high near the market open and market close and reversed during the daytime (i.e., U-shape pattern), especially for trading-related variables. This result is again different from that of the US market in the sense that most effective anomalies earn their premium at intraday, as more arbitrageurs (mostly institutions) take trades during day trading sessions (Lou et al., 2019; Bogousslavsky, 2021).

We next investigate the impacts of heterogeneous investors' trades on stocks prices over a trading day by linking the U-shape anomaly return pattern with investors' trade directions. We find that stocks with higher selling pressure from institutions at market open tend to experience large price drops for the first and last half-hour period after the market opens. By contrast, stocks with higher buying pressure from retail investors perform better over the rest times of the day. This reveals a relatively important role played by institutions at market open and close and pronounced impacts on stock returns by retail investors over daytime session, as stock price movements go in the same direction with institution/retail investors trades for corresponding sessions. This is also consistent with our prior findings that large order trades account for a significant portion of trading for the opening and closing periods, whereas small trades provide significant contributions for the day session. When we use trading volume from two clienteles as an indicator for investor involvement, we find that stocks with high volume traded by institutions present an enhanced relationship between these firm characteristics and future returns of overnight and last half-hour components. This also corroborates our hypothesis that heterogeneous investor trading influences return patterns and institutions provide important contributions.

The above results have shown that institutions tend to open positions early at market open, whereas retail investors are inclined to trade more during the daytime except for the last half-hour, and this trading pattern is associated with larger return spreads of overnight and last half-hour components, especially for trading-related variables. A natural question that follows is for what reasons do institutions trade. Prior literature generally considers institutions as sophisticated arbitrageurs that correct mispricing (Bogousslavsky, 2021). We discuss this issue by considering two scenarios.

First, as most firm-specific information such as earnings announcements (EAs) and other important declarations are released at non-trading hours, the mispricing would be most severe at market open. If institutions seek mispricing profits, they tend to open their positions as early as possible. Thus, we should observe higher anomalous profit if we use opening prices sampled at an earlier time. We confirm this argument by showing that the zero-cost strategy earns the largest profits at 9:35 compared with those earned at 9:40 and 9:45.

Second, we consider the unique T+1 trading arrangement to gauge evidence for the intentions of institutions trading early in the day. We argue that the T+1 rule prevents investors from selling their perceived overpriced stocks on the same day of their purchase. Rather, it does not restrict investors from collectively buying perceived undervalued stocks they sold on the same day. Thus, stock buying pressure would gradually accrue over the day, probably reaching its peak at market close. This T+1 induced excess buying pressure can cause stocks to become overpriced at market close, leading to more arbitrary activities presumably by rational and more sophisticated institutions at the next day's market open (Zhang, 2020). Zhang (2020) shows that there are stocks with particular features that are more affected by the T+1 rule and are likely to be overpriced at market close; hence they tend to experience a large opening price discount. We show that stocks with more T+1 affected attributes can generate more negative returns of overnight components compared with those less affected. Our results support the idea of institutions trading on mispricing at market open.

Our study is closely related to Lou et al. (2019) and Bogousslavsky (2021), who examine intraday return patterns; however, our study differs from theirs. First, to the best of our knowledge, this is an early attempt to link the heterogeneity of investors and the intraday return patterns in the Chinese stock market. Second, we analyze possible reasons unique to the Chinese stock market. We find that the Chinese institutions trade more actively at market open, which leads to different findings from that of the US market.

Our work is also related to Qiao et al. (2020), Bai (2020), and Zhang (2020), who suggest that the overall negative overnight return in the Chinese stock market can be explained by the T+1 trading rule. However, these studies do not provide evidence on how the T+1 rule affects investor trading preferences, resulting in intraday return patterns. Our study looks into details of investors' trading behavior during the day and shows that the T+1 rule is one of the potential reasons for distinct return patterns in China.

This chapter contributes to the literature in several aspects. First, it is among few studies that apply investor heterogeneity assumption to examine the intraday return pattern in Chinese stock market. In particular, we provide a comprehensive analysis on heterogeneous investors' trading times over a daily trading cycle and their preferences by decomposing component returns by a list of well-known anomalies. Second, we highlight the unique setting of T+1 rule and investor composition to explain the differences in return patterns between the Chinese and US markets. Finally, we shed light on the roles of institution and/or retail trades on stock returns over a daily trading cycle.

The rest of the chapter is organized as follows: Section 2.2 reviews the literature, and Section 2.3 introduces data, variables, and methodology. Sections 2.4 and 2.5 present our main empirical results. Section 2.6 concludes.

## 2.2 Literature review

Substantial studies have investigated equity day and night return patterns in recent decades (Wood et al., 1985； Harris, 1989； Jain and Joh, 1988; Smirlock and Starks, 1986). A general consensus has been achieved regarding the US market that the overnight stock premium is significantly positive, whereas the intraday premium is mostly zero or even negative depending on the chosen periods (Cliff et al., 2008; Kelly and Clark, 2010; Berkman et al., 2012).

Theoretical evidence has shown that overnight and intraday are different in several aspects, such as information release, volatility, market liquidity as well as price impact, which may manifest themselves as differences in returns over different intervals across a day. For example, overnight returns may contain more firm-specific information than intraday returns, as firm-specific news and EAs are mostly released out of trading time (Barclay and Hendershott, 2003). In addition, the market illiquidity is higher, and there is substantial risk in large price movements over the market closure (Longstaff, 1995; Bogousslavsky, 2021). Information asymmetry is less severe approaching market open (Hong and Wang, 2000), whereas volatility is higher during trading hours than after hours (Fama, 1965; French and Roll, 1986).

Under this framework, a strand of literature establishes a link between investor heterogeneity and stock returns. Berkman et al. (2012) document that the positive overnight return and daytime reversal are caused by individual investors buying attention-grabbed stocks overnight and at market open, followed by institutional trading during daytime. Aboody et al. (2018) show that persistent overnight returns are consistent with short-term persistence in demand by sentiment-influenced investors.

Lou et al. (2019) attribute the recurring return continuation and reversal pattern to different investor clienteles trading at different times of a day. In particular, they illustrate a U-Shape pattern of the percent dollar trading volume for both institutions and retail investors. They also document a relatively large fraction of small orders for the first half-hour and a relatively large fraction of big orders for the last half-hour. Therefore, they argue that retail investors are inclined to trade at or near morning open, whereas institutional investors trade more actively approaching market close for portfolio rebalancing purposes. Price pressures induced by excessive demands from these two clienteles owing to different preferences may pull prices in opposite directions and thus create a *tug of war* that leads to a recurring cross-period reversal effect.

Under a heterogenous investor framework, Hendershott et al. (2020) document that risk-loving speculators buy high beta stocks at the open and reverse their positions approaching market closure, whereas long-term investors dominate night trades.

In addition, institutions are generally regarded as more sophisticated and rational, and that correct mispricing. Akabs et al. (2021) suggest daytime arbitrageurs tend to overweight the role of noise traders and discount the possibility that positive news arrives overnight and thus overcorrects the persistent upward overnight price pressure. Bogousslavsky (2021) considers institutional constraints and overnight risk as reasons that make daytime arbitrageurs reduce their positions toward the end of the day, thus leading to worsened mispricing near market end. More recent studies that explore the day-night return pattern also include Barardehi et al. (2022), Lou et al. (2022) and Rossie and Steliaros (2022).

Note that the above results are mostly based on the US market, and evidence in China reveals a different day/night pattern compared with the US market. Studies document that, on average, negative overnight returns are followed by positive intraday returns in China, and they attribute this phenomenon to the unique T+1 trading rule. Specifically, Qiao et al. (2020) argue that the asymmetric trading rule would lead to a price discount for the stock at market opening relative to the previous day's closing price. Similarly, Bai (2020) explains the negative overnight return as the price paid for the sell-at-the-max put option embedded in the closing price of stocks on day *T* compared with the open price on day T+1. Zhang (2020) shows that stocks with high divergent opinions, high volatility, large retail involvement, more limits to arbitrage, and high illiquidity are more likely affected by the T+1 rule, and these stocks tend to experience large opening price discounts as their closing prices are relatively high.

By investigating investor trading behavior in China, our study speaks to the literature on intraday return patterns in general and the investor clientele effect in particular. We shed light on this area by comprehensively investigating heterogeneous investors' trading preferences in the Chinese stock market.

## 2.3 Data, variables, and methodology

Our sample consists of common A-share stocks listed on Shanghai and Shenzhen Stock Exchange from January 2009 to March 2021. We chose the sample period from 2009 to 2021 because a new accounting standard for business enterprises was implemented in effect in 2007. The stocks are required to trade for at least 200 days in a calendar year and for at least 10 days in a calendar month to be included. We obtain trade price and trading volume data from China Securities Market Level-1 Trade & Quote Research Database. Firm characteristics data are acquired from China Stock Market Accounting Research database. The closing prices are adjusted for stock splits and dividends. The final sample contains 3120 stocks after filtering.

We use the VWAP over 9:30 and 10:00 as the open price to calculate returns, following Lou et al. (2019). We calculate VWAP as the sum of volume-weighted trade price using 1-minute intervals, as described in Equation (2.1). The overnight return of a stock is calculated by close-to-close daily return and intraday return which is computed using VWAP, as shown in the below equations.

$$Open\ Price = VWAP^{i}_{9:30,10:00} = \sum_{h=1}^{30} \frac{Volume_t \times Price_t}{Total\ Volume_{9:30,10:00}} \tag{2.1}$$

$$r^{i}_{close-to-close,t} = \frac{close^{i}_{t}}{close^{i}_{t-1}} - 1 \tag{2.2}$$

$$r^{i}_{intraday,t} = \frac{close^{i}_{t}}{open^{i}_{t}} - 1 \tag{2.3}$$

$$r^{i}_{overnight,t} = \frac{1+r^{i}_{close-to-close,t}}{1+r^{i}_{intraday,t}} - 1 \tag{2.4}$$

Where $h$ represents one minute. $close^{i}_{t}$ represents the closing price of stock $i$ on day $t$, $open^{i}_{t}$ represents the open price (VWAP) of day $t$. $r^{i}_{intraday,t}$, $r^{i}_{overnight,t}$ and $r^{i}_{close-to-close,t}$ denote the intraday, overnight, and daily returns of stock $i$ on day $t$, respectively.

We compute intraday interval return for each half-hour, from 9:30 to 15:00, using Equation (2.5). For the initial minute of six half-hour intervals from 10:00 to 14:30, we use the average of high and low trade prices ((high+low)/2). The first half-hour return (9:30 to 10:00) is computed using the average high and low price of 10:00 and VWAP, and the last half-hour return (14:30 to 15:00) is calculated using the closing auction price of a trading day and average high and low price of 14:30.

$$r^i_{k,t} = \frac{P^i_{k+1,t}}{P^i_{k,t}} - 1,\ k = 1,2 \ldots 8 \tag{2.5}$$

where $r^i_{k,t}$ denotes each intraday half-hour return. $P^i_{k,t}$ is the initial minute price for each interval *k*. $P^i_{0,t}$ is the opening price VWAP, and $P^i_{9,t}$ is the closing auction price for stock *i* on day *t*.

We then accumulate returns from the same interval of a day *t* over a month *m* and obtain monthly interval returns. We repeat this procedure for each stock.

$$r^i_{overnight,m} = \prod_{t\in m}(1 + r^i_{overnight,t}) - 1 \tag{2.6}$$

$$r^i_{k,m} = \prod_{t\in m}(1 + r^i_{k,t}) - 1,\ k = 1,2,\ldots,8 \tag{2.7}$$

We calculate monthly value-weighted overnight/intraday interval portfolio returns in the following form:

$$r^P_{overnight,m} = \sum_i w^i_{m-1} r^i_{overnight,m} \tag{2.8}$$

$$r^P_{k,m} = \sum_i w^i_{m-1} r^i_{k,m}\ k = 1,2,\ldots,8 \tag{2.9}$$

where $w^i_{m-1}$ is the market value weight at lagged month *m-1* for stock *i*.

In this chapter, we use a set of firm characteristics variables in our empirical analysis. The list comprises two categories: trading-related and accounting-related, as in Hou et al. (2021). Within the trading-related category, we include liquidity, risk (volatility), and past return measures, whereas, within the accounting-based category, we include profitability, value, and investment measures. The definitions of these 11 characteristic variables are listed in Appendix 2.1.

Table 2.1 presents the descriptive statistics of overnight/intraday components of monthly returns, as well as firm characteristic variables for the sample. It shows that the average monthly overnight return negatively accounts for 1.58%, similar to prior studies on the Chinese market (Qiao et al., 2020; Bai, 2020). However, this result is different from the US market, where there is a significant positive overnight return. Two subsequent intervals experience positive returns at 0.53% and 0.71%, respectively. To summarize, this table shows that the intraday return reversal mainly occurs during the first two and last half-hour periods.

The standard deviation of overnight returns is slightly larger than that of intraday returns. The skewness of overnight return is -0.99, whereas that of intraday component returns is either a positive or of a smaller negative value. This suggests that outlier risk is more pronounced during the night. The kurtosis of all interval returns is greater than 3, suggesting that investors are more likely to experience extreme returns than a normal distribution.

Panel B of Table 2.1 presents time-series averages of the monthly cross-sectional summary statistics for a set of firm characteristics in our main analysis. Panel C reports the time-series means of the monthly cross-sectional correlations across these variables. The results show that turnover, risk, and past return measures are significantly positively correlated with each other.

To depict the overall trading activity at intraday intervals, in Figure 2.1, we show the half-hour interval trading volume pattern from 9:30 to 15:00 (eight intervals in total) during a trading day. To conduct, we first sum up all stocks' trading volume in CNY for each half-hour interval of each day. Then we calculate fractions of the total trading volume of that day over each interval such that the total cross-sectional fraction sums up to one. We report the time-series average of the daily trading volume fraction for each interval in Figure 2.1.

The fraction of trading volume during a day exhibits a U-shaped pattern, with the fraction being relatively large around market open and market close and relatively small during periods in the middle of the day. The largest trading volume occurs during the first half-hour, accounting for 20.35%, followed by the closing trading session (14:30-15:00), which accounts for 16.12%. Overall, our result is consistent with most prior literature (Hong and Wang, 2000; Lou et al., 2019), focusing on the US market, where intensive trading happens just when the market opens and near closes.

## 2.4 Empirical analyses

### 2.4.1 Return continuation and reversal pattern

Lou et al. (2019) document a continuation in overnight and intraday returns, as well as a cross-period reversal in the US market, and they interpret it as *overnight* and *intraday* clienteles having the tendency to trade in one particular period. We follow their methodology to examine the persistence of overnight and intraday returns and return reversals across different periods in the Chinese stock market. We first sort stocks into deciles based on the previous month's returns in each interval (eight intraday and overnight intervals). We then conduct a long-short strategy that longs the winner decile, shorts the loser decile, and hold for one month. We report the value-weighted monthly long-short portfolio returns in excess of the risk-free rate, adjusted by the capital asset pricing model and Fama-French (FF) three-factor model.

Table 2.2 shows strong evidence of the return continuation. For each intraday interval, a strategy that longs stocks with relatively high returns and shorts stocks with relatively low returns can earn significant positive *intraday* excess returns for the corresponding interval in the following month, with the magnitudes ranging from 0.10% (*t=2.3*) to 2.40% (*t=13.8*). Similarly, a hedge portfolio based on lagged-month overnight return yields a positive monthly *overnight* excess return of 2.64%, with *t*-stat being 14.63, and this finding also holds with risk adjustment.

By contrast, we find a cross-period reversal pattern as shown in columns (4), (5), and (6). That is, the long-short strategy based on each past-month intraday interval return earns a significantly negative value-weighted *overnight* excess return in the following month, with magnitudes ranging from -0.25% (*t=-1.75*) to -2.32% (*t=-16.88*). Again, these findings hold for risk adjustments.

The above findings show that the persistence of intraday returns and reversal patterns also exist in China. This indicates that two groups of clienteles may have different preferences regarding stock attributes and timing of trades, considering that return components reflect specific demands by a certain type of investors (Lou et al., 2019).

### 2.4.2 Heterogeneous investor trading time

In this subsection, we examine when two groups of investors, that is, institutions and retail investors, trade more actively over a day. We first use order size to distinguish trading activities (Lee and Radhakrishna, 2000; Barber et al., 2009; Lou et al., 2019) from institutional and retail investors. Following the standard of Choice Financial Terminal, we define small orders as that below CNY40,000 and classify these trades as being from retail investors. Similarly, we define large orders as that above CNY500,000 and classify them as being from institutions.[4] As some institutions may split their orders into smaller ones to avoid a large price impact shock, we also consider medium orders as those with order sizes between CNY40,000 and CNY500,000. For each 30-minute interval, we calculate the trading volume as a proportion of daily volume for each order size.[5] For example, the percentage trading volume for small orders in a particular interval is the ratio of small order trading volume during that interval to small order trading volume of the whole day.

Figure 2.2 shows the results. We observe interesting trading patterns: institutional trades are more intensive near the market open and close, whereas retail investors' trading exhibits similar but smoother trading activities in terms of trading volume during the day. That is, the two highest trading volume fractions are from large orders, accounting for 18.96% and 17.53% over the first and last half-hour, whereas trading volume for small orders accounts for 16.27% and 13.83%, respectively. However,

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[4] Choice Financial Terminal is a popular financial terminal for different types of users, such as investment institutions, research institutions, and individuals in China.

[5] We do not have data that allows us to distinguish between open and close-auction trading volume that is due to institutions and retail investors. Therefore, we exclude open and close auction trading volumes in Figure 2.2 and 2.3.

during the daytime, trades from institutions are less than those from individuals. Hence, we observe deeper U-shaped trading activities for institutions. These results indicate that institutions tend to trade relatively more at market open and close, whereas individuals' trading activities are more evenly distributed throughout the day. The trading percentage for medium orders also exhibits a deeper U-shaped pattern than small orders, with figures of 19.67% and 17.11% for the first and last half hour, respectively, similar to the large orders.

Next, we divide the first half-hour (i.e., 9:30-10:00) into six sub-intervals (5 min each) to examine whether the institutional investors indeed tend to trade when the market is just open. Figure 2.3 reports CNY trading volume fractions of large, medium, and small orders over 5-min intervals for the 9:30-10:00 period. The result shows that in the first 5-minute, large orders trade accounts for over 25% of total trading volume during the first half-hour, whereas for the rest of the 5-minute intervals, the trades are almost evenly distributed, about 15% of total trading volume each. While for small orders, it contributes 17% of their total trading volume in the first 5-minute interval, which is almost constant for the rest of the 5 intervals. This confirms our argument that institutions trade even more actively when the market just opens compared with other intervals.

As order size is just a proxy to distinguish trading activities from heterogeneous investors, we also use changes in IO to gauge the relationship between investor type and component returns, following Lou et al. (2019). Specifically, we first divide stocks into quintiles based on institutional ownership in the previous quarter and then run Fama-Macbeth regression of its quarterly changes on the nine intervals of contemporaneous returns, as we expect returns to stocks with higher institutional ownership are more affected by institution trading activities. We report the coefficients for the top and bottom IO quintiles in Table 2.3, Panel A. Under the assumption that investors' trading behavior can move prices, a larger positive coefficient in magnitude would indicate higher sensitivity of interval component returns to institutional trading, thus reflecting more active trading activity of institutions.

The results show that IO change significantly increases with overnight returns for both top and bottom IO quintiles, with the magnitudes of coefficients relatively larger for stocks with high IO than that of with low IO, indicating institutional trades contribute to opening price movements. The coefficients for the rest of the intervals are mixed for low and high IO groups; that is, many cases are significant in the low IO quintile but no significant coefficients for the high IO quintile.

Panel B reports coefficient differences among each pair of nine intervals for two extreme IO quintiles. At the first stage of our Fama-Macbeth regression, we obtain a time series of estimated coefficients for each interval. We calculate the coefficient differences using Newey-West standard errors of 8 legs to address serial dependence.[6] The value corresponding to the column "9:30" and the row "CO" 0.052 is the difference between the coefficient estimated by regressing IO change on overnight return, and that of on first half-hour interval returns, for stocks with high IO. The first column shows that for the high IO quintile, overnight returns are more sensitive to IO changes than that of the other seven intraday interval returns except for the last half-hour interval from 14:00 to 14:30. Four out of seven are statistically significant at least 10% level. Similarly, the bottom row shows that the magnitude of coefficient of the last-half hour return on IO change is larger than that of coefficients over other intervals, although the significance is weak. These results align with our argument that institutions play more pronounced roles in stock price movements for the opening and closing sessions. In contrast, we find that the coefficient differences are much smaller in magnitudes for the low IO quintile, as shown in the upper right panel, than those for high IO stocks, suggesting that the impacts of institutional trades on returns are much the same across different intervals of a trading day among stocks with low IO. This is not surprising given the less important roles played by institutions for low IO stocks.

To conclude, we provide indirect evidence that institutional investors trade more actively near market open and close, and the impacts of their trading on overnight and

[6] We also compare the coefficient difference by putting two component returns in the right-hand side, and the results are qualitatively same. We report results in Appendix 2.3.

last half-hour returns are larger than those on the rest seven interval returns.

### 2.4.3 Intraday return patterns of trading strategies

We then decompose component returns by a list of commonly studied anomalies and further analyze the return pattern as persistent investor preference may be tied to different firm characteristics.

#### A. Portfolio sorting

In the spirit of Hou et al. (2021), we classify the 11 trading strategies into trading-related and accounting information-related. Among seven trading-related strategies, four are constructed based on liquidity proxies, such as market capitalization (SIZE), past 12-month turnover (TO), abnormal past month turnover (ATO), and Amihud illiquidity (ILLIQ); one of them is on risk proxy, that is, the standard deviation of past month returns (VOL); two are on past return information, that is, short-term reversal (STR) and maximum daily returns of the past month (Max). For accounting-based strategies, one is constructed on profitability proxy, return on equity asset (ROE), and one on value proxy, earnings-to-price ratio (EP). The remaining two are on investment proxies, asset growth rate (ASSET) and net operating asset (NOA). The description and construction of these anomaly variables are described in Appendix 2.1.

We decompose the abnormal profits associated with the above asset pricing anomalies into overnight and eight half-hour-interval return series. At the beginning of each month, we sort stocks into deciles based on the previous month's end value of each variable mentioned above. Within each decile, we calculate value-weighted average excess returns of overnight and eight intraday interval components in the subsequent month, as shown in Equations (2.8) and (2.9). We then compute long-short portfolio returns and risk-adjusted returns for each interval. Tables 2.4 and 2.5 show the results.[7]

<u>*Trading-related variables*</u>

[7] We also report long-short portfolio returns based on these 11 anomalies from August 2005 to March 2021 in Appendix 2.4. The results are qualitatively similar.

We first examine the trading-related strategy. For liquidity measure, TO, we long stocks with bottom past 12-month turnover and short stocks with top past 12-month turnover.[8] The value-weighted long-short portfolio returns for nine intervals are reported in Table 2.4. We can see that the monthly overnight long-short portfolio return and FF three-factor adjusted return are 1.52% (*t=7.93*) and 1.69% (*t=10.24*), respectively, whereas the premium sign reverses shortly after market open and lasts until the second to last half-hour trading session. The zero-cost trading strategy generates a monthly return and FF-three-factor alpha of 1.45% (*t=10.02*) and 1.54% (*t=11.29*), respectively, during the last half hour of the trading day. Notably, both short and long legs of the TO anomaly exhibit similar return patterns as the overall component returns. For example, the short and long leg overnight returns are -2.56% (*t=-8.65*) and -1.04% (*t=-3.17*), respectively, whereas the mean overnight component return for the full sample is -1.58% per month while the sign reverses during intraday intervals. This suggests that the negative overnight and positive intraday returns are not driven by specific firm characteristics.[9] Similar patterns exist when we use the ATO as an alternative liquidity measure. The strategy that buys stocks with the lowest abnormal turnover and shorts stocks with the highest abnormal turnover can produce significant monthly alpha of 1.91% (*t=12.81*) overnight and 0.86% (*t=7.40*) in the last half hour, whereas this sign is opposite during the rest day after the market is open.

We next conduct strategies on SIZE and ILLIQ that long small SIZE (high ILLIQ) decile and short large SIZE (low ILLIQ) decile. The long-short SIZE/ILLIQ portfolio FF-3 alpha gradually accrues over daytime and generates -2.09%(*t=-12.82*)/ -1.02%(*t=-4.32*) overnight component return. This is at odds with anomaly premiums mainly being reflected in overnight returns, and we will discuss it later.

The strategy based on risk, measured by VOL, is long low-volatility decile and short high-volatility decile. The low-volatility premium mainly occurs overnight and during the last half-hour trading session. There is either a negative or marginally significant

[8] The descriptions and constructions of the 11 anomaly variables are described in Appendix 2.1.

[9] The negative overnight and positive intraday return patterns are not affected by other firm characteristics as well and we don't discuss them separately in the rest of the chapter.

positive premium for the other seven intraday intervals. The magnitude of the premium adjusted by FF three-factor for the overnight returns and last half-hour is 2.14% and 1.72%, respectively, and both are highly significant. While for the other seven intervals, returns are mostly negatively significant.

The next two strategies we study relate to past returns, which have been documented as effective trading strategies in China, namely Max and short-term reversal (Cakici et al., 2017; Hsu et al., 2018; Carpenter et al., 2018). Table 2.4 reports the returns over nine intervals for longing low-Max portfolio and shorting high-Max portfolio. Similar to previous findings, the low-Max risk premium mainly occurs overnight and during the last half-hour trading period. For the remaining intervals, there is either a negative or insignificant premium.

Next, we analyze an STR strategy that longs the low past one-month return decile portfolio and shorts the high past one-month return decile portfolio. Our results show that this well-known contrarian strategy mainly affects overnight returns as the long-short portfolio returns of the overnight component are roughly 10 times larger than during the daytime. Specifically, the overnight hedge portfolio FF three-factor alphas of the strategy amount to 1.49% per month (*t=4.65*), and the long-short returns over the daytime session are mostly negligible except for the first half-hour after lunch break (from 11:30 to 13:30).

*Accounting-related variables*

Researchers have documented several strategies constructed based on accounting items from financial reports that can generate cross-sectional profits in expected returns. Chief among these are profitability, value, and investment-related variables.

We first examine the strategy based on the profitability measure, ROE, that longs the high profitability decile portfolio and shorts the low profitability decile portfolio. Table 2.5 reports the overnight and intraday interval components of long-short raw excess returns and FF three-factor alphas. ROE has a significant long-short portfolio spread at the overnight interval, with a risk-adjusted return of 1.74% (*t=6.73*) per month. The sign of the premium reverses after market-open, and the return gradually increases over the day.

Next, we examine the value strategy that longs the high earnings-to-market (EP) ratio portfolio and shorts low the earnings-to-market ratio portfolio. According to Liu et al. (2019), the EP ratio better captures the value effect than the book-to-market ratio and cash-to-price ratio. Table 2.5 shows the overnight and intraday long-short portfolio excess returns based on EP. Similarly, the strategy generates abnormal profits of 1.28% per month with a *t*-statistic of 6.31 for the overnight period, whereas the return becomes negative in the two subsequent intervals. In the last half-hour, we do not witness any significant positive returns as the magnitude is 0.11% with a *t*-statistic of 1.00.

We finally decompose returns on the investment-related strategy that longs a low-investment portfolio and shorts a high-investment portfolio. Many prior studies have documented a negative relationship between various forms of corporate investment and the cross-section of returns in developed countries (Fama and French, 2015; Hou et al., 2019). However, recent studies focusing on China reveal that there is no investment effect (Liu et al., 2019; Hou et al., 2021). We construct two investment anomalies, that is, ASSET and NOA. Our results of overnight and intraday portfolio returns based on these measures exhibit trivial long-short portfolio premium, consistent with prior literature.

In summary, the above results generally show that the overall negative overnight excess return that is followed by a positive intraday excess return pattern is not affected by a specific firm characteristic. In addition, the high-minus-low spread profits of variables associated with trading frictions essentially occur mainly overnight, and some of them happen in the last half-hour of a trading day when institutional trading is more active. This pattern is different from the evidence in the US market, in which most anomaly profits occur during the daytime session. We also find a weaker anomalous return pattern regarding accounting-based variables.

**B. Fama-Macbeth regressions**

Although portfolio sorting is useful as a robust, non-parametric approach to documenting the link between characteristics and the cross-sectional component returns, this approach cannot simultaneously account for multiple characteristics. Therefore, we adopt Fama-Macbeth (Fama and Macbeth, 1973) regression to describe the cross-sectional returns at different intervals controlling for all return predictors mentioned above. Observations are weighted by lagged market capitalization in each cross-sectional regression to be consistent with our portfolio analysis. Table 2.6 reports the estimation results for each intraday interval and the overnight period. In each regression, we include characteristics studied above except for Max, as it is highly correlated with the standard deviation of daily returns (VOL). The Pearson correlation coefficients between them is 0.88, as shown in Panel C of Table 2.1.[10]

To account for the persistence and reversals of overnight/intraday returns we have documented in Table 2.2, in each regression, we include the lagged one-month overnight and interval returns. The results show that the overnight return (R_CO) positively predicts subsequent month overnight return and negatively predicts the subsequent month intraday component returns except for the period between 13:00 and 13:30. In addition, each intraday interval return (R-INTL) significantly positively predicts its subsequent month corresponding interval returns with coefficients ranging from 0.011(*t=2.91*) to 0.173 (*t=12.47*). These results are consistent with the findings on intraday/overnight return persistence and reversal pattern in Table 2.2.

Column (1) of Table 2.6 shows results for overnight returns. There are significant positive premiums associated with TO, ATO, VOL, EP and ASSET. For example, a 1% decrease in TO results in a 0.00215% (*t=-5.68*) increase in the subsequent monthly overnight return, and a 1% decrease in ATO results in a 0.001467% (*t=-11.35*) increase in overnight return in the next month. The premiums for ROE and NOA are statistically insignificant. In addition, the premiums for SIZE and ILLIQ are both significantly negative. The last column reports the estimations of the last half-hour interval return on

[10] We also conduct regressions by replacing VOL with Max, the result is qualitatively similar. We report the results in Appendix 2.5.

the same set of firm characteristics. The significant positive premiums can be observed for the majority of firm features such as SIZE, ILLIQ, TO, ATO, VOL, ROE, and EP. The premiums for NOA and ASSET are relatively small but significantly negative. Columns (2) to (7) report the estimation results for the rest seven intervals. We can see that variables associated with trading frictions such as TO, ATO, and VOL, caused significantly negative premiums. By contrast, for those accounting-related anomalies such as ROE, NOA, and ASSET, the intraday returns do not exhibit clear patterns. Overall, our Fama-Macbeth results are broadly consistent with our portfolio sort findings that abnormal profits associated with firm characteristics, especially those related to trading frictions, occur mainly overnight and in the last half hour of a trading day.

**C. Firm-specific news**

For robustness of the above findings, we examine whether our reported return pattern is caused by firm-specific news announcements. As a large amount of firm-specific news, such as EAs, is released after market closure (Barclay and Hendershott, 2003; Engelberg et al., 2018). Different news exposure to investors may be the reason for the differences between overnight and intraday returns. Table 2.7 reports the differences in nine interval component returns to firm characteristic long-short strategies as shown in Table 2.4 and 2.5 between months with and without EAs. EA months are defined as those months with EAs for a given firm. In China, all firms are required to report their financial statements to regulators before four preset deadline dates each year.[11] The results show that there is no statistical difference in anomaly return between EA and non-EA months, indicating that the U-shape pattern of anomalous returns is not driven by news releases.

### 2.4.4 The role of heterogeneous investors

In this section, we examine whether the heterogeneous clienteles' trades have

[11] According to CSRC, annual report should be disclosed within 4 months from the date of end of each fiscal year. Interim and quarterly reports should be disclosed within 2 and 1 month respectively from the date of end of each fiscal year.

different influences on stock prices at different times of a trading day by relating the U-shape anomaly return pattern to investors' trade directions. We use order imbalance (OIB) to measure direction of trade.

We construct order imbalance from institutions and retail investors following the method of Chordia and Subramanyam (2004) and Kaniel et al. (2012). For stock $i$, month $m$, interval $k$, we compute

$$OIB(i,m,k,G) = \frac{\sum_{j \in G} BuyVol(i,m,k,j) - \sum_{j \in G} SellVol(i,m,k,j)}{\sum TradingVol(i,m,j)} \tag{2.10}$$

where group G indicates either institutions or retail investors. For each stock $i$, the numerator is the difference between the buy and sell volumes summed up over all orders $j$ within each investor group G, and the denominator is the total trading volume in month $m$. We identify the retail investor group as trades with order size below CNY40,000 and the institution group as trades with order size above CNY500,000. When a group of investors buys (sell) more than they sell (buy), the order imbalance is positive (negative).

Table 2.8 reports time-series averages of cross-sectional Fama-Macbeth regression estimates that regress order imbalance from one investor group G on constants and each of 11 firm characteristic $f$ in the following form:

$$OIB_{i,m,k,j} = a_0 + b_{1fk} \times FC_{i,m-1,f} + \varepsilon_{im} \qquad j \in G \tag{2.11}$$

where group G indicates either institutions or retail investors, $FC_{i,m-1,f}$ indicates each one of the 11 firm characteristics $f$ for firm $i$ in month $m$-$1$. We find that for variables that are associated with trading frictions such as ATO, TO, VOL, and Max, institutions' sell pressure increases with these lagged firm characteristics at market open and close, as reflected from negative coefficients, which are statistically significant. For example, a one unit increase in lagged month ATO is associated with a 0.21% decrease in institutions' order imbalance for the first half-hour trade, indicating increased selling pressure. Notably, stocks with higher ATO yield lower future overnight and last half-hour component returns, as shown in Tables 2.4 and 2.6. Thus, it is reasonable to infer that the overnight anomalous return related to ATO is likely to be caused by institutions exerting more selling pressure on stocks with high turnover at market open and close. Similar reasoning can also apply to other trading-related variables such as TO, VOL, AND Max. Therefore, our evidence suggests that stocks having high selling pressure by institutions over the first and last half-hour tend to experience more price drops during that period.

By contrast, there is a significant positive relation between retail investors' order imbalance and lagged ATO, TO, VOL, and Max for the rest 7 half-hour intervals (10:00-14:00), suggesting that retail investors exert more buying pressure on stocks with high TO, ATO, VOL, and Max in the last month. Combined with the baseline results in Tables 2.4 and 2.6, we conjecture that stocks with higher buying pressure by retail investors for the daytime session are likely to perform better than those with lower pressure. Under the interpretation that retail investors tend to trade more over daytime session, we conjecture that the reversed anomalous profits of day components are due to retail trading activities.

In summary, the above results indicate that stock opening price movements go in the same direction with institution trades at market open and closure, whereas they move with retail investors' trades at the rest times of the day. Therefore, we argue that institutions play a relatively important role in influencing price at market open and close while retail investors' trades significantly contribute to the stock returns over daytime session. This echoes our prior findings of large order trades accounting for significant parts over two extreme time sessions and small order trades over other intervals.

In terms of accounting-related variables, the signs of the coefficients for institutions during the first half-hour are all significantly negative, indicating that institutions exert more selling pressure on stocks with large ROE, EP, ASSET, and NOA. As to retail investors, the signs of the coefficients are mixed. These reveal weak evidence for the differences in trading behavior between institutions and retail investors, indicating that the investor clienteles' *tug of war* mainly applies to firm characteristics related to trading frictions.

For robustness check, we also use the trading volume of each investor group instead of the order imbalance to measure the trading activities of two clienteles. For each stock $i$, month $m$, interval $k$, we compute the trading volume from institutions and retail investors as follows:

$$TradingVol(i,m,k,G) = \frac{\sum_{j\in G} TradingVol(i,m,k,j)}{\sum TradingVol(i,m,k,j)} \tag{2.12}$$

where Group G indicates either institutions or retail investors. For each stock $i$, the numerator is the monthly aggregate trading volume of trades $j$ from one group (either institutions or retail investors) over a certain interval $k$, and the denominator is the monthly aggregate trading volume of all trades over interval $k$. Institutional and retail investor trading is based on trade order size, as mentioned above.

In Table 2.9 Panel A, we run Fama-Macbeth regressions that regress cross-sectional stock returns on each one of the 11 firm characteristics $f$ in the lagged month and its interaction with contemporary investor intensive trading volume dummy TV in the form:

$$\begin{aligned} Return_{im} = a_0 + b_{1fk} \times FC_{i,m-1,f} + b_{2fk} \times TV_{i,m-1,k,j} + b_{3fk} \\ \times FC_{i,m-1,f} \times \quad TV_{i,m-1,k,j} + Controls_{i,m-1} + \varepsilon_{im} \quad j \in G \end{aligned} \tag{2.13}$$

where Group G indicates either institutions or retail investors. We define the dummy variable $TV_{i,m-1,k,j}$ to represent intensive trading from one group of investors G for firm $i$ in month $m$-$1$ that equals one if the trading volume is above the median in month $m$-$1$, and otherwise zero. $FC_{i,m-1,f}$ represents one of the 11 firm characteristics $f$ for firm $i$ in month $m$-$1$. Stock returns are weighted by lagged market capitalization in each cross-sectional regression. For each firm characteristic $f$, we control for the remaining firm characteristics as in Table 2.4 and 2.5. We report results for the first and last half-hour trading sessions, as the anomaly profits are mainly revealed through overnight and last half-hour component returns. We aim to examine the impact of each clientele's trading activity on the returns of these two components. Coefficient estimate results of each firm characteristic for institutional investors are shown in each column of Panel A and results for the retail investor group in Panel B.

Results in Panel A show that the coefficients of the interaction term between institutional intensive trading and TO, ATO, VOL, and Max are all significantly negative, suggesting that more active institutional participation enhances the negative predictions of these characteristics on future returns over the opening and closing trading periods of a day. In addition, when we regress future returns on firm characteristics interacted with retail investor intensive trading volume dummy, we find a significant positive coefficient for TO, ATO, VOL, and Max both near market open and close, as shown in Panel B. These findings suggest that institution trading activities account for the return prediction on trading-related characteristics such as TO, ATO, VOL, and Max, whereas individuals' trades deteriorate the predictive power of these variables.

Also, the coefficients of ILLIQ interacted with institutions' TV dummy are positively significant for the last half-hour, and those of ILLIQ interacted with retail investors' TV dummy are negatively significant for both periods. Combined with results in Tables 2.4 and 2.6, this indicates that institutional trades can enhance the return prediction on ILLIQ for the closing period, whereas retail trades reduce this predictability for both periods. As to the SIZE characteristics, the coefficients of SIZE interacted with the TV dummy are all insignificant from zero, regardless of institutional and retail trading for both periods, indicating no evidence for the impact of clienteles' trades on return prediction in terms of SIZE.

For accounting-related variables, we find a relatively weak prediction pattern. For example, we find that active institution trading can only enhance the prediction of ASSET and NOA for overnight component returns and that of ROE for the last half-hour interval component returns. Also, there is a weakened return prediction of EP for both overnight and last half-hour intervals, as the interaction term coefficients are significantly negative (-0.404 vs. -0.084). The coefficient estimates of interaction terms for retail investor trading reveal no enhancement effects for ASSET, NOA, and ROE and enhancement effects for EP.

To conclude, our evidence that institutions' trades move in the same direction of stock opening and closing prices corroborates the investor heterogeneity assumption, and findings that the prediction enhancement effect mainly exists among institutional investors at market open and close reinforce our argument that trading activities by heterogenous investors are the reasons behind overnight/intraday return patterns.

### 2.5 Further analyses on institutional trading

In this subsection, we discuss the potential motives for institutions to trade actively near market open and close by considering two scenarios. Several studies have considered institutions as sophisticated arbitrageurs who correct mispricing (Bogousslavsky, 2021; Akbas et al., 2022). We examine whether zero-cost long-short strategy profits of overnight and last-half hour components can be explained as the tendency for institutional investors seeking for mispricing profits.

#### 2.5.1 Anomaly profits with different opening prices

As most firm-specific information such as EAs and other important declarations are released after market close (Barclay and Hendershott, 2003), mispricing tends to be highest at market open. Also, it could be the case that information accumulated overnight is gradually incorporated into prices among informed traders at market open, and mispricing corrects gradually (Bogousslavsky, 2021). If institutions trade for mispricing profits, they tend to open their positions as early as possible. Thus, we should observe more anomalous profits of the overnight component when we use opening prices sampled at an earlier time. We zoom in on the period of the first 15 minutes after market open and observe the abnormal profit pattern using different sampled opening prices.

Table 2.10 reports overnight returns of trading strategies calculated using different opening prices sampled at 9:35, 9:40, and 9:45. The results generally show that the overnight long-short strategy return decreases with time. That is, the zero-cost strategy earns the largest profits at 9:35 compared with those earned at 9:40 and 9:45. Together with the evidence that institutions trade actively at market open, this result is consistent with our argument that institutions trade for mispricing at market open.

### 2.5.2 The T+1 trading rule

Next, we consider the unique T+1 trading arrangement as one of the reasons that institutions trade more at market open. This arrangement does not allow investors to sell stocks they have bought earlier on the same day yet does not restrict buying stocks back. It is virtually a one-day selling lockup, as the trading barrier is removed at the market open of the following trading day. Miller (1977) theorizes that selling constraints could prevent negative information from being impounded into stock prices, thus resulting in overvalued stocks. We hypothesize that the buying pressure will generally increase with the time within a trading day because the T+1 rule allows investors to buy their perceived undervalued stocks, whereas perceived overpriced stocks cannot be sold out on a given day. The accumulated buying pressure will lead to a relatively high closing price that attracts more sophisticated arbitrageurs to correct mispricing at the next day's market open.

Zhang (2020) documents that stocks with particular features are more affected by the T+1 rule. These stocks tend to experience a large opening price discount as their closing prices are relatively high. Specifically, he argues that stocks with high divergent opinions, high volatility, and high limits to arbitrage are more likely to be constrained by the T+1 rule, therefore resulting in higher intraday return and lower overnight return. We use ATO and TO as proxies for divergent opinions, following Diether et al. (2002) and Berkman et al. (2009). High ATO (or TO) indicates a higher degree of divergent opinions. Also, as stocks with Max and STR properties are sensitive to speculative demands and costly to arbitrage (Bali et al., 2011; Da et al., 2014), we use Max and STR as indicators to reflect the extent of limits to arbitrage. Stocks with high levels of these variables are more likely to cause overvaluation toward the end of a day. Furthermore, stocks with small market capitalization and less liquidity are generally regarded as more difficult and costly in arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006); they may also get overpriced at market close.

If institutions trade on mispricing at market open, we will observe more negative overnight returns for stocks that are more affected by the T+1 rule than those that are less affected. Our results in Tables 2.4 and 2.6 support this argument by showing that stocks with high divergent opinions (ATO and TO), high volatility (VOL), and more limits to arbitrage (high STR, high Max, small SIZE, and high ILLIQ) are associated with more negative returns of overnight components than stocks with lower values of these characteristics. Notably, several studies have reported positive small-size and high-illiquidity premiums in China.[12] In contrast, our results document negative anomalous premiums of the overnight component returns related to these two variables. We attribute it to the asymmetric trading rule that causes more affected stocks to be overvalued at market close, thus leading to more arbitrary activities by sophisticated institutions in the next day's market. To sum up, our evidence indicates that at least partial overnight anomalous profits can be attributed to arbitrary activities against mispricing induced by the T+1 rule at market open.

## 2.6 Conclusion

In this study, we examine the existence of intraday/overnight return patterns in the Chinese stock market and use investor heterogeneity as the explanation. We find a strong persistence and reversal of overnight and intraday component returns. We also link overnight and intraday component returns to a set of well-documented trading strategies and find that the abnormal profits tend to be high near the market-open and market-close (i.e., a U-shaped pattern), especially for trading friction variables. We provide evidence that heterogeneous investors trading in different periods is the reason behind this pattern. Results show that institutions trade more actively at market open and the last half-hour before market close.

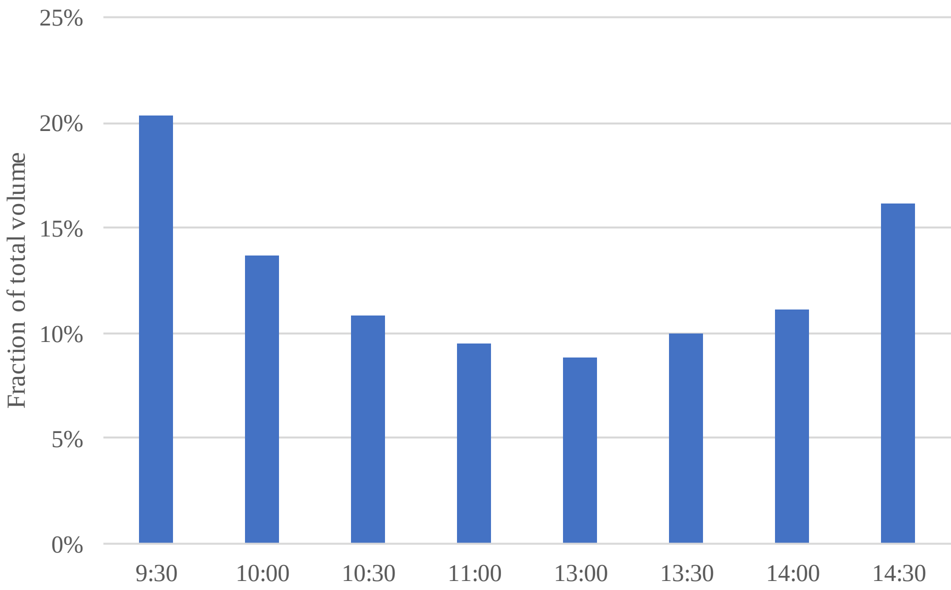
Our results differ from those on the US market in that we reveal a U-shape pattern of anomalous component returns within a trading day, whereas the long-short strategy

[12] See Cheung et al. (2015); Cakici et al. (2017), Hsu et al. (2018); Carpenter et al. (2018), and Hu et al. (2019) for small size premium. See Carpenter et al. (2018) and Chen et al. (2010) for a high illiquidity premium.

yields returns of an inverse U-shape pattern in the US market. Our evidence suggests that the anomalous profits of overnight returns can be explained as the tendency for institutions to correct mispricing at market open, presumably caused by the one-day selling lockup (i.e., T+1 rule) in China. However, what incentives institutions to trade heavily for the last half hour is still vague and we hope this is a promising venue for future studies, given that many institutions rely on closing prices as their benchmarks and the proportion of institutions' trades increases with the time.

**Figure 2.1**

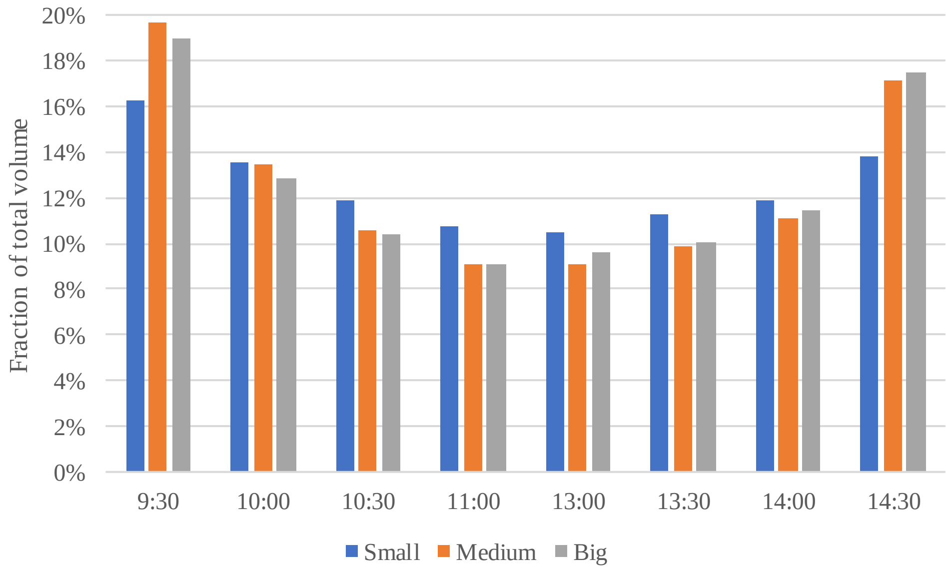
**Distribution of total trading volume in intraday intervals**




This figure plots CNY trading volume fraction over 30-min intervals throughout the trading day over 2009 and 2021. We first sum up the CNY trading volume over each interval for each day and then divide it by total daily trading volume (the sum over 8 intervals). Then we calculate the time-series average of the fraction of trading volume for each interval such that the total fraction equals to 1. The first interval starts at 9:30 and includes pre-open auction and the last interval ends at 15:00 that includes end auction. Stocks are required to trade for at least 200 days in a calendar year and for at least 10 days in a calendar month.

**Figure 2.2**

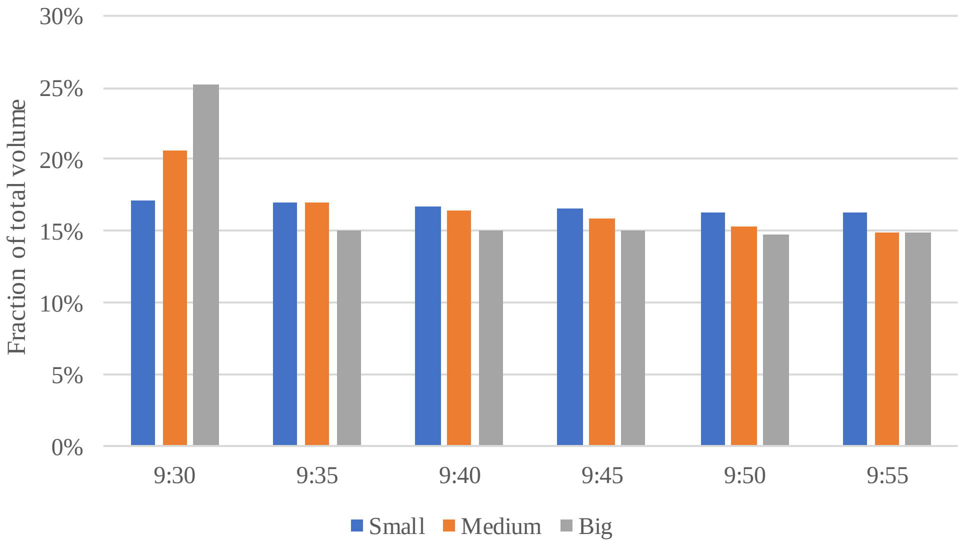
**Distribution of trading volume of large, medium, and small orders in intraday intervals**




This figure shows CNY trading volume of large, medium vs small orders over 30-min intervals throughout the trading day for the period 2009 to 2021. We define small orders as those below CNY40,000, large orders as those above CNY500,000 and medium orders as those between. More specifically, we first sum up the amount of yuan volume for each size order in each half-hour window. We then compute the trading volume for each order size of each interval as the fraction of total trading volume in Yuan for each order size (i.e., the sum of over 8 intervals). The first half-hour window that starts at 9:30 exclude the open auction trading volume due to data access limitation. The last half-hour window that starts at 14:30 also excludes closing auction trading volume.

**Figure 2.3**

**Distribution of trading volume of large, medium, and small orders over the first half-hour**




This figure shows CNY trading volume of large, medium vs small orders over 5-min intervals throughout the first half-hour (9:30-10:00) of a trading day for the period 2009 to 2021. We define small orders as those below CNY40,000, large orders as those above CNY500,000 and medium orders as those between. More specifically, we first sum up the amount of yuan volume traded in each 5-min windows. We then compute the fraction of total volume in Yuan (i.e., the sum over these 6 windows). fort each order size. The first 5-min window that starts at 9:30 exclude the open auction trading volume.

**Table 2.1**

**Summary statistics of main variables and correlation of firm characteristics**

Panel A: Overnight/intraday components of monthly returns

| | MEAN | STD | P25 | P50 | P75 | Skew. | Kurt. |
|---|---|---|---|---|---|---|---|
| R_CC | 1.17* | 0.08 | -3.42 | 0.79 | 5.47 | 0.06 | 4.02 |
| R_CO | -1.58*** | 0.04 | -3.42 | -1.20 | 0.56 | -0.99 | 5.74 |
| 9:30 | 0.53*** | 0.01 | -0.20 | 0.30 | 1.01 | 0.71 | 4.20 |
| 10:00 | 0.71*** | 0.02 | -0.41 | 0.44 | 1.43 | 1.19 | 6.44 |
| 10:30 | -0.29** | 0.02 | -1.17 | -0.22 | 0.98 | -0.24 | 4.82 |
| 11:00 | -0.05 | 0.02 | -1.05 | 0.14 | 1.08 | -0.69 | 3.94 |
| 13:00 | 0.26* | 0.02 | -1.02 | 0.17 | 1.59 | 0.12 | 3.29 |
| 13:30 | 0.18 | 0.02 | -0.70 | 0.08 | 0.97 | 1.37 | 11.35 |
| 14:00 | -0.26** | 0.02 | -1.12 | -0.44 | 0.57 | 0.82 | 5.70 |
| 14:30 | 0.67*** | 0.02 | -0.38 | 0.89 | 1.59 | -0.92 | 7.98 |

Panel B: Firm characteristics

| | MEAN | STD | P25 | P50 | P75 | Skew. | Kurt. |
|---|---|---|---|---|---|---|---|
| SIZE | 15.29 | 0.41 | 15.01 | 15.30 | 15.64 | -0.25 | 2.88 |
| STR | 1.21 | 0.08 | -3.26 | 0.78 | 5.48 | 0.07 | 3.99 |
| Max | 4.02 | 0.01 | 3.25 | 3.71 | 4.51 | 1.74 | 6.84 |
| TO | 2.45 | 0.75 | 1.88 | 2.15 | 2.92 | 0.93 | 2.59 |
| ATO | 0.97 | 0.32 | 0.75 | 0.88 | 1.17 | 1.07 | 3.67 |
| ILLIQ | 0.05 | 0.03 | 0.03 | 0.04 | 0.06 | 1.41 | 5.46 |
| VOL | 2.67 | 0.01 | 2.19 | 2.40 | 2.92 | 2.45 | 10.88 |
| ROE | 0.03 | 0.01 | 0.02 | 0.03 | 0.04 | 0.02 | 1.95 |
| EP | 0.019 | 0.010 | 0.012 | 0.018 | 0.028 | 0.57 | 2.61 |
| ASSET | 1.17 | 0.05 | 1.14 | 1.16 | 1.21 | -0.23 | 2.25 |
| NOA | 0.54 | 0.02 | 0.53 | 0.54 | 0.55 | 0.07 | 3.04 |

Panel C: Pearson cross-sectional correlations

| | SIZE | ILLIQ | TO | ATO | VOL | STR | Max | ROE | EP | ASSET |
|---|---|---|---|---|---|---|---|---|---|---|
| ILLIQ | -0.31 | | | | | | | | | |
| TO | -0.42 | -0.02 | | | | | | | | |
| ATO | 0.02 | -0.11 | -0.10 | | | | | | | |
| VOL | -0.14 | 0.04 | 0.30 | 0.54 | | | | | | |
| STR | 0.04 | 0.04 | -0.01 | 0.34 | 0.32 | | | | | |
| Max | -0.07 | 0.02 | 0.21 | 0.54 | 0.88 | 0.56 | | | | |
| ROE | 0.06 | -0.03 | -0.01 | -0.00 | -0.03 | 0.02 | 0.02 | | | |
| EP | 0.12 | -0.08 | -0.02 | -0.00 | -0.09 | -0.00 | -0.00 | -0.00 | | |
| ASSET | -0.01 | -0.01 | 0.05 | -0.00 | 0.01 | -0.01 | -0.01 | -0.01 | 0.05 | |
| NOA | -0.09 | -0.01 | 0.03 | 0.01 | 0.02 | -0.00 | -0.00 | -0.00 | -0.04 | 0.03 |

This table reports time-series averages of monthly cross-sectional statistics of close-to-close (R_CC) and intraday/overnight component returns (Panel A), cross-sectional summary statistics of firm characteristics (Panel B) and Pearson correlations (Panel C). The sample consists of common A-share stocks listed on Shanghai and Shenzhen Stock Exchange from January 2009 to March 2021. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. Returns are in percent. All variables are winsorized at 1%. We require stocks trading for at least 200 days in a calendar year and for at least 10 days in a calendar month to be included in our sample. *, ** and *** indicate 10%, 5% and 1% statistical significance respectively.

**Table 2.2**

**Persistence and reversal of overnight/intraday returns**

| | Intraday interval returns | | | Overnight returns | | |
|---|---|---|---|---|---|---|
| Interval | Excess | CAPM | 3-Factor | Excess | CAPM | 3-Factor |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 9:30 | 0.73*** | 0.73*** | 0.73*** | -0.25* | -0.29* | -0.31* |
| | (11.97) | (11.49) | (11.04) | (-1.75) | (-1.78) | (-1.79) |
| 10:00 | 0.51*** | 0.50*** | 0.51*** | -1.04*** | -1.07*** | -1.08*** |
| | (6.25) | (5.94) | (6.21) | (-5.50) | (-4.88) | (-4.75) |
| 10:30 | 0.15*** | 0.14*** | 0.15*** | -1.04*** | -1.07*** | -1.08*** |
| | (2.87) | (2.59) | (2.67) | (-5.00) | (-4.54) | (-4.50) |
| 11:00 | 0.40*** | 0.40*** | 0.39*** | -1.32*** | -1.32*** | -1.31*** |
| | (6.88) | (6.69) | (7.12) | (-9.47) | (-10.4) | (-9.45) |
| 13:00 | 0.39*** | 0.38*** | 0.39*** | -1.03*** | -1.02*** | -1.02*** |
| | (5.59) | (5.63) | (5.93) | (-6.02) | (-5.76) | (-6.05) |
| 13:30 | 0.10** | 0.10** | 0.10** | -1.27*** | -1.24*** | -1.25*** |
| | (2.30) | (2.32) | (2.22) | (-8.16) | (-7.88) | (-7.89) |
| 14:00 | 0.24*** | 0.24*** | 0.24*** | -0.95*** | -0.92*** | -0.93*** |
| | (6.25) | (6.78) | (6.82) | (-7.13) | (-6.86) | (-7.36) |
| 14:30 | 2.40*** | 2.44*** | 2.46*** | -2.32*** | -2.32*** | -2.35*** |
| | (13.80) | (14.32) | (14.88) | (-16.88) | (-16.24) | (-16.6) |
| CO | | | | 2.64*** | 2.60*** | 2.67*** |
| | | | | (14.63) | (14.51) | (16.55) |

This table presents overnight/intraday return persistence and reversal patterns of each half-hour interval over the trading day. At the beginning of each month, all stocks are sorted into deciles based on their previous month returns in a given interval (indicated in the 'Interval' column). For example, the interval 9:30 corresponds to the first half hour of the trading period. We then go long the value-weighted portfolio of past month winners and short the value-weighted portfolio of past losers in a given interval and hold portfolios for the subsequent month. The left three columns show the corresponding interval component returns of the long-short portfolio in the subsequent month, and the right three columns show the overnight component returns of the long-short portfolio in the subsequent month. Stocks are required to trade for at least 200 days in a calendar year and for at least 10 days in a calendar month. Sample period is from January 2009 to March 2021. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. We report portfolio returns in excess of risk-free rate, adjusted by CAPM model and Fama-French 3-factor model. Returns are in percent. We compute Newey-West *t*-statistics to adjust heteroskedasticity and autocorrelation. *, ** and *** indicate 10%, 5% and 1% statistical significance respectively.

**Table 2.3**

**Institutional trading and contemporaneous returns**

Panel A: Change in IO and contemporaneous returns

| IO | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| Low | 0.028*** | -0.024 | 0.023*** | 0.050** | 0.026 | 0.037*** | 0.019 | 0.003 | 0.030** |
| | (3.43) | (-0.67) | (2.63) | (2.25) | (1.09) | (3.22) | (0.90) | (0.11) | (2.26) |
| High | 0.051** | -0.001 | 0.028 | -0.013 | -0.076 | -0.048 | -0.052 | -0.03 | 0.078 |
| | (2.14) | (-0.06) | (1.51) | (-0.37) | (-1.60) | (-1.17) | (-1.22) | (-1.15) | (1.53) |

Panel B: Coefficient difference matrix

| High \ Low | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| CO | | **-0.053** | -0.005 | 0.002 | -0.003 | 0.008 | -0.009 | -0.026 | 0.001 |
| 9:30 | **0.052** | | 0.047 | 0.075 | 0.050 | **0.061** | 0.043 | 0.027 | 0.054 |
| 10:00 | 0.023 | -0.028 | | 0.027 | 0.003 | 0.014 | -0.004 | -0.020 | 0.007 |
| 10:30 | 0.064 | 0.012 | 0.041 | | -0.025 | -0.014 | -0.031 | -0.048 | -0.021 |
| 11:00 | **0.13** | **0.076** | **0.104** | **0.063** | | 0.011 | -0.007 | -0.023 | 0.004 |
| 13:00 | **0.096** | 0.044 | 0.073 | 0.032 | -0.032 | | -0.018 | -0.034 | -0.007 |
| 13:30 | 0.100 | 0.052 | 0.080 | **0.039** | -0.024 | 0.008 | | -0.016 | 0.011 |
| 14:00 | **0.084** | 0.032 | 0.061 | 0.02 | -0.043 | -0.012 | -0.019 | | 0.027 |
| 14:30 | -0.027 | -0.078 | -0.050 | -0.091 | -0.154 | -0.123 | **-0.13** | -0.111 | |

This table reports Fama-MacBeth regression estimate results and coefficient differences between each pair of intervals. Panel A presents coefficients regressing changes in institutional ownership ( $\Delta$ IO) on contemporaneous interval returns. The dependent variable is the change in the fraction of shares outstanding held by institutions. The independent variable in each column is the cumulative raw return over 9 intervals measured in the contemporaneous period. We sort stocks into quintiles based on previous quarter's institutional ownership and conduct Fama-MacBeth regressions for the first and fifth quintile, denoted as Low and High respectively. Panel B reports the differences between the estimated coefficients in different intervals. The value corresponding to column 'X' and row 'Y' is the difference between the coefficient estimated by regressing IO change on the interval returns (the interval is indicated from column 'X') and that on the interval returns (the interval is indicated from row 'Y'). We compute Newey-West *t*-statistics with 8 lags. *, ** and *** indicate 10%, 5% and 1% statistical significance respectively.

## Table 2.4

**Intraday and overnight returns of long-short portfolios for trading-related variables**

| | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| TO | | | | | | | | | |
| Low | -1.04*** | 0.35*** | 0.46*** | -0.27** | -0.01 | 0.08 | 0.07 | -0.15 | 1.36*** |
| | (-3.17) | (4.02) | (2.84) | (-2.09) | (-0.09) | (0.63) | (0.58) | (-1.59) | (12.9) |
| High | -2.56*** | 0.57*** | 1.06*** | -0.02 | 0.13 | 0.56*** | 0.38* | -0.30* | -0.09 |
| | (-8.65) | (3.33) | (4.71) | (-0.12) | (0.70) | (2.64) | (1.88) | (-1.88) | (-0.44) |
| L-H (Raw) | 1.52*** | -0.22* | -0.60*** | -0.25** | -0.15* | -0.47*** | -0.30*** | 0.15 | 1.45*** |
| | (7.93) | (-1.82) | (-5.72) | (-2.28) | (-1.70) | (-3.76) | (-3.10) | (1.49) | (10.02) |
| L-H (Alpha) | 1.69*** | -0.21* | -0.55*** | -0.23** | -0.09 | -0.40*** | -0.27*** | 0.20** | 1.54*** |
| | (10.24) | (-1.82) | (-5.46) | (-2.02) | (-0.95) | (-3.56) | (-2.61) | (2.08) | (11.29) |
| ATO | | | | | | | | | |
| Low | -1.27*** | 0.39*** | 0.71*** | -0.21 | 0.07 | 0.29* | 0.17 | -0.26** | 0.93*** |
| | (-3.74) | (3.57) | (3.34) | (-1.51) | (0.40) | (1.70) | (1.10) | (-2.17) | (6.06) |
| High | -3.17*** | 0.72*** | 1.07*** | -0.01 | 0.12 | 0.34* | 0.37* | -0.35** | 0.07 |
| | (-8.45) | (4.80) | (5.13) | (-0.09) | (0.57) | (1.71) | (1.78) | (-1.98) | (0.33) |
| L-H (Raw) | 1.90*** | -0.33*** | -0.36*** | -0.20*** | -0.05 | -0.05 | -0.18** | 0.09 | 0.86*** |
| | (13.93) | (-5.00) | (-4.88) | (-2.69) | (-0.67) | (-0.54) | (-2.33) | (1.22) | (7.84) |
| L-H (Alpha) | 1.91*** | -0.33*** | -0.38*** | -0.20*** | -0.04 | -0.03 | -0.20** | 0.09 | 0.86*** |
| | (12.81) | (-4.30) | (-4.76) | (-3.14) | (-0.43) | (-0.41) | (-2.38) | (1.14) | (7.40) |
| SIZE | | | | | | | | | |
| Small | -2.34*** | 0.79*** | 1.15*** | -0.07 | 0.14 | 0.75*** | 0.42** | -0.10 | 0.93*** |
| | (-7.20) | (5.00) | (4.84) | (-0.40) | (0.76) | (3.75) | (2.37) | (-0.61) | (4.89) |
| Big | -0.44 | 0.30*** | 0.45** | -0.25* | -0.13 | -0.03 | 0.05 | -0.23** | 0.58*** |
| | (-1.37) | (2.98) | (2.52) | (-1.81) | (-0.87) | (-0.21) | (0.36) | (-2.16) | (4.06) |
| S-B (Raw) | -1.90*** | 0.49*** | 0.71*** | 0.18** | 0.27*** | 0.78*** | 0.37*** | 0.14 | 0.35* |
| | (-9.71) | (4.56) | (4.61) | (2.06) | (2.80) | (5.08) | (4.25) | (1.21) | (1.90) |
| S-B (Alpha) | -2.09*** | 0.45*** | 0.65*** | 0.16* | 0.24** | 0.65*** | 0.35*** | 0.07 | 0.24 |
| | (-12.82) | (4.79) | (4.26) | (1.72) | (2.41) | (6.84) | (4.13) | (0.78) | (1.42) |

## Table 2.4 - *Continued*

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ILLIQ | | | | | | | | | |
| Low | -0.80** | 0.35*** | 0.57*** | -0.21 | -0.09 | -0.02 | 0.13 | -0.30*** | 0.15 |
| | (-2.32) | (3.01) | (3.13) | (-1.39) | (-0.60) | (-0.11) | (0.88) | (-2.57) | (0.95) |
| High | -1.67*** | 0.75*** | 0.89*** | -0.15 | 0.19 | 0.48*** | 0.30* | -0.10 | 1.52*** |
| | (-4.61) | (5.93) | (3.99) | (-0.97) | (1.10) | (2.65) | (1.74) | (-0.74) | (9.33) |
| H-L (Raw) | -0.86*** | 0.40*** | 0.33*** | 0.05 | 0.29*** | 0.50*** | 0.17*** | 0.20** | 1.37*** |
| | (-3.65) | (5.58) | (2.96) | (0.69) | (3.21) | (3.43) | (3.18) | (2.06) | (8.62) |
| H-L (Alpha) | -1.02*** | 0.36*** | 0.27*** | 0.03 | 0.28*** | 0.42*** | 0.16*** | 0.16** | 1.30*** |
| | (-4.32) | (5.67) | (3.00) | (0.37) | (2.79) | (4.52） | (2.95) | (1.97) | (8.56) |
| VOL | | | | | | | | | |
| Low | -1.27*** | 0.33*** | 0.46*** | -0.30** | 0.07 | 0.13 | 0.08 | -0.17* | 1.34*** |
| | (-3.30) | (4.16) | (2.56) | (-2.55) | (0.45) | (0.94) | (0.62) | (-1.90) | (11.25) |
| High | -3.34*** | 0.86*** | 1.38*** | 0.09 | 0.17 | 0.51** | 0.42* | -0.38** | -0.31 |
| | (-10.1) | (5.19) | (6.36) | (0.46) | (0.84) | (2.32) | (1.89) | (-2.03) | (-1.53) |
| L-H (Raw) | 2.07*** | -0.53*** | -0.92*** | -0.39*** | -0.10 | -0.38*** | -0.34*** | 0.21 | 1.65*** |
| | (10.06) | (-4.46) | (-8.71) | (-3.60) | (-1.09) | (-3.00) | (-2.74) | (1.63) | (9.89) |
| L-H (Alpha) | 2.14*** | -0.56*** | -0.91*** | -0.37*** | -0.05 | -0.31** | -0.31** | 0.24* | 1.72*** |
| | (9.74) | (-4.51) | (-7.78) | (-3.40) | (-0.49) | (-2.53) | (-2.30) | (1.92) | (10.35) |
| Max | | | | | | | | | |
| Low | -1.42*** | 0.41*** | 0.52*** | -0.27** | 0.07 | 0.13 | 0.14 | -0.20** | 1.13*** |
| | (-4.07) | (4.34) | (2.80) | (-2.19) | (0.43) | (0.93) | (0.84) | (-2.09) | (8.83) |
| High | -3.51*** | 0.84*** | 1.34*** | 0.08 | 0.13 | 0.50** | 0.40* | -0.38** | -0.22 |
| | (-10.47) | (4.97) | (5.94) | (0.41) | (0.66) | (2.39) | (1.79) | (-2.02) | (-1.10) |
| L-H (Raw) | 2.09*** | -0.43*** | -0.82*** | -0.35*** | -0.06 | -0.37*** | -0.28*** | 0.18 | 1.35*** |
| | (11.14) | (-4.35) | (-8.93) | (-3.62) | (-0.73) | (-3.18) | (-2.60) | (1.62) | (11.28) |
| L-H (Alpha) | 2.16*** | -0.45*** | -0.83*** | -0.34*** | -0.02 | -0.33*** | -0.27** | 0.18 | 1.37*** |
| | (10.78) | (-3.98) | (-7.62) | (-3.73) | (-0.16) | (-2.88) | (-2.38) | (1.59) | (10.99) |
| STR | | | | | | | | | |
| Low | -1.57*** | 0.66*** | 0.89*** | -0.16 | 0.13 | 0.27 | 0.29* | -0.21 | 0.51*** |

**Table 2.4 -** ***Continued***

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| High | -3.06*** | 0.64*** | 0.99*** | -0.08 | 0.01 | 0.47** | 0.29 | -0.32* | 0.38** |
| | (7.68) | (4.80) | (4.76) | (-0.44) | (0.07) | (2.49) | (1.46) | (-1.92) | (2.23) |
| L-H (Raw) | 1.49*** | 0.02 | -0.10 | -0.07 | 0.12 | -0.19* | -0.00 | 0.11** | 0.13 |
| | (5.07) | (0.26) | (-1.11) | (-0.79) | (1.49) | (-1.93) | (-0.06) | (2.03) | (1.43) |
| L-H (Alpha) | 1.49*** | 0.03 | -0.14 | -0.07 | 0.15 | -0.22** | -0.01 | 0.08 | 0.07 |
| | (4.65) | (0.37) | (-1.35) | (-0.74) | (1.64) | (-2.25) | (-0.17) | (1.49) | (0.87) |

This table reports raw excess returns and Fama-French 3-factor alphas of long-short portfolios where we go long one extreme value-weight decile and short the other extreme value-weight decile based on a particular firm characteristic across a day for overnight and intraday intervals. At the end of each month, within each interval, we sort stocks into deciles based on month-end's firm characteristics and hold for a month. The construction of the anomaly variables is described in Appendix 2.1. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. CO indicates overnight period. Sample period spans from January 2009 to March 2021. Returns are in percent. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1% level.

**Table 2.5**

**Intraday and overnight returns of long-short portfolios for accounting-related variables**

| | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| ROE | | | | | | | | | |
| Low | -2.40*** | 0.83*** | 0.94*** | -0.16 | 0.16 | 0.30 | 0.26 | -0.28** | 0.67*** |
| | (-6.58) | (5.48) | (3.91) | (-0.96) | (0.82) | (1.59) | (1.44) | (-2.03) | (3.62) |
| High | -0.85*** | 0.50*** | 0.64*** | -0.25* | -0.15 | 0.20 | 0.14 | -0.13 | 0.86*** |
| | (-2.66) | (4.68) | (3.60) | (-1.65) | (-0.99) | (1.32) | (1.05) | (-1.08) | (6.49) |
| H-L (Raw) | 1.55*** | -0.34*** | -0.30** | -0.08 | -0.30*** | -0.10 | -0.12 | 0.15** | 0.20** |
| | (6.53) | (-4.39) | (-2.31) | (-1.36) | (-4.11) | (-1.04) | (-1.63) | (2.18) | (2.13) |
| H-L (Alpha) | 1.74*** | -0.30*** | -0.22* | -0.06 | -0.27*** | -0.05 | -0.09 | 0.18*** | 0.27*** |
| | (6.73) | (-3.85) | (-1.84) | (-0.98) | (-3.34) | (-0.68) | (-1.30) | (2.71) | (3.39) |
| EP | | | | | | | | | |
| Low | -2.26*** | 0.88*** | 0.94*** | -0.16 | 0.17 | 0.27 | 0.26 | -0.26* | 0.64*** |
| | (-6.32) | (5.94) | (3.96) | (-0.98) | (0.87) | (1.45) | (1.43) | (-1.87) | (3.22) |
| High | -1.14*** | 0.44*** | 0.69*** | -0.20 | 0.00 | 0.22 | 0.15 | -0.17 | 0.75*** |
| | (-3.37) | (4.33) | (3.65) | (-1.38) | (0.02) | (1.43) | (1.07) | (-1.48) | (5.73) |
| H-L (Raw) | 1.12*** | -0.43*** | -0.26*** | -0.03 | -0.17** | -0.04 | -0.11* | 0.09 | 0.11 |
| | (5.86) | (-5.56) | (-2.79) | (-0.60) | (-2.17) | (-0.62) | (-1.81) | (1.33) | (1.00) |
| H-L (Alpha) | 1.28*** | -0.42*** | -0.23*** | -0.01 | -0.13 | -0.00 | -0.08 | 0.11* | 0.15 |
| | (6.31) | (-5.78) | (-2.62) | (-0.18) | (-1.55) | (-0.01) | (-1.38) | (1.76) | (1.48) |
| NOA | | | | | | | | | |
| Low | -1.16*** | 0.55*** | 0.74*** | -0.13 | 0.06 | 0.07 | 0.15 | -0.26** | 0.62*** |
| | (-3.45) | (5.09) | (3.76) | (-0.80) | (0.34) | (0.47) | (0.95) | (-2.24) | (4.24) |
| High | -1.48*** | 0.52*** | 0.70*** | -0.27 | 0.01 | 0.29 | 0.20 | -0.24 | 0.74*** |
| | (-4.61) | (3.96) | (3.60) | (-1.63) | (0.05) | (1.64) | (1.15) | (-1.82) | (4.43) |
| L-H (Raw) | 0.32*** | 0.03 | 0.05 | 0.14*** | 0.05 | -0.22*** | -0.05 | -0.02 | -0.12* |
| | (3.55) | (0.64) | (0.80) | (3.84) | (0.90) | (-3.43) | (-1.39) | (-0.61) | (-1.65) |
| L-H (Alpha) | 0.35*** | 0.04 | 0.07 | 0.15*** | 0.06 | -0.18*** | -0.04 | -0.01 | -0.09 |
| | (4.27) | (0.91) | (1.03) | (3.69) | (1.05) | (-3.79) | (-0.90) | (-0.30) | (-1.29) |

**Table 2.5 - *Continued***

| ASSET | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Low | -1.84*** | 0.84*** | 0.88*** | -0.16 | 0.15 | 0.24 | 0.26 | -0.23 | 0.61*** |
| | (-4.90) | (5.69) | (3.89) | (-0.91) | (0.79) | (1.38) | (1.40) | (-1.60) | (3.69) |
| High | -1.23*** | 0.39*** | 0.68*** | -0.31** | -0.03 | 0.26 | 0.17 | -0.23* | 0.74*** |
| | (-3.79) | (3.20) | (3.17) | (-2.10) | (-0.17) | (1.48) | (1.03) | (-1.85) | (4.42) |
| L-H (Raw) | -0.61*** | 0.44*** | 0.20** | 0.15*** | 0.18*** | -0.01 | 0.08** | -0.01 | -0.13** |
| | (-2.97) | (8.32) | (2.50) | (2.91) | (3.33) | (-0.21) | (2.19) | (-0.11) | (-2.00) |
| L-H (Alpha) | -0.71*** | 0.45*** | 0.19** | 0.12*** | 0.16*** | -0.02 | 0.08** | -0.01 | -0.16*** |
| | (-3.13) | (7.68) | (2.51) | (2.99) | (2.71) | (-0.38) | (2.16) | (-0.21) | (-2.80) |

This table reports raw excess returns and Fama-French 3-factor alphas of long-short strategy that long one extreme decile and short the other extreme decile based on a particular accounting-related variable across a day for overnight and intraday intervals. At the end of each month, within each interval, we sort stocks into deciles based on month-end's firm characteristics and hold for a month. The construction of the anomaly variables is described in Appendix 2.1. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. CO indicates overnight period. Sample period spans from January 2009 to March 2021. Returns are in percent. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1% level.

**Table 2.6**

**FM regressions of component returns on firm characteristics**

| | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| R_CO | 0.115*** | -0.007*** | -0.010*** | -0.007*** | -0.016*** | -0.002 | -0.008*** | -0.011*** | -0.003** |
| | (18.07) | (-3.80) | (-4.17) | (-2.74) | (-7.76) | (-0.63) | (-5.46) | (-5.07) | (-2.20) |
| R_INTL | | 0.079*** | 0.029*** | 0.017*** | 0.034*** | 0.027*** | 0.011*** | 0.021*** | 0.173*** |
| | | (15.05) | (5.67) | (3.76) | (7.91) | (5.04) | (2.91) | (6.88) | (12.47) |
| TO $\times 10^{-2}$ | -0.215*** | -0.028** | 0.041*** | 0.050*** | 0.039*** | 0.036** | 0.046*** | -0.023** | -0.302*** |
| | (-5.68) | (-2.24) | (3.51) | (4.49) | (4.39) | (2.07) | (3.78) | (-2.44) | (-10.74) |
| ATO$\times 10^{-2}$ | -1.467*** | 0.026 | 0.113** | 0.086** | 0.070* | -0.034 | 0.103*** | -0.048 | -0.441*** |
| | (-11.35) | (0.54) | (1.97) | (2.02) | (1.76) | (-1.09) | (3.11) | (-1.24) | (-5.02) |
| SIZE$\times 10^{-2}$ | 0.205** | -0.085*** | -0.050* | -0.018 | -0.029 | -0.137*** | -0.042* | -0.053 | -0.264*** |
| | (2.43) | (-3.10) | (-1.75) | (-0.80) | (-0.96) | (-2.91) | (-1.85) | (-1.53) | (-5.47) |
| ILLIQ | -0.036*** | 0.009** | 0.003 | 0.011** | 0.011*** | 0.005* | 0.006* | 0.010** | 0.031*** |
| | (-4.35) | (2.30) | (0.64) | (2.24) | (3.48) | (1.68) | (1.93) | (1.97) | (3.70) |
| VOL | -0.246*** | 0.118*** | 0.193*** | 0.065** | -0.002 | 0.113*** | 0.049 | -0.039 | -0.209*** |
| | (-2.69) | (2.71) | (4.79) | (2.33) | (-0.06) | (3.16) | (1.58) | (-1.14) | (-4.85) |
| ROE | 0.001 | -0.001* | 0.000 | -0.001** | -0.001** | 0.000 | -0.000 | 0.000 | 0.002*** |
| | (0.44) | (-1.71) | (0.53) | (-2.35) | (-2.21) | (1.39) | (-0.04) | (0.80) | (2.70) |
| EP | 0.099** | -0.037*** | -0.011 | 0.024 | 0.019 | 0.032*** | -0.006 | 0.040*** | 0.057*** |
| | (2.14) | (-3.08) | (-0.59) | (1.57) | (0.95) | (2.63) | (-0.67) | (3.14) | (2.72) |
| NOA | -0.104 | -0.093*** | -0.089** | -0.092*** | -0.058* | 0.069** | 0.001 | 0.020 | 0.089*** |
| | (-1.06) | (-3.93) | (-2.24) | (-2.97) | (-1.74) | (2.24) | (0.05) | (0.66) | (2.93) |
| ASSET | -0.014* | -0.013** | -0.014 | -0.005 | -0.005 | -0.008 | -0.002 | 0.005 | 0.015** |
| | (-1.78) | (-2.32) | (-1.51) | (-1.13) | (-0.91) | (-1.55) | (-0.43) | (1.30) | (2.40) |
| N | 277,297 | 277,295 | 277,270 | 277,270 | 277,270 | 277,270 | 277,270 | 277,270 | 277,270 |
| Adj_$R^2$ | 0.07 | 0.04 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | 0.08 |

This table reports estimation results of Fama-Macbeth regressions. For each interval in each month, we regress returns on a set of characteristics in the previous month and calculate time-series averages of cross-sectional estimated coefficients. Each column represents a separate regression where stock returns of different interval components are regressed on a set of characteristics. These characteristics include past 12-month turnover (TO), abnormal turnover over the past month (ATO), market

**Table 2.6 - *Continued***

capitalization (SIZE), Amihud illiquidity (ILLIQ), standard deviation of daily returns (VOL), return-on-equity (ROE), earnings-to-price ratio (EP), net-operating-assets (NOA) and asset growth rate (ASSET). The construction of the anomaly variables is described in Appendix 2.1. The independent variables also include the most recent one-month overnight return (R_CO), the most recent one-month corresponding interval returns (R_INTL). The sample period is from January 2009 to March 2021. Observations are weighted by lagged market capitalization in each cross-sectional regression. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. Stocks are required to trade for at least 200 days in a calendar year and for at least 10 days in a calendar month. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors.

**Table 2.7**

**Anomaly return differences between EA and Non-EA months**

| | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| TO | -0.83 | 0.02 | -0.09 | -0.04 | -0.00 | -0.31 | 0.03 | -0.13 | 0.28 |
| | (-1.37) | (0.11) | (-0.41) | (-0.26) | (-0.01) | (-1.44) | (0.16) | (-0.76) | (1.20) |
| ATO | 0.65 | -0.23 | 0.54** | -0.15 | 0.07 | -0.17 | -0.31 | -0.20 | -0.29 |
| | (1.24) | (-1.06) | (2.15) | (-0.71) | (0.38) | (-0.74) | (-1.45) | (-1.07) | (-1.29) |
| SIZE | -0.00 | -0.05 | 0.16 | 0.16 | 0.07 | 0.15 | -0.27 | 0.28** | -0.39* |
| | (-0.01) | (-0.24) | (0.66) | (0.79) | (0.41) | (0.83) | (-1.59) | (1.97) | (-1.69) |
| ILLIQ | -0.35 | 0.10 | 0.14 | 0.19 | -0.26 | 0.25 | -0.30 | 0.27 | -0.27 |
| | (-0.79) | (0.41) | (0.45) | (1.01) | (-1.16) | (1.18) | (-1.42) | (1.36) | (-1.10) |
| VOL | 0.67 | -0.19 | 0.10 | 0.06 | 0.27* | -0.23 | -0.26 | -0.18 | -0.10 |
| | (0.94) | (-0.91) | (0.36) | (0.27) | (1.70) | (-1.26) | (-0.80) | (-1.20) | (-0.38) |
| Max | 0.13 | -0.07 | 0.25 | -0.14 | 0.12 | -0.40 | -0.09 | -0.16 | 0.04 |
| | (0.21) | (-0.30) | (1.01) | (-0.63) | (0.66) | (-1.60) | (-0.36) | (-1.02) | (0.18) |
| STR | -0.36 | 0.11 | -0.30 | -0.23 | -0.10 | -0.10 | -0.33 | -0.40 | -0.02 |
| | (-1.04) | (0.56) | (-1.13) | (-1.22) | (-0.48) | (-0.37) | (-1.10) | (-1.91) | (-0.08) |
| EP | -1.19* | -0.19 | 0.12 | 0.11 | 0.12 | 0.05 | 0.25 | 0.23 | 0.29 |
| | (-1.82) | (-1.40) | (0.34) | (0.82) | (0.71) | (0.27) | (1.06) | (1.06) | (0.97) |
| ROE | -1.14** | -0.08 | -0.45 | 0.17 | 0.33* | -0.20 | 0.14 | -0.03 | 0.17 |
| | (-2.11) | (-0.53) | (-1.40) | (1.00) | (1.94) | (-0.81) | (0.65) | (-0.19) | (0.67) |
| ASSET | 0.41 | -0.12 | 0.02 | -0.23 | -0.10 | -0.22 | -0.04 | -0.08 | -0.11 |
| | (0.71) | (-0.61) | (0.08) | (-1.22) | (-0.55) | (-0.80) | (-0.19) | (-0.45) | (-0.46) |
| NOA | 0.76 | -0.09 | -0.32 | 0.26 | -0.25 | -0.07 | 0.11 | -0.14 | 0.09 |
| | (1.38) | (-0.39) | (-1.27) | (1.53) | (-1.42) | (-0.38) | (0.66) | (-0.87) | (0.38) |

This table presents long-short portfolio return differences in 9 interval component returns to various cross-sectional firm characteristics between months with and without firm-specific earnings announcements. EA month is defined as the month that releases an earnings announcement for a specific firm, while Non-EA month is the month without earnings announcements release. Each month, we sort stocks into two groups, one that have EA release and the other that have no EA release. Within each group, we further sort stocks into deciles based on a specific firm characteristic indicated in the left column at month end. We hold each portfolio for one month and calculate the value-weighted long-short portfolio returns for each group (i.e., EA and Non-EA). We report excess raw return differences between stocks with and without EA release regarding each firm characteristic. The construction of the anomaly variables is described in Appendix 2.1. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. CO indicates overnight period. The sample period spans from January 2009 to March 2021. Returns are in percent. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors to adjust heteroskedasticity and autocorrelation. *, ** and *** denote significance at the 10%, 5%, and 1% level.

**Table 2.8**

**FM regressions of order imbalances on lagged firm characteristics**

| | Trading related variables | | | | | | | Accounting-based variables | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Liquidity | | | | Risk | Past Returns | | Profitability | Value | Investment | |
| Panel A: Institutional OIB as dependent variables | | | | | | | | | | | |
| | SIZE | ATO | TO | ILLIQ | VOL | STR | Max | ROE | EP | ASSET | NOA |
| 9:30 | -0.15 | -0.21*** | -0.11** | 0.33*** | -0.39*** | -6.14 | -0.37*** | -0.94* | -0.09* | -0.10** | -0.25* |
| | (-1.61) | (-3.8) | (-2.42) | (3.28) | (-3.94) | (-1.47) | (-5.23) | (-1.82) | (-1.86) | (-2.04) | (-1.93) |
| 10:00 | -0.12 | -0.05 | 0.13*** | 0.17 | -0.07 | 0.09 | -0.09 | -0.4 | -0.07* | 0.02 | -0.18** |
| | (-1.26) | (-1.44) | (3.19) | (1.62) | (-0.95) | (1.51) | (-1.3) | (-1.24) | (-1.72) | (0.28) | (-2.44) |
| 10:30 | -0.18* | -0.02 | 0.25*** | 0.18* | 0.07 | 0.05 | 0.02 | -0.93 | -0.06* | -0.04 | -0.25 |
| | (-1.71) | (-0.4) | (5.25) | (1.67) | (0.92) | (0.85) | (0.28) | (-1.49) | (-1.75) | (-0.39) | (-1.57) |
| 11:00 | -0.16* | -0.01 | 0.26*** | 0.17* | 0.07 | 0.03 | -0.01 | -1.01 | -0.08** | 0.70 | -0.23 |
| | (-1.74) | (-0.22) | (4.94) | (1.65) | (0.74) | (0.59) | (-0.16) | (-1.50) | (-2.27) | (0.83) | (-0.85) |
| 13:00 | -0.18** | 0.07 | 0.38*** | 0.06 | 0.24*** | 0.04 | 0.13 | -0.63 | -0.07* | -0.05 | 0.05 |
| | (-2.46) | (1.29) | (5.74) | (0.75) | (2.42) | (0.53) | (1.62) | (-1.14) | (-1.73) | (-0.63) | (0.33) |
| 13:30 | -0.31*** | 0.09 | 0.44*** | 0.18*** | 0.31*** | 0.20*** | 0.17** | 0.41 | -0.18*** | -0.10 | 0.21* |
| | (-3.89) | (1.56) | (7.92) | (2.21) | (3.32) | (4.02) | (2.37) | (1.09) | (-4.46) | (-1.38) | (1.91) |
| 14:00 | -0.37*** | -0.04 | 0.38*** | 0.27*** | 0.15* | 0.15** | 0.04 | 0.54 | -0.12*** | 0.10 | -0.02 |
| | (-3.93) | (-0.73) | (7.08) | (2.92) | (1.82) | (2.42) | (0.56) | (1.06) | (-3.34) | (1.06) | (-0.21) |
| 14:30 | -0.37*** | -0.17*** | -0.09*** | 0.41*** | -0.24*** | 0.15** | -0.25*** | 0.14 | -0.01 | 0.20** | 0.06* |
| | (-4.74) | (-3.28) | (-2.78) | (4.72) | (-2.68) | (2.20) | (-3.67) | (0.55) | (-0.21) | (2.18) | (1.93) |
| Panel B: Retail investor OIB as dependent variables | | | | | | | | | | | |
| | SIZE | ATO | TO | ILLIQ | VOL | STR | Max | ROE | EP | AS | NOA |
| 9:30 | 0.24*** | 0.08*** | 0.07*** | -0.37*** | 0.10** | -0.09*** | 0.08* | -0.11 | -0.02** | -0.08** | -0.03 |
| | (2.78) | (2.57) | (3.37) | (-3.25) | (2.41) | (-3.44) | (1.85) | (-0.85) | (-2.00) | (-2.02) | (-0.58) |
| 10:00 | 0.28*** | 0.16*** | 0.12*** | -0.44*** | 0.2*** | 0.02 | 0.17*** | -0.18 | 0.01 | 0.06** | -0.13** |
| | (3.38) | (4.87) | (5.39) | (-4.05) | (5.46) | (0.5) | (4.2) | (-1.13) | (0.78) | (1.98) | (-2.32) |
| 10:30 | 0.44*** | 0.21*** | 0.10*** | -0.60*** | 0.25*** | 0.13*** | 0.21*** | 0.79 | 0.08*** | 0.12*** | -0.14** |
| | (4.69) | (5.61) | (4.72) | (-5.25) | (6.08) | (3.19) | (5.83) | (1.25) | (3.95) | (2.71) | (-2.01) |

**Table 2.8 -** ***Continued***

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 11:00 | 0.32*** | 0.14*** | 0.05*** | -0.44*** | 0.17*** | 0.09*** | 0.12*** | 0.99 | 0.06*** | 0.05** | -0.18** |
| | (4.21) | (4.10) | (2.37) | (-4.89) | (3.61) | (2.59) | (3.3) | (1.55) | (2.75) | (2.02) | (-2.06) |
| 13:00 | 0.14* | 0.13*** | 0.08*** | -0.25*** | 0.17*** | 0.07** | 0.12*** | -0.02 | 0.03 | 0.02 | -0.05 |
| | (1.93) | (4.87) | (4.61) | (-2.88) | (4.04) | (2.45) | (3.83) | (-0.10) | (1.25) | (0.60) | (-0.88) |
| 13:30 | 0.32*** | 0.16*** | 0.07*** | -0.45*** | 0.18*** | 0.15*** | 0.15*** | 0.31 | 0.07*** | 0.06*** | -0.19** |
| | (3.58) | (4.65) | (3.25) | (-4.19) | (4.92) | (4.26) | (4.08) | (1.33) | (2.57) | (2.74) | (-2.17) |
| 14:00 | 0.41*** | 0.19*** | 0.03 | -0.52*** | 0.18*** | 0.18*** | 0.16*** | 0.78 | 0.10*** | 0.09*** | -0.22*** |
| | (4.38) | (4.68) | (1.07) | (-4.82) | (4.59) | (5.57) | (4.19) | (1.31) | (2.94) | (3.19) | (-2.63) |
| 14:30 | 0.23*** | 0.07*** | 0.08*** | -0.23*** | 0.00 | 0.10*** | -0.01 | 0.06 | 0.05* | 0.02 | -0.12** |
| | (3.18) | (3.27) | (4.65) | (-2.98) | (0.01) | (5.42) | (-0.31) | (0.82) | (1.93) | (0.76) | (-2.40) |

This table reports estimate results of Fama-Macbeth regression of firm-level order imbalance on lagged monthly firm characteristics. For each stock $i$, each interval $k$ in each month $m$, we regress the order imbalance from one investor group on one of the firm characteristics $f$: $OIB_{i,m,k,j} = a_0 + b_{1kfj} \times FC_{i,m-1,f} + \varepsilon_{im}\ j \in G$, where G indicates either institutional or retail investor group. $FC_{i,m-1,f}$ represents each one of previous month end's firm characteristics. The construction of the anomaly variables is described in Appendix 2.1. We calculate time-series averages of the coefficients $b_{1kfj}$ using Newey-West standard errors to adjust heteroskedasticity and autocorrelation. Panel A reports estimate results for institutional investors and Panel B reports results for retail investors. We define small (big) orders that are below CNY40,000 (above CNY500,000) as trades from retail investors (institutions).

We use Lee and Ready (1991) algorithm to idetify buy- and sell-initiated orders. Trades with trade price above (below) the midpoint (average of bid and ask prices) are identified as buy-initiated (sell-initiated) trades. The order imbalance of a stock in a month is calculated as the difference between buy order trading volume in yuan and sell order trading volume in yuan divided by the total trading volume. Each firm characteristic is standardized to have zero mean and unit standard deviation. Stocks are required to trade for at least 200 days in a calendar year and for at least 10 days in a calendar month. The sample period spans from January 2009 to March 2021. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1% level.

**Table 2.9**

**FM regressions of return predictions conditional on institutions/retail investor trading volume**

| | | SIZE | ATO | TO | ILLIQ | VOL | Max | ROE | EP | ASSET | NOA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Institutions | | | | | | | | | | | |
| Overnight | FC | -0.004*** | -0.012*** | -0.003*** | -0.034*** | -0.093 | -0.215*** | 0.002 | 0.47*** | 0.025 | 0.090 |
| | | (-4.74) | (-7.76) | (-6.06) | (-4.05) | (-1.26) | (-8.54) | (1.02) | (2.70) | (1.02) | (0.98) |
| | TV | 0.029** | 0.034*** | 0.030*** | 0.024*** | 0.034*** | 0.034*** | 0.026*** | 0.026*** | 0.027*** | 0.028*** |
| | | (2.19) | (13.88) | (12.35) | (9.52) | (12.91) | (12.84) | (10.51) | (10.57) | (9.66) | (10.44) |
| | FC×TV | -0.000 | -0.008*** | -0.002*** | 0.025 | -0.346*** | -0.210*** | 0.005 | -0.404** | -0.072* | -0.418** |
| | | (-0.33) | (-9.18) | (-5.51) | (1.60) | (-5.43) | (-7.33) | (1.04) | (-2.57) | (-1.68) | (-2.35) |
| | N | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 |
| | Adj_R2 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 14:30-15:00 | FC | -0.006*** | -0.005*** | -0.001*** | 0.037*** | -0.112*** | -0.046*** | 0.002*** | 0.146*** | 0.017* | 0.095** |
| | | (-7.52) | (-4.68) | (-6.42) | (4.15) | (-3.10) | (-3.25) | (3.26) | (2.82) | (1.78) | (2.52) |
| | TV | 0.005 | 0.013*** | 0.016*** | 0.009*** | 0.018*** | 0.014*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** |
| | | (0.78) | (11.75) | (10.85) | (10.12) | (9.98) | (11.56) | (12.28) | (12.03) | (11.70) | (10.04) |
| | FC×TV | 0.000 | -0.002*** | -0.002*** | 0.077*** | -0.200*** | -0.061*** | 0.004** | -0.084** | -0.008 | -0.038 |
| | | (1.19) | (-3.40) | (-7.97) | (3.69) | (6.62) | (-5.34) | (2.54) | (-2.18) | (-0.67) | (-0.49) |
| | N | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 |
| | Adj_R2 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |
| Panel B: Retail investors | | | | | | | | | | | |
| | | SIZE | ATO | TO | ILLIQ | VOL | Max | ROE | EP | ASSET | NOA |
| Overnight | FC | -0.005*** | -0.022*** | -0.005*** | 0.028* | -0.535*** | -0.458*** | 0.014** | 0.046 | -0.015 | -0.371** |
| | | (-4.06) | (-12.84) | (-11.66) | (1.80) | (-5.10) | (-12.35) | (2.50) | (1.08) | (-0.86) | (-2.02) |
| | TV | -0.021* | -0.037*** | -0.034*** | -0.026*** | -0.040*** | -0.039*** | -0.028*** | -0.029*** | -0.029*** | -0.031*** |
| | | (-1.71) | (-15.89) | (-13.55) | (-9.81) | (-14.12) | (-15.18) | (-11.33) | (-11.63) | (-11.26) | (-11.96) |
| | FC×TV | -0.000 | 0.010*** | 0.002*** | -0.056*** | 0.504*** | 0.272*** | -0.012** | 0.445*** | 0.043 | 0.507*** |
| | | (-0.64) | (10.62) | (7.44) | (-3.38) | (7.12) | (8.18) | (-2.18) | (3.19) | (1.32) | （2.62） |
| | N | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 | 273,410 |
| | Adj_R2 | 0.09 | 0.09 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |

**Table 2.9 - *Continued***

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 14:30-15:30 | FC | -0.005*** | -0.006*** | -0.006*** | 0.127*** | -0.348*** | -0.120*** | 0.008*** | 0.062*** | 0.007 | 0.073 |
| | | (-9.08) | (-6.03) | (-11.19) | (3.76) | (-6.31) | (-6.00) | (4.18) | (2.69) | (0.81) | (0.96) |
| | TV | -0.001 | -0.012*** | -0.015*** | -0.009*** | -0.018*** | -0.014*** | -0.011*** | -0.011*** | -0.011*** | -0.011*** |
| | | (-0.13) | (-8.74) | (-11.51) | (-8.86) | (-9.54) | (-10.39) | (-10.38) | (-10.33) | (-7.92) | (-7.92) |
| | FC×TV | -0.001 | 0.001*** | 0.002*** | -0.087*** | 0.250*** | 0.078*** | -0.007*** | 0.056* | 0.002 | 0.029 |
| | | (-1.33) | (2.79) | (8.66) | (-3.46) | (6.95) | (5.86) | (-3.71) | (1.91) | (0.18) | (0.31) |
| | N | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 | 273,383 |
| | Adj_R2 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |

This table presents results from Fama-Macbeth (FM) regressions that relate overnight and last half-hour (14:30-15:00) returns to the firm characteristics, conditional on the trading volume of institutions and retail investors. For each stock $i$, each interval $k$ in each month $m$, we regress the following equation: $Return_{im} = a_0 + b_{1f} \times FC_{i,m-1,f} + b_{2k} \times TV_{i,m-1,k,j} + b_{3kf} \times FC_{i,m-1,f} \times TV_{i,,m-1,k,j} + Controls_{i,m-1} + \varepsilon_{im}\ j \in G$, where G indicates either institutional or retail investor group. $FC_{i,m-1,f}$ represents each one of previous month end's firm characteristics of interest. The construction of the anomaly variables is described in Appendix 2.1. For each interval in each month, the dummy variable TV of a stock is set to equal one if the trading volume of a particular group (institutions or retail investors) is above the median and otherwise zero. The trading volume (TV) of institutions/retail investors over a certain interval is calculated as the aggregate trading volume in yuan from big/small orders divided by the total trading volume over that interval. We define small/big orders as those below CNY40,000/above CNY500,000. Panel A reports estimate results for institutional investors and Panel B reports results for retail investors. Each column represents a separate regression where stock returns of different interval components are regressed on one of 11 firm characteristics. For each firm characteristic, we control for the remaining firm characteristics as in Table 2.4 and 2.5. The sample period spans from January 2009 to March 2021. Observations are weighted by lagged market capitalization in each cross-sectional regression. The $t$-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1% level.

**Table 2.10**

**Overnight returns of long-short portfolios with different opening prices**

| | 9:35 | | 9:40 | | 9:45 | |
|---|---|---|---|---|---|---|
| TO | Raw | *t*-stat | Raw | *t*-stat | Raw | *t*-stat |
| Low | -1.60*** | (-5.50) | -1.21*** | (-4.00) | -1.14*** | (-3.79) |
| High | -3.22*** | (-11.71) | -2.60*** | (-8.76) | -2.64*** | (-9.76) |
| L-H (Raw) | 1.62*** | (9.17) | 1.38*** | (6.52) | 1.51*** | (7.41) |
| L-H (Alpha) | 1.73*** | (10.93) | 1.53*** | (8.49) | 1.66*** | (9.56) |
| ATO | | | | | | |
| Low | -1.94*** | (-6.38) | -1.36*** | (-4.26) | -1.38*** | (-4.44) |
| High | -3.89*** | (-11.73) | -3.26*** | (-9.37) | -3.21*** | (-9.73) |
| L-H (Raw) | 1.95*** | (14.37) | 1.90*** | (12.87) | 1.84*** | (13.74) |
| L-H (Alpha) | 1.97*** | (12.90) | 1.91*** | (11.23) | 1.84*** | (12.41) |
| SIZE | | | | | | |
| Small | -3.14*** | (-10.48) | -2.54*** | (-8.24) | -2.36*** | (-7.93) |
| Big | -1.03*** | (-3.77) | -0.57* | (-1.94) | -0.58** | (-1.97) |
| S-B (Raw) | -2.11*** | (-12.83) | -1.97*** | (-10.26) | -1.78*** | (-8.88) |
| S-B (Alpha) | -2.24*** | (-13.88) | -2.15*** | (-13.70) | -1.98*** | (-13.27) |
| ILLIQ | | | | | | |
| Low | -1.39*** | (-4.72) | -0.86*** | (-2.68) | -0.90*** | (-2.82) |
| High | -2.50*** | (-7.45) | -1.86*** | (-5.53) | -1.65*** | (-4.84) |
| H-L (Raw) | -1.11*** | (-5.48) | -1.00*** | (-4.75) | -0.75*** | (-3.31) |
| H-L (Alpha) | -1.20*** | (-5.64) | -1.14*** | (-5.33) | -0.90*** | (-4.07) |
| VOL | | | | | | |
| Low | -1.77*** | (-5.44) | -1.38*** | (-3.89) | -1.30*** | (-3.67) |
| High | -4.15*** | (-13.93) | -3.43*** | (-10.43) | -3.36*** | (-11.50) |
| L-H (Raw) | 2.38*** | (13.12) | 2.05*** | (9.33) | 2.06*** | (9.85) |
| L-H (Alpha) | 2.45*** | (12.77) | 2.11*** | (8.83) | 2.12*** | (9.39) |
| STR | | | | | | |
| Low | -2.32*** | (-7.92) | -1.66*** | (-4.92) | -1.61*** | (-5.17) |
| High | -3.77*** | (-10.90) | -3.13*** | (-8.54) | -3.07*** | (-8.36) |
| L-H (Raw) | 1.45*** | (5.31) | 1.47*** | (5.15) | 1.46*** | (4.90) |
| L-H (Alpha) | 1.46*** | (4.90) | 1.47*** | (4.62) | 1.45*** | (4.48) |
| Max | | | | | | |
| Low | -1.92*** | (-6.36) | -1.49*** | (-4.59) | -1.43*** | (-4.42) |
| High | -4.33*** | (-14.19) | -3.63*** | (-11.28) | -3.56*** | (-11.62) |
| L-H (Raw) | 2.41*** | (14.77) | 2.14*** | (11.20) | 2.14*** | (10.57) |
| L-H (Alpha) | 2.49*** | (14.80) | 2.21*** | (10.70) | 2.19*** | (10.09) |
| ROE | | | | | | |
| Low | -3.33*** | (-10.21) | -2.57*** | (-7.75) | -2.39*** | (-7.29) |
| High | -1.55*** | (-5.45) | -0.94*** | (-3.17) | -0.88*** | (-2.91) |
| H-L (Raw) | 1.79*** | (9.19) | 1.63*** | (7.87) | 1.51*** | (6.35) |
| H-L (Alpha) | 1.91*** | (8.97) | 1.79*** | (7.78) | 1.68*** | (6.38) |
| EP | | | | | | |
| Low | -3.23*** | (-10.20) | -2.45*** | (-7.50) | -2.24*** | (-6.82) |
| High | -1.77*** | (-6.44) | -1.26*** | (-4.11) | -1.22*** | (-3.85) |
| H-L (Raw) | 1.46*** | (9.96) | 1.19*** | (7.39) | 1.02*** | (5.44) |

**Table 2.10 – *Continued***

| | | | | | | |
|---|---|---|---|---|---|---|
| H-L (Alpha) | 1.58*** | (9.86) | 1.32*** | (7.59) | 1.17*** | (5.72) |
| ASSET | | | | | | |
| Low | -2.72*** | (-8.06) | -1.94*** | (-5.53) | -1.78*** | (-5.33) |
| High | -1.84*** | (-6.72) | -1.25*** | (-4.03) | -1.28*** | (-4.20) |
| L-H (Raw) | -0.88*** | (4.41) | -0.68*** | (-3.64) | -0.49** | (-2.55) |
| L-H (Alpha) | -0.96*** | (-4.35) | -0.77*** | (-3.61) | -0.58*** | (-2.67) |
| NOA | | | | | | |
| Low | -1.90*** | (-6.51) | -1.31*** | (-4.30) | -1.20*** | (-3.80) |
| High | -2.15*** | (-7.39) | -1.55*** | (-5.11) | -1.52*** | (-5.19) |
| L-H (Raw) | 0.25*** | (3.01) | 0.24*** | (2.93) | 0.32*** | (3.49) |
| L-H (Alpha) | 0.24*** | (3.16) | 0.26*** | (3.20) | 0.34*** | (3.85) |

This table reports overnight raw returns and Fama-French 3-factor alphas of long-short portfolios where we go long one extreme value-weight decile and short the other extreme value-weight decile based on a particular firm characteristic using 9:35, 9:40 and 9:45 as opening prices respectively. At the end of each month, we sort stocks into deciles based on previous month-end's firm characteristics and hold for a month. The construction of the anomaly variables is described in Appendix 2.1. The sample period spans from January 2009 to March 2021. Returns are in percent. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1% level.

**Appendix 2.1**

**Descriptions and constructions of a set of anomalies**

| | |
|---|---|
| Trading-related: | |
| 1. Liquidity | |
| Market capitalization (SIZE) | It's computed as the logarithm of previous month's closing price times A-shares outstanding in thousands. |
| Past 12-month turnover (TO) | It's computed as the average daily share turnover over the past 12 months. A firm's daily turnover is calculated as its share trading volume divided by its outstanding shares. |
| Abnormal past month turnover (ATO) | It's computed as the ratio of its average daily turnover over the past month to its average daily turnover over the past 12 months. |
| Amihud illiquidity (ILLIQ) | The firm's monthly Amihud (2002) illiquidity measure: $ILLIQ\_M_{im} = \frac{1}{D_{im}} \sum_{t=1}^{D_{im}} \frac{\lvert R_{imt} \rvert}{VOLD_{imt}}$, where $R_{imt}$ is the stock return for firm $i$ on day $t$ of month m, $VOLD_{imt}$ is the corresponding Yuan daily volume (in million), and $D_{im}$ is the number of days in month $m$ for which data are available. |
| 2. Risk | |
| One month volatility (VOL) | It's computed as the standard deviation of daily returns over the past month. |
| 3. Past returns | |
| Maximum daily return (Max) | It's defined as the average of three largest daily returns over the past month. |
| Short term reversal (STR) | It's defined as the past month's returns. |
| Accounting-based | |
| 4. Profitability | |
| Return on equity (ROE) | It's calculated as the ratio of earnings to book equity. Earnings is the most recently reported net profit excluding nonrecurrent gains/losses. Book equity equals total shareholder equity minus the book value of preferred stocks. |
| 5. Value | |
| Earnings-to-Price (EP) | It's calculated as the ratio of earnings to the product of last month-end's close price and outstanding shares. Earnings equals the most recently reported net profit excluding nonrecurrent gains/losses. |
| 6. Investment | |
| Asset growth (ASSET) | It's defined as total assets in the most recent annual report divided by total assets in the previous annual report. |

| | |
|---|---|
| Net operating asset (NOA) | It's defined as operating asset minus operating liability in the most current quarter divided by total assets in the previous quarter. Operating asset is calculated as total assets minus cash and short investment. Operating liability is calculated as total assets minus short-term debt, long-term debt, minority interest, book preferred stock and book common equity. |

## Appendix 2.2

**Summary statistics of component returns using different sample period**

| | MEAN | STD | P25 | P50 | P75 | Skew. | Kurt. |
|---|---|---|---|---|---|---|---|
| R_CC | 1.60** | 0.09 | -3.47 | 1.30 | 6.35 | -0.00 | 3.93 |
| R_CO | -1.52*** | 0.04 | -3.36 | -1.18 | 0.96 | -1.14 | 6.49 |
| 9:30 | 0.38*** | 0.01 | -0.29 | 0.23 | 0.99 | 0.29 | 4.48 |
| 10:00 | 0.66*** | 0.02 | -0.57 | 0.34 | 1.71 | 0.67 | 4.89 |
| 10:30 | -0.28** | 0.18 | -1.21 | -0.21 | 1.02 | 0.10 | 4.93 |
| 11:00 | -0.15 | 0.02 | -1.18 | 0.12 | 1.18 | -0.63 | 3.29 |
| 13:00 | 0.29* | 0.02 | -1.02 | 0.17 | 1.63 | -0.09 | 4.75 |
| 13:30 | 0.51*** | 0.02 | -0.51 | 0.16 | 1.28 | 1.03 | 6.22 |
| 14:00 | -0.13 | 0.02 | -1.12 | -0.33 | 0.85 | 0.26 | 4.68 |
| 14:30 | 0.73*** | 0.02 | -0.38 | 0.94 | 1.78 | -0.81 | 6.33 |

This table reports time-series averages of monthly cross-sectional statistics of close-to-close (R_CC) and intraday/overnight component returns from August 2005 to March 2021. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. Returns are in percent. All variables are winsorized at 1% for each year. We require stocks trading for at least 200 days in a calendar year and for at least 10 days in a calendar month to be included in our sample. *, ** and *** indicate 10%, 5% and 1% statistical significance respectively.

## Appendix 2.3

### Coefficient difference between institutional trading and component returns

| Low \ High | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| CO | | **-0.061** | -0.006 | 0.021 | 0.010 | 0.013 | 0.001 | -0.002 | 0.008 |
| 9:30 | **0.065** | | 0.055 | **0.072** | 0.052 | **0.058** | 0.044 | 0.027 | 0.041 |
| 10:00 | 0.022 | -0.031 | | 0.027 | 0.001 | 0.012 | -0.003 | -0.021 | 0.003 |
| 10:30 | 0.046 | 0.013 | 0.034 | | -0.028 | -0.016 | -0.036 | -0.047 | -0.017 |
| 11:00 | **0.106** | **0.076** | **0.102** | **0.069** | | 0.016 | -0.008 | -0.025 | 0.016 |
| 13:00 | **0.090** | 0.050 | 0.071 | 0.033 | -0.025 | | -0.012 | -0.031 | -0.011 |
| 13:30 | 0.090 | 0.053 | 0.086 | **0.037** | -0.024 | 0.075 | | -0.012 | 0.009 |
| 14:00 | **0.066** | 0.041 | 0.062 | 0.018 | -0.045 | -0.010 | -0.012 | | 0.026 |
| 14:30 | -0.045 | -0.068 | -0.042 | -0.073 | -0.140 | -0.110 | **-0.126** | -0.108 | |

This table reports the differences between the estimated coefficients in different intervals using the following equation: $\Delta IO_{iq} = \alpha_0 + \beta_1 \times (RET_{ikq} - \overline{RET_{kq}}) + \beta_2 \times (RET_{imq} - \overline{RET_{mq}}) + \beta_3 \times (RET_{ikq} - \overline{RET_{kq}}) \times (RET_{imq} - \overline{RET_{mq}}) + \varepsilon$, where the dependent variable is the quarterly change of institutional ownership for stock $i$ in quarter $q$. The explanatory variables include cumulative quarterly returns of two components for stock $i$ minus the average component return in that quarter, and their interactions. $k$ and $m$ indicate two intervals (e.g., overnight, 9:30-10:00 etc.), $m \neq k$. We first divide stocks into quintiles based on institutional ownership in the previous quarter and then we run cross-sectional regression in each quarter for the first and fifth quintile, denoted as Low and High respectively. We obtain a time-series estimated coefficients of $\beta_1$ *and* $\beta_2$. As the marginal effect of delta IO on one component return $RET_{ikq}$ is $\beta_1 + \beta_3 \times (RET_{imq} - \overline{RET_{mq}})$ and that on another component return $RET_{imq}$ is $\beta_2 + \beta_3 \times (RET_{ikq} - \overline{RET_{kq}})$, the differences between effects of delta IO on one component return and that on another component return can be estimated as $\widehat{\beta_1} - \widehat{\beta_2}$. We calculate the mean and the significance of $\widehat{\beta_1} - \widehat{\beta_2}$, using Newey-West standard errors with 8 legs to address serial dependence. he value corresponding to column 'X' and row 'Y' is the difference between the coefficient of one centralized interval return (as indicated from column 'X') and that of another centralized interval return (as indicated from row 'Y'). We compute Newey-West *t*-statistics with 8 lags. Numbers in bold indicate that difference is significant at 10% significance level.

**Appendix 2.4**

**Intraday and overnight returns of long-short portfolios using different sample period**

| | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| TO | | | | | | | | | |
| L-H (Raw) | 1.37*** | -0.19* | -0.55*** | -0.19* | -0.09 | -0.48*** | -0.41*** | 0.06 | 1.72*** |
| | (7.31) | (-1.83) | (-5.10) | (-1.82) | (-0.98) | (-3.99) | (-3.58) | (0.63) | (8.83) |
| ATO | | | | | | | | | |
| L-H (Raw) | 2.02*** | -0.23*** | -0.33*** | -0.17* | 0.04 | -0.10 | -0.27*** | 0.01 | 1.02*** |
| | (11.03) | (-2.72) | (-3.10) | (-1.84) | (0.47) | (-1.04) | (-2.98) | (0.13) | (6.24) |
| SIZE | | | | | | | | | |
| S-B (Raw) | -1.94*** | 0.55*** | 0.51*** | 0.09 | 0.36*** | 0.80*** | 0.39*** | 0.28*** | 0.47*** |
| | (-10.54) | (5.85) | (3.31) | (0.95) | (3.89) | (6.13) | (5.05) | (2.58) | (2.84) |
| ILLIQ | | | | | | | | | |
| H-L (Raw) | -0.99*** | 0.46*** | 0.17 | 0.03 | 0.46*** | 0.51*** | 0.14** | 0.30*** | 1.49*** |
| | (-4.43) | (6.65) | (1.38) | (0.41) | (4.16) | (4.25) | (2.01) | (3.33) | (8.69) |
| VOL | | | | | | | | | |
| L-H (Raw) | 2.10*** | -0.38*** | -0.82*** | -0.42*** | -0.09 | -0.38*** | -0.47*** | 0.08 | 1.74*** |
| | (10.21) | (-2.88) | (-6.97) | (-4.35) | (-0.89) | (-3.45) | (-3.72) | (0.64) | (7.64) |
| Max | | | | | | | | | |
| L-H (Raw) | 2.13*** | -0.31*** | -0.76*** | -0.40*** | -0.04 | -0.32*** | -0.36*** | 0.09 | 1.48*** |
| | (12.94) | (-3.09) | (-7.38) | (-4.44) | (-0.43) | (-3.19) | (-3.50) | (0.81) | (7.54) |
| STR | | | | | | | | | |
| L-H (Raw) | 1.30*** | -0.05 | -0.14* | -0.09 | 0.13* | -0.11 | 0.01 | 0.12** | 0.28*** |
| | (5.10) | (-0.60) | (-1.77) | (-1.01) | (1.89) | (-1.17) | (0.10) | (2.35) | (2.63) |
| ROE | | | | | | | | | |
| H-L (Raw) | 1.70*** | -0.32*** | -0.27** | -0.00 | -0.37*** | -0.19* | -0.18** | 0.09 | 0.17* |
| | (6.78) | (-4.22) | (-2.30) | (-0.06) | (-4.64) | (-1.91) | (-2.33) | (1.14) | (1.84) |
| EP | | | | | | | | | |
| H-L (Raw) | 1.36*** | -0.43*** | -0.24*** | 0.02 | -0.29*** | -0.10 | -0.13** | 0.01 | 0.03 |
| | (5.71) | (-5.78) | (-2.83) | (0.40) | (-2.81) | (-1.45) | (-2.34) | (0.11) | (0.24) |
| NOA | | | | | | | | | |
| L-H (Raw) | 0.22* | 0.10** | 0.09 | 0.20*** | 0.12** | -0.23*** | -0.07* | -0.05 | -0.02 |

**Appendix 2.4 - *Continued***

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1.78) | (2.05) | (1.53) | (5.02) | (2.22) | (-3.71) | (-1.69) | (-1.10) | (-0.25) |
| ASSET | | | | | | | | | |
| L-H (Raw) | -0.80*** | 0.44*** | 0.13* | 0.11 | 0.25*** | 0.06 | 0.11*** | 0.07 | -0.05 |
| | (-4.11) | (8.58) | (1.68) | (1.60) | (4.12) | (1.00) | (3.00) | (1.12) | (-0.62) |

This table reports raw excess returns of long-short portfolios where we go long one extreme value-weight decile and short the other extreme value-weight decile based on a particular firm characteristic across a day for overnight and intraday intervals over August 2005 and March 2021. At the end of each month, within each interval, we sort stocks into deciles based on month-end's firm characteristics and hold for a month. The half-hour interval that starts at 9:30 and ends at 10:00 appears as 9:30. CO indicates overnight period. Sample period spans from August 2005 to March 2021. The construction of the anomaly variables is described in Appendix 2.1. Returns are in percent. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1% level.

## Appendix 2.5

### FM regressions of return predictions replacing VOL with Max

| | CO | 9:30 | 10:00 | 10:30 | 11:00 | 13:00 | 13:30 | 14:00 | 14:30 |
|---|---|---|---|---|---|---|---|---|---|
| R_CO | 0.128*** | -0.007*** | -0.012*** | -0.008*** | -0.015*** | -0.004 | -0.009*** | -0.011*** | -0.000 |
| | (18.98) | (-3.87) | (-5.73) | (-3.47) | (-8.16) | (-1.39) | (-6.05) | (-5.16) | (-0.22) |
| R_INTL | | 0.080*** | 0.027*** | 0.016*** | 0.034*** | 0.025*** | 0.011*** | 0.021*** | 0.178*** |
| | | (15.23) | (5.31) | (3.41) | (8.30) | (4.52) | (2.81) | (6.78) | (12.22) |
| TO×$10^2$ | -0.162*** | -0.006 | 0.059*** | 0.056*** | 0.043*** | 0.043** | 0.050*** | -0.028*** | -0.321*** |
| | (-4.42) | (-0.41) | (3.96) | (4.19) | (4.25) | (2.15) | (3.56) | (-2.88) | (-11.14) |
| ATO×$10^2$ | -1.107*** | 0.113*** | 0.173** | 0.089* | 0.082** | -0.023 | 0.123*** | -0.068 | -0.502*** |
| | (-11.59) | (2.86) | (3.13) | (1.85) | (2.14) | (-0.74) | (3.29) | (-1.63) | (-6.16) |
| SIZE×$10^2$ | 0.223*** | -0.088*** | -0.056* | -0.020 | -0.028 | -0.135*** | -0.043** | -0.057 | -0.262*** |
| | (2.62) | (-3.08) | (-1.95) | (-0.88) | (-0.90) | (-2.93) | (-1.97) | (-1.63) | (-5.52) |
| ILLIQ | -0.031*** | 0.010*** | 0.003 | 0.011** | 0.013*** | 0.005* | 0.005* | 0.008* | 0.028*** |
| | (-3.67) | (2.82) | (0.68) | (2.48) | (3.76) | (1.75) | (1.82) | (1.68) | (3.53) |
| Max | -0.307*** | 0.017 | 0.071*** | 0.029*** | -0.008 | 0.049*** | 0.016 | -0.012 | -0.068*** |
| | (-9.33) | (1.13) | (3.94) | (2.56) | (-0.68) | (3.36) | (1.34) | (-0.93) | (-4.49) |
| ROE | 0.000 | -0.004* | 0.000 | -0.001** | -0.001** | 0.000 | -0.000 | 0.000 | 0.002*** |
| | (0.37) | (-1.82) | (0.36) | (-2.32) | (-2.21) | (1.28) | (-0.15) | (0.78) | (2.72) |
| EP | 0.076* | -0.048*** | -0.019 | 0.022 | 0.019 | 0.029** | -0.090 | 0.039*** | 0.067*** |
| | (1.70) | (-3.78) | (-0.97) | (1.39) | (0.92) | (2.40) | (-0.98) | (2.73) | (3.03) |
| NOA | -0.103 | -0.092*** | -0.090** | -0.094*** | -0.059* | 0.070** | -0.002 | 0.023 | 0.086*** |
| | (-1.03) | (-3.86) | (-2.30) | (-3.00) | (-1.72) | (2.26) | (-0.08) | (0.78) | (2.88) |
| ASSET | -0.014* | -0.012** | -0.014 | -0.005 | -0.005 | -0.007 | -0.002 | 0.005 | 0.014** |
| | (-1.82) | (-2.38) | (-1.50) | (-1.12) | (-0.89) | (-1.51) | (-0.41) | (1.28) | (2.44) |
| N | 277,297 | 277,295 | 277,270 | 277,270 | 277,270 | 277,270 | 277,270 | 277,270 | 277,270 |
| Adj_R2 | 0.07 | 0.05 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | 0.08 |

This table reports estimation of Fama-Macbeth (FM) regressions. For each interval in each month, we regress returns on a set of characteristics in the previous month and calculate time-series averages of cross-sectional estimated coefficients. Each column represents a separate regression where stock returns of different interval components are regressed on a set of characteristics. These characteristics include past 12 -month turnover (TO), abnormal turnover over the past month (ATO), market capitalization (SIZE), Amihud illiquidity (ILLIQ), past month daily maximum (Max), return-on-equity (ROE), earnings-to-price ratio (EP), net-operating-assets (NOA) and asset growth rate (ASSET). The construction of the anomaly variables is described in

## Appendix 2.5 - *Continued*

Appendix 2.1. The independent variables also include the most recent one-month overnight return (R_CO), the most recent one-month corresponding interval returns (R_INTL). The sample period is from January 2009 to March 2021. Observations are weighted by lagged market capitalization in each cross-sectional regression. Stocks are required to trade for at least 200 days in a calendar year and for at least 10 days in a calendar month. Returns are in percent. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 8 lags. *, ** and *** denote significance at the 10%, 5%, and 1%, respectively.

# Chapter 3

# A Closer Look at Intraday Return Reversals in China: The Role of Retail Investors

## 3.1 Introduction

The literature extensively documents return reversals between successive night and day periods in both US and the other countries (Cliff et al., 2008; Berkman et al., 2012; Lou et al., 2019). A commonly accepted explanation for this phenomenon is investor heterogeneity. For example, Berkman et al. (2012) show that a positive overnight return is caused by individual investors buying attention-grabbing stocks overnight and at market open, which is reversed presumably by institutional trading later in the daytime. More specifically, the opposing price pressures induced by excessive demands from retail investors, who are inclined to trade at or near morning open, and institutions, that trade more actively at the approach of market close, can create a *tug of war* (Lou et al., 2019) owing to their different preferences.

In this vein of literature, the asset pricing implication of intraday return reversal has drawn immense attention from practitioners and academicians. For example, Akbas et al. (2022) document that stocks with a higher frequency of positive overnight returns, followed by negative daytime reversals during a month, are associated with higher subsequent month returns in the US market. Based on the premise that retail investors and institutions persistently dominate overnight and daytime trading, respectively, Akbas et al. (2022) explain this positive relationship as the tendency of daytime arbitrageurs to discount the possibility of positive news arrival overnight by overweighting the role of noise traders, and thus overcorrecting the persistent upward overnight price pressure.

Importantly, by extending the analysis to the Chinese stock market, we uncover the link between the intensity of intraday return reversal and future stock returns in the

Chinese stock market, and the potential mechanism thereof.

The Chinese stock market is a good setting for investigating the relationship between the intraday return reversal and cross-sectional stock returns. First, the literature documents the existence of a return reversal over successive night and daytime periods in China—that is, an overall negative overnight return followed by a positive daytime return. This phenomenon is systematically different from the US and most other countries, wherein positive overnight returns are followed by negative day returns (Cliff et al., 2008; Branch and Ma, 2012; Berkman et al., 2012; Abdi, 2018; Lou et al., 2019). This difference could be attributed to the unique T+1 trading rule in China, which prohibits traders from selling shares they have bought on the same day, thus leading to a daily opening price discount (Qiao and Dam, 2020; Bai, 2020; Zhang, 2020) and an average negative overnight return.

Second, the Chinese stock market is characterized by a large population of retail traders, most of whom are likely to be overconfident and trade excessively (Barber and Odean, 2000, 2008).[13] In terms of trading time, it is evidenced that these traders tend to trade more actively during daytime sessions.[14] Kang et al. (2022) suggest that daytime investors tend to trade against opening prices by providing excessive liquidity during the daytime session, resulting in a night–day return reversal pattern. By contrast, in the US market, institutional investors account for 90% of the trading volume in the market, and retail investors are more likely to initiate their trades near or at market open (Lou et al., 2019). Therefore, we argue that the potential driving force behind the intraday return reversal in China might be different from that in the US market, where the daily reversals are mainly driven by daytime arbitrageurs correcting mispricing (Akbas et al., 2022; Bogousslavsky, 2021). These two differences between the Chinese and US markets raise the question of whether the intensity of the daily tug of war (i.e., night-day return reversal), documented by Akbas et al. (2022), predicts stock returns in

[13] According to the Shanghai Stock Exchange, retail trading accounts for at least 80% of the total trading volume in China, but this figure only amounts to 10% in the US market.
[14] The findings in Chapter 2 suggest that institutional investors are more likely to initiate trades at market open, whereas retail investors tend to trade more actively during daytime sessions.

China and what the mechanism behind it is.

Our sample consists of common A-share stocks listed on the Shanghai and Shenzhen stock exchanges over the period of 2009–2020. A daytime return reversal is when the product of the respective overnight and daytime return is negative, i.e., the occurrence of either a positive overnight return followed by a negative daytime return, or a negative overnight return followed by a positive daytime return. We capture the intensity of return reversals during a month by calculating the abnormal frequency of return reversal days in a calendar month. The correlation and regression analyses indicate significant persistence in these reversal intensity measures, as they are significantly autocorrelated, in line with the literature.

Our main findings are as follows. First, our univariate portfolio sorts show that stocks with a high abnormal frequency of positive overnight returns, followed by negative daytime returns (ABNR), outperform stocks with a low ABNR; the average monthly long–short portfolio returns range from 0.46% ($t=3.90$) to 0.53% ($t=4.76$). By contrast, the long–short strategy based on the abnormal frequency of negative overnight returns, followed by positive daytime reversals (ABPR), yields negative monthly returns.

To control for multiple characteristics, we run Fama–Macbeth regressions on future returns against two return reversal intensity measures and various firm characteristics. The coefficients of ABNR for one-month ahead returns are positive at the 5% or 1% significance level depending on which controls are used. The coefficients of ABPR are not significant at any significance level.

The predictive power of the intensity of negative daytime reversals is not long lasting, as the coefficients become negligible when we use the two-month ahead returns as the dependent variables. Our results are robust when we use a double-sort method based on a set of firm characteristics and ABNR. They are also robust to transaction costs.

We attribute the drive of the predictive power of the ABNR to trading by retail investors. On the one hand, an intraday return reversal may indicate an ongoing tug of war between institutional and retail investors. This is evidenced by the findings in Chapter 2 that suggest that, in China, institutions trade more actively early at market open, whereas retail investors mostly trade actively during daytime sessions.

On the other hand, most announcements and firm declarations are released after market close (Barclay and Hendershott, 2003; Engelberg et al., 2018). It is likely that mispricing tends to be high at market open and thus sophisticated institutional investors would increase their trading activities for profits. Their trades would incorporate a sequence of positive news into stock prices. In this sense, high opening price would reflect firms' fundamentals. Therefore, the relationship between the intensity of negative daytime reversals and future returns depends on the extent to which daytime retail investors react to the overnight returns. If they drag prices too much away from fundamentals, there will be stronger return prediction as stock prices will eventually converge to their fair values.

Therefore, we hypothesize that the positive relationship between ABNR and future stock returns could be attributed to the noise trading of retail investors during the day—in particular, the overtrade against the high opening prices. We know that individuals tend to be overconfident (Griffin and Tversky, 1992; Gervais and Odean, 1998); they may overestimate their own information-processing skills or the precision of their private information, and ultimately trade in the wrong direction (DeBondt and Thaler, 1985; Odean, 1998; Barber and Odean, 2000, 2009). We argue that, as the daytime retail investors drag the opening prices to larger distances below the fundamental values, stocks with more negative intraday reversals generate positive returns in subsequent months as prices will eventually revert toward to the correct level.

Notably, our explanation for the return prediction on ABNR is built upon the assumption that overnight returns capture firms' fundamental information through trades by sophisticated investors with their less sophisticated counterparts, mainly retail investors at market open.[15] Supportive evidence can be found in Kaniel et al. (2008), in which they show that the positive return prediction of individual trades can be explained as risk-averse individuals trading with institutions to meet their immediacy

[15] Evidence in Chapter 2 suggests that institutions generally trade in different directions with retail investors, especially for the open and closing sessions.

demands. However, as there exists a unique one-day selling lockup trading rule (i.e., T+1 rule) in China, which may lead to an opening price discount, it is likely that negative overnight returns are not induced by a sequence of negative news arrivals overnight, but by this T+1 arrangement. Therefore, irrational trading against low opening prices by daytime noise traders may not trade on news hence not necessarily drive stock prices away from their fair values, and there will be no return prediction. This might be the reason for the non-existence of the predictive power of ABPR on the next month returns, as shown by our baseline results.

We provide a series of empirical evidence to support our argument. First, we rule out the liquidity provision hypothesis that daytime return reversals serve as compensations for providing liquidity, as we show that there is a lack of evidence that stocks in the bottom quintile of liquidity (i.e., more illiquid stocks) have higher level ABNR compared with those in the top liquidity quintile. We also evidence that retail investors tend to trade excessively against high opening prices by exerting high selling pressure, but they limit their trading activity when negative overnight returns occur more often, which corroborates our argument that daytime retail traders tend to largely trade against a high opening price. Further, for the subset of stocks with positive overnight returns, followed by negative daytime reversals, we show that larger daytime price movements are associated with more retail investor trading turnover. This at least partially lends support to the idea that daytime retail investors contribute to daytime reversals.

We report that stocks with small size, high turnover, high illiquidity, high volatility, and low institutional ownership can generate large long–short profits based on ABNR. Indeed, firms with these attributes tend to be more susceptible to noise trading (Baker and Wurgler, 2006), presumably initiated by retail investors. As retail investors tend to be overconfident and trade in the wrong directions (Odean, 1998; Barber and Odean, 2000, 2009), which generate higher price errors, our baseline result should be stronger among stocks that attract more retail investors. As predicted, we observe a more pronounced return prediction for these stocks. By contrast, we show that there is no return predictability when we use abnormal frequency of positive (negative) overnight returns, followed by positive (negative) daytime returns as the sorting variable—that is, no reversal occurs during the day. This result establishes that the return predictability only occurs when there is a daytime reversal—in particular, negative reversal—when daytime noise traders trade against high opening prices. This finding rules out the possibility that the return predictability is simply due to the continuation of past returns.

We also conduct a placebo test that uses an alternative sequence of return reversals that proceeds from negative daytime return, followed by the next day positive overnight return, to examine the return predictability. Although this is also a reversal pattern, this alternative sequence measure is not characterized by daytime traders responding to overnight returns; therefore, it should not predict returns. As expected, we find no predictive power of this alternative day-to-night measure for future returns.

We further show that the return predictability of the ABNR is revealed through overnight return components rather than daytime return components, as the long–short strategy yields positive overnight and negative daytime component returns. This result suggests that daytime traders are likely to be on the wrong side of the future return prediction, which is consistent with our hypothesis that daytime noise traders trade irrationally.

As our explanation of ABNR on the future returns relies on retail investors trading in the wrong direction of opening prices, the implication is that the opening price, at least partially, is rational. To provide more evidence on this, we investigate whether the abnormal frequency of positive overnight returns, followed by negative daytime reversals, conveys firms' specific fundamental information. We show that the intensified frequency of negative daytime reversals is associated with positive earnings surprises in the future. Analogously, we reveal the clustering of ABNR around firms' specific information release. This evidence corroborates our argument that high opening price contains essential fundamental information.

Our study builds on the literature that explores the asset pricing implication of intraday return reversals. In this regard, our work is most relevant to that of Akbas et al. (2022), who document a significant positive relationship between the intensity of daily return reversals, proxied by a monthly frequency of negative daytime reversals, and future returns in the US market. Our work applies their method to the second-largest stock market in the world, China, in which the intuitional setting differs in multiple aspects. Similar to other markets, the abnormal negative day time reversals positively predict future returns; however, the underlying mechanism is very different to that of the US market. In this chapter, we attempt to explain these distinct findings on the Chinese stock market.

Relatedly, Kang et al. (2022) argue that the pronounced intraday return reversal in China reflects a pricing error, presumably induced by irrational retail traders overly trading against previous price movements owing to their physiological anchoring bias. Yet, Kang et al. (2022) do not distinguish between the different types of intraday return reversals, whereas we provide evidence that retail investors tend to overly trade against high opening prices. They reduce their trades in the context of low opening prices. We also extend Kang et al. (2022)'s work by investigating whether the intensity of intraday return reversal caused by retail investors can generate a return prediction in the future.

This study makes contributions to existing literature in several aspects. First, we document an intraday return reversal intensity measure that is characterized by high opening prices that can deliver significant hedge portfolio returns. This profit is robust to a set of other firm characteristics and transaction costs. Second, this study provides additional evidence for the role of retail investors on stock prices in China where retail investors take the dominance. Our study is a complement to the existing literature that examines the effect of retail trading on stock returns.

The remaining chapter is organized as follows. Section 3.2 reviews the related literature. Section 3.3 introduces the sample, variables, and summary statistics. Sections 3.4 and 3.5 present the empirical results and section 3.6 concludes.

## 3.2 Literature review

### 3.2.1 Intraday/Overnight return pattern

This study builds on three strands of literature. First, it is complementary to the emerging literature that examines intraday and overnight return patterns. A large corpus of literature investigates the cross-sectional differences in return patterns between day and night in the US market, and attributes them to the recurring *tug of war* between different groups of investors who trade at different times of the day. For instance, Berkman et al. (2012) argue that the positive returns during the overnight period, followed by reversals during the trading day, are likely due to the high opening prices caused by retail investors who buy attention-grabbing stocks overnight or at the open. Lou et al. (2019) document a recurring return continuation and reversal pattern, and attribute it to investor heterogeneity. They argue that retail investors are inclined to trade at or near morning open, whereas institutional investors trade more actively approaching market close to rebalance their portfolio. The price pressures induced by excessive demands from these two clienteles owing to different preferences may pull prices in opposite directions, and thus create a *tug of war* that leads to a recurring cross-period reversal effect.

Using the framework of investor heterogeneity, Hendershott et al. (2020) explain their findings of different performances in betting-against-beta anomaly between day and night as risk-loving speculators buying high beta stocks at the open and reversing their positions approaching market closure, whereas long-term investors dominate night trades.

Given the interpretation that heterogeneous investor clienteles may persistently dominate the respective overnight and trading day, Akbas et al. (2022) investigate whether the intensity of the daily tug of war affects stock prices over time. They explain their findings of positive return prediction for stocks involved in an intense tug of war based on negative daytime reversals as the overcorrection of a sequence of positive overnight returns by daytime arbitrageurs due to overweighting the role of noise traders.

However, there is a *negative* overnight return followed by an intraday reversal (i.e., positive daytime return) in China. The differences in the return pattern between the Chinese and US markets are commonly attributed to the unique T+1 trading rule in China. Qiao et al. (2020) argue that the asymmetric trading rule leads to a price discount for the stock at the opening relative to previous day's closing price. Similarly, Bai (2020) explains the negative overnight returns as prices paid for the sell-at-the-max put option embedded in the closing price of stocks on day *T* compared with the open price on day T+1. However, evidence on the relationship between the intensity of daily night-day reversals and future stock returns is still lacking, and we attempt to fill this gap by comprehensively investigating this issue.

### 3.2.2 Explanation on intraday reversal

A widely accepted explanation for the short-term reversal phenomenon is the liquidity provision hypothesis (Campbell et al., 1993; Avramov et al., 2006; Da et al., 2014). For example, in Campbell et al.'s (1993) model, informed and/or uninformed trades lead to a temporary price concession that, when absorbed by liquidity providers, will result in a reversal in price that serves as compensation for providing liquidity. However, these studies mainly focus on weekly and monthly frequencies.

Kang et al. (2022) argue that the typical illiquidity-based mechanism does not effectively explain the intraday return reversal in China; they find that, although subsequent intraday returns can be negatively predicted by the previous overnight returns (i.e., there exists a cross-sectional intraday reversal), the effect of liquidity on the intraday reversal is weak. In particular, they show that the return reversal between low and high illiquidity group stocks is much smaller in China compared with that in the US market. This result is at odds with the traditional liquidity provision conjecture. Given the large population of retail investors in the Chinese market, Kang et al. (2022) propose a novel explanation for the intraday return reversal by considering the return reversal: a pricing error caused by oversupply of liquidity from uninformed retail traders. That is, uninformed noise traders irrationally provide excessive liquidity and generate opposing price relative to previous price movements. Consequently, their trading results in return reversals and generates pricing errors.

### 3.2.3 Retail investors' trading behavior

This study is also relevant to the literature on retail investor's trading behavior. As retail investors account for an overwhelming number of trades in Chinese stock market, the predictability of future returns may be associated with the noise trading of retail investors.

Studies on noise traders argue that demands from retail investors are affected by their sentiments that are not fully justified by fundamental news (Shleifer and Summers, 1990; DeLong et al., 1990, 1991; Shleifer and Vishny, 1997). Barber et al. (2009) find that stocks bought heavily by individual investors outperform those sold heavily in the contemporaneous and subsequent week but underperform in the following year. They interpret it as evidence that retail investors push prices too far from fundamentals.

Studies also extensively document behavioral biases exhibited by retail investors, such as overconfidence and overtrading; and as a result, retail investors make sub-optimal investment choices (Odean, 1998; Barber and Odean, 2000, 2008). For example, Barber and Odean (2000) report that the net return of an average household with high turnover is significantly lower than that with low turnover. Their results are consistent with the prediction in Odean's (1998) theoretical model of financial markets, where investors are overconfident and trade too much. Jones et al. (2021) investigate the dynamics and performance of retail investors trading in China by using account-level data. They find that individuals with small account sizes cannot predict future price movements correctly because of their inferiority in processing public news, and thus display more behavioral biases such as overconfidence and gambling preferences.

Motivated by these studies, we extend the three strands of literature reviewed herein by investigating the relationship between intraday return reversal intensity and future returns. We offer additional evidence for the effect of retail trading behavior on future stock returns in the second-largest stock market in the world.

### 3.3 Data, variables, and methodology

Our sample consists of common A-share stocks listed on the Shanghai and Shenzhen stock exchanges over the period from January 2009 to December 2020. We choose the sample period from 2009 to 2020 because a new accounting standard for business enterprises has been implemented since 2007. We exclude stocks listed on the Sci-Tech Innovation Board (STaR) owing to its short history since launch.[16]

Daily dividend adjusted open/close price, stock trading data, accounting data, and risk factors are obtained from China Stock Market and Accounting Research. Following the literature, we apply several filters to clean our data. First, we exclude stocks that have become public within the past six months to avoid extreme volatility and illiquidity in stock prices right after the initial public offerings. Second, we only keep firms that have a minimum of 75% of non-zero-volume trading days with trading records during our recent sample periods in order to guarantee stock liquidity and data quality. Third, for each stock, we exclude months that have fewer than 15 days of trading records to construct variables of our interests. The final full sample contains 3,767 firms, and the average firm number is 2,467 per month.

### 3.3.1 Constructing intraday return reversal intensity measures

We first decompose daily close-to-close returns into overnight and daytime components. Following Lou et al. (2019), for stock $i$ on day $t$, we calculate the daytime return (open-to-close) using the following equation:

$$R\_OC_{i,t} = \frac{P_{it,close}}{P_{it,open}} - 1 \tag{3.1}$$

where $P_{it,close}$ and $P_{it,open}$ denote the close and open price on day $t$ for firm $i$, respectively. We then calculate the overnight return (close-to-open) using an equation in the following form:

$$R\_CO_{i,t} = \frac{1+R\_CC_{it}}{1+R\_OC_{it}} - 1 \tag{3.2}$$

where $R\_CC_{it}$ is the daily close-to-close return. We define the negative (positive) daytime reversal as a positive (negative) overnight return followed by a negative (positive) daytime return.

We construct intraday return reversal intensity measures as the frequency and

[16] The STaR Market was launched on the Shanghai Stock Exchange on July 22, 2019.

abnormal frequency of negative and positive daytime reversals. We count the number of days with negative daytime reversals in a month $m$ and divide it by the total trading days for each stock $i$, denoted as $NR_{im}$ following Akbas et al. (2022). Similarly, we divide the number of days with positive daytime reversals by the total trading days in a month and denote it as $PR_{im}$. These two measures capture the level of variation in the return reversal intensity in a particular month. To construct the monthly abnormal frequency of negative daytime reversals ($ABNR_{im}$), we calculate the ratio of $NR_{im}$ in month $m$ to the moving average of $NR_{im}$ over the past 12 months. The monthly abnormal frequency of positive daytime reversals ($ABPR_{im}$) is constructed in a similar way by dividing $PR_{im}$ with the moving average $PR_{im}$ over the past 12 months. These two measures capture the shock of variation in the return reversal intensity in a month relative to its moving averages over the past 12 months.

### 3.3.2 Summary statistics of the main variables

We now present the descriptive statistics of the variables of our interest. Panel A of Table 3.1 reports the time-series averages of monthly cross-sectional statistics of our four return reversal intensity measures: $NR_{im}$, $ABNR_{im}$, $PR_{im}$ and $ABPR_{im}$. The mean level of the NR is 0.211, indicating that, on average, there are about a quarter of days in a month that have a positive overnight return followed by a negative daytime return. Also, about 30% of days in a month have a negative overnight component return followed by a positive daytime return. Notably, our results of the average mean of NR and PR in China are different from those of Akbas et al. (2022), who focus on the US market. In their study, negative and positive daytime reversal frequencies are very close to 0.25, which are more evenly distributed. This indicates structural differences in the return patterns of the two markets.

In addition, the ABNR has a mean of 1.045—that is, the typical monthly frequency of NR is roughly 4.5% higher than its average over the previous 12 months. The variation of ABNR ranges from 0 to 3.571, which corresponds to a 100% decrease versus a 257% increase in the frequency of negative reversals, respectively. The mean of the ABPR is close to 1, indicating almost no difference between the PR and its own average over the past 12 months. The variation in ABPR is less pronounced than in ABNR, ranging from 0.173 to 2.189.

Panel B of Table 3.1 presents the contemporaneous correlations, first-order autocorrelations, and cross-order autocorrelations between these four variables. The correlations are calculated cross-sectionally each month, and the time-series averages are reported. NR (PR) and ABNR (ABPR) are highly positively correlated because they capture similar variations in the return reversal frequency by construction. However, NR (ABNR) and PR (ABPR) are negatively correlated, with correlations ranging from -0.376 to -0.323. Also, the first-order autocorrelations for all four variables are positive, ranging from 0.072 to 0.144, indicating significant persistence in both the abnormal level of the return reversal intensity and the level itself.

Next, we examine this persistence pattern of the four return reversal measures by running regressions of each one of these variables, NR, ABNR, PR and ABPR, in the next three months ($m$+$k$: $k$=1, 2, 3) on the corresponding values in the current month $m$ with or without controls, in the following form:

$$Reversal_{i,m+k} = \alpha_0 + \alpha_1 \times Reversal_{im} + controls_{im} + \varepsilon_{im} \qquad (3.3)$$

where $Reversal$ indicates NR, ABNR, PR, or ABPR. We use a set of control variables that are described in section 3.3.3. Table 3.2 shows that the coefficients of all four intensity variables are mostly significantly positive, and they decrease monotonically in future months. For example, the coefficients of ABNR on the one-, two-, and three-month ahead are 0.058 (*t=14.98*), 0.021 (*t=5.99*), and 0.003 (*t=1.35*), respectively. These results suggest that return reversals are persistent across months and may not last long, especially for the variables that capture the abnormal frequency of the return reversal intensity, as the coefficients of ABNR and ABPR using their three-leads as dependent variables are not significantly different from zero, with or without controls, as shown in column (5) and (6) of Panels B and D.

### 3.3.3 Control variables

The literature documents a series of firm characteristics that can affect future returns. We use these variables as controls in our baseline Fama–Macbeth regressions in section 3.4.1, as well as in most other regressions in our study. These variables include SIZE, book-to-market ratio, turnover rate, volatility, and liquidity etc. Appendix 3.1 lists a detailed description of the variable construction process. Table 3.3 presents the time-series averages of the cross-sectional summary statistics and correlations of these variables. The results in Panel B show that ABNR (or NR) is negatively correlated with contemporaneous monthly returns, indicating that the ABNR (or NR) decreases with the standard close-to-close monthly return in the same month. Note that a tendency for months with higher frequency of negative daytime reversals (i.e., larger ABNR or NR) reveals the firms' higher cumulative overnight return and lower daytime return by construction. Therefore, the negative correlation between ABNR (or NR) and the contemporaneous monthly return may be because the magnitude of the negative daytime return, on average, is larger than that of the positive overnight return. Similarly, the positive correlation between ABPR (or PR) and the contemporaneous monthly return might be simply because the magnitude in the positive daytime return is generally larger than that of the negative overnight return.

In addition, the degree of correlations between the abnormal frequency of return reversals (ABNR or ABPR) and other controls is overall smaller than that between the level (NR or PR) and controls, suggesting that the abnormal frequency measures offer incremental information beyond that provided by other firm characteristics than the level. Therefore, we focus on the abnormal frequency of daytime reversals rather than the level itself in the later analysis.

## 3.4 Empirical analyses

### 3.4.1 Single-sort portfolio analyses

To evaluate the predictability of the frequency of intraday reversals, we sort all sample stocks into quintiles based on ABNR and ABPR at the end of each month and hold each portfolio in the following month. Panel A of Table 3.4 reports the value- and equal-weighted average raw returns, one-factor alphas based on the market model, and three-factor alphas based on the Fama–French three-factor model. The results show that the long–short strategy that long stocks with a high level of ABNR and short stocks with a low level of ABNR can generate a significant value-weighted monthly raw return of 0.49% (*t=4.34*) and a significant equal-weighted return of 0.51% (*t=4.63*) in the next month. The results are qualitatively unchanged after risk adjustments. In contrast, the highest quintile based on ABPR underperforms the lowest quintile by the average monthly value-weighted (equal-weighted) hedge portfolio returns of 0.42% (0.43%), with *t*-statistics of -4.20 (-4.34). We also report long–short portfolio returns sorted by NR and PR in Appendix 3.2 and the results are qualitatively the same.

The prediction in ABNR and ABPR for future returns points toward a possible explanation that daytime noise traders sell too much against high opening price and drag prices below their fundamentals, which revert in the next month. Therefore, the estimated coefficient would be determined by the sign of overnight returns. That is, the abnormal frequency of daytime reversal that is characterized by positive overnight return can positively predict future returns while for the reversal intensity with negative overnight return, there is a negative predicted return in the future. We assume that the opening price sufficiently incorporates available information, given that corporate news is normally released in non-trading hours (Barclay and Hendershott, 2003) and institutional investors trade actively upon market open (see results in Chapter 2). We argue that, in a prolonged, intense tug of war, daytime retail investors overestimate their ability to digest information contained in the opening price and trade toward the wrong directions. We thus observe stock prices during the day that move in the opposite direction to the opening price movements. When they go below the fair values, the prices eventually adjust back to fundamentals in the subsequent month. Consequently, for stocks that face such phenomenon frequently, predictivity is observed in the future month(s).

We also use abnormal frequencies of negative (positive) overnight returns, followed by negative (positive) daytime momentum (ABNM and ABPM) as sorting variables, and conduct similar portfolio analyses. We report equal- and value-weighted long–short portfolio returns in Panel B of Table 3.4. The results show no predictive power by the night–day momentum. Hence, only when daytime investors trade against the opening price (intraday reversal), pushing the price too far from fundamentals, does the return predictability exist.

### 3.4.2 Fama–Macbeth regressions

To take account of the effect on future returns by popularly documented firm characteristics, we run a Fama–Macbeth regression to control those predictors.[17] One might argue that months with a higher frequency of ABNR tend to be months with a lower frequency of ABPR by construction, as the correlation between ABNR and ABPR is -0.323 (see Table 3.1).[18] To examine this issue, we also add ABNR and ABPR simultaneously in the regression, following Akbas et al. (2022).

$$Ret_{i,m+k} = \alpha_0 + \alpha_1 \times ABNR_{im} + \alpha_2 \times ABPR_{im} + controls_{im} + \varepsilon_{im} \quad (3.4)$$

We run Fama–Macbeth regressions of future returns on the key variables of interests (ABNR and ABPR) and a set of control variables mentioned in section 3.3.3. We report the time-series averages of the coefficient estimates from the cross-sectional regressions using the Newey–West standard errors with 12 lags.[19] The coefficients of ABNR are significantly positive when we use the return in the next month as the dependent variable, ranging from 0.13 (*t=2.27*) to 0.19 (*t=2.62*). This suggests that a higher level of ABNR can predict higher one-month ahead returns. The coefficient of ABNR becomes negligible when we use two-month ahead returns as the dependent variable, indicating a short-lasting return predictability.

In contrast, the coefficients of ABPR are not significant in all cases, suggesting that ABNR dominates ABPR regarding the predictive power for future returns.[20] In this regard, we focus on the ABNR in our later analyses.

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[17] See section Appendix 3.1 for the list of variables.
[18] The correlation between NR and PR is -0.376, as shown in Table 3.1.
[19] Results for other lags are qualifiedly similar and are available upon request.
[20] We also replace these abnormal measures with their levels and conduct the above regressions. We report the estimate results in Appendix 3.3. Our results are qualitatively unchanged.

### 3.4.3 Controlling firm characteristics: double-sort analyses

To further examine the predictability of the ABNR controlling for other predictors mentioned above, we also conduct a double-sort portfolio exercise. We are also interested in the differences in the firm characteristics across the ABNR portfolios.

We first examine firm attributes in different ABNR groups, and then the predictive power of ABNR across firms with different characteristics. To compare the characteristics across firms with different ABNR, we sort stocks into quintiles based on monthly ABNR. We then calculate the time-series averages of the cross-sectional summary statistics for 10 firm characteristics in the same month. We report the results in Panel A of Table 3.6.

We observe that contemporaneous standard monthly returns decrease monotonically with ABNR, with a return difference between the low and high ABNR portfolio being -5.6% (*t=-25.02*). The negative relationship between ABNR and contemporaneous monthly returns indicates that a more intense tug of war that is characterized by high opening prices is likely to be associated with a larger degree of price drop. This corroborates our argument that daytime noise traders trade against high opening prices to an extent below their fundamental values. In addition, firms with a high ABNR tend to be winning stocks in terms of the past six-month returns (RET_6M) and tend to have low turnover (TOVR_M), low volatility (SD_RET_M), high illiquidity (ILLIQ_M), low book-to-market ratio (LNBM), low asset growth rate (ASSET), and high mutual-fund ownership (IO). There are no differences for LNSIZE and ROE across the ABNR groups. The results are generally consistent with the correlations (see Panel B of Table 3.3).

Next, we conduct a double-sort exercise to examine whether the return predictability on ABNR varies across firms with different characteristics. We first sort stocks into quintiles based on each firm characteristic at the end of each month. Within each quintile, we further sort stocks into quintiles by ABNR and hold for one month. We report value-weighed long–short portfolio returns based on ABNR across firms with different characteristics, with and without risk-adjustment, in Panel B of Table 3.6. The results show that our findings are robust across different firm characteristics, while the long–short portfolio profits are generally larger in stocks with small size, high turnover, high illiquidity, high volatility, and low institutional ownership. For example, stocks with high ABNR outperform those with low ABNR by an average monthly return of 0.77% (*t=3.76*) across firms with the bottom 20% size. For the other size quintiles, ABNR predicts the next month return in all cases except the top 20% quintile, indicating size can explain the predictivity only partially. Note that stocks with small size, high turnover, high illiquidity, high volatility, and low institutional ownership tend to be more opaque in terms of information and more susceptible to speculative trading by retail traders (Baker and Wurgler, 2006). Therefore, in a prolonged tug of war based on negative daytime reversals, daytime noise traders are more likely to trade these stocks against the opening price, generating higher pricing errors, which might be corrected later. Consequently, we observe stronger predictability among these stocks. Taken together, this evidence at least indirect supports our hypothesis that daytime noise traders play an important role for the return predictability of ABNR. In addition, the remaining panels of Table 3.6 show that the returns for long–short portfolios based on ABNR are significant for all quintiles based on LNBM, RET_6M, ASSET, and ROE.

### 3.4.4 Economic value

We explore the issue of transaction costs, given that the profits of our long–short strategy might be overwhelmed by the high turnover rates. Following Grundy and Martin (2001), Barroso and Santa-Clara (2015), and Han et al. (2016), we first calculate the turnover rates of ABNR portfolios in each month. The turnover of a leg of the ABNR portfolio is defined as follows:

$$x_t = 0.5 \times \sum_i^{N_t} |w_{i,t} - \widetilde{w}_{i,t-1}| \tag{3.5}$$

$$\widetilde{w}_{i,t-1} = \frac{w_{i,t-1}(1+r_{i,t})}{\sum_i^{N_t} w_{i,t-1}(1+r_{i,t})} \tag{3.6}$$

where $w_{i,t}$ is the value weight of stock $i$ in the leg of the portfolio at time $t$, $N_t$ is the stock number in the leg of the portfolio at time $t$, and $r_{i,t}$ is the monthly return of stock $i$ at time $t$. $w_{i,t-1}$ refers to the value weight of stock $i$ before portfolio rebalancing. The strategy turnover for each month is the sum of the turnover of the short leg and the long leg of that month. We report the time-series average of the turnover in Table 3.7. The results reveal that the ABNR strategy turnover is 42.8%, roughly 22.8% lower than that of the trend factor (65.6%), but 5.3% higher than that of momentum factor (37.5%), as Han et al. (2016) report. This indicates that our hedge strategy based on ABNR has, on average, a similar turnover to the well-known momentum strategy.

Next, we compute two types of break-even transaction costs of the ABNR strategy. The first one, zero-return transaction cost, is defined as the percentage cost per RMB paid to make our long–short strategy based on ABNR to have exactly zero return. The other one, the 5%-insignificance transaction cost, is the percentage cost per RMB of trading that one pays so that the strategy yields a return insignificant from zero at the 5% level. The zero-return transaction cost is calculated as the ratio of the time-series average of the long–short portfolio returns to the strategy turnover we calculated above, and the 5%-insignificance transaction cost is computed using the average of the upper and lower bound of the long–short portfolio return at the 5% significance level. We report these two break-even costs for raw and returns adjusted by the capital asset pricing model and Fama–French three-factor model. As shown in Table 3.7, it takes about 1.19% of transaction costs to offset our long–short strategy profits. This is similar to that of the trend strategy (1.24%) and higher than that of the momentum strategy (0.68%), as Han et al. (2016) document. The transaction costs needed to yield insignificant profits at the 5% level are also higher than the common standard.[21]

## 3.5 Mechanism of the positive return prediction on ABNR

### 3.5.1 Liquidity provision hypothesis

Return reversals are known to occur when price pressures are absorbed by liquidity providers (Campbell et al., 1993; Avramov et al., 2006; Da et al., 2014). If this is the

[21] Stock trading fees mainly comprise three components in China: roughly 0.03% of commission fee per trade, 0.1% of stamp tax per sale of shares, and 0.002% of transfer fee per trade.

case, we should observe higher frequencies of overnight-to-daytime return reversals for less liquid stocks that are more likely to create price concessions which will be corrected by liquidity suppliers. By contrast, if return reversals are not induced by the liquidity provision, there would be no such patterns.

We investigate this conjecture by conducting univariate sorts based on a series of liquidity measures. Specifically, we sort stocks into quintiles based on a series of liquidity measures at the end of each month and hold for one month. The equal-weighted averages of ABNR for each group are reported in Table 3.8. We employ four types of liquidity measures from the literature: Amihud illiquidity measure (ILLIQ), market capitalization (SIZE), quoted spread (QSP), and effective spread (ESP) (see descriptions in Appendix 3.1). ILLIQ measures the price effect of order flows. Quoted spread and effective spread capture the transaction cost of a trade. Higher ILLIQ, QSP, and ESP suggest that investors either incur higher transaction costs or price effects to buy or sell a certain stock, thus reflecting less liquidity. In addition, stocks with smaller market capitalization tend to be less liquid than those with larger size.

As can be seen in the first and second columns of Table 3.8, there are no significant differences in ABNR between stocks with the highest and lowest illiquidity, as proxied by Amihud and SIZE measures. This reveals no evidence for the liquidity provision hypothesis. As to the two liquidity measures, QSP and ESP, from the market microstructure literature, the ABNR differences for stocks in the high and low quintiles are marginally significant, for example, with differences in magnitudes of roughly 0.038 and *t*-statistics around -1.70 for the QSP case. These values suggest that liquid stocks are associated with a higher occurrence of the ABNR compared with less liquid stocks, which is inconsistent with the liquidity provision hypothesis. In sum, the results in Table 3.8 show no supportive evidence that intraday return reversals serve as a compensation for liquidity provision.

### 3.5.2 Abnormal retail trading and ABNR

Our explanation for the return prediction on ABNR is based on the premise that daytime retail investors actively trade against high opening prices. We assume high opening prices reflect firms' positive fundamentals, given that institutions are sophisticated and trade actively at market open. We argue that the positive predictive power of ABNR for future returns can be attributed to the tendency of daytime noise traders to drag prices too far away from firms' fair values owing to their inability to process information. If this is the case, the daytime retail trading volume should be positively associated with the occurrence of positive overnight returns (i.e., high opening price).

We examine this issue by running cross-sectional Fama–Macbeth regressions. Following the literature, we identify retail trading by using trades with order size below CNY 50,000 (Lee and Radhakrishna, 2000). For each stock, we aggregate daily retail trading volume across days in a month and divide it by the firm's total trading volume in that month. We then construct the monthly abnormal retail trading measure (AB_RETAIL) by scaling this measure to its own moving average over the previous 12 months, similar to how we constructed ABNR. We also calculate the analogous measures for abnormal selling and net buying, as we want to examine the direction of retail trading in response to high opening prices.

We start by regressing the monthly retail trading activity on ABNR and other control variables. In column (1), the dependent variable is the abnormal total volume of retail sales and buy, where total retail sales and buy volume is calculated as the proportion of total trading volume . We investigate the intensity of monthly retail sales in column (2) and net buy (buy minus sales) in column (3).

We also add other three day-night return pattern variables on the right-hand side of the regression—for comparisons.[22] Among them, ABNR and ABPM are characterized by positive overnight return (i.e., high opening price), whereas ABPR and ABNM are characterized by negative overnight return (i.e., low opening price).

[22] These variables include ABPR (low opening prices followed by positive daytime returns), ABNM (negative overnight returns followed by negative daytime returns, and ABPM (positive overnight returns followed by positive daytime returns).

$$AB\_RETAIL_{im} = \alpha_0 + \alpha_1 \times ABNR_{im} + Controls_{im} + \varepsilon_{im} \qquad (3.7)$$

We report time-series averages of the coefficient estimates in Table 3.9. The positive coefficients of ABNR and ABPM in columns (1) and (2) reveal an intensified total retail trading and retail selling activity in a prolonged, intense tug of war that is characterized by high opening prices. The negative coefficients of ABNR and ABPM in column (3) suggest that retail selling pressure tend to increase with more occurrence of high opening prices.

By contrast, the coefficients of ABPR and ABNM for in all three columns are either significantly negative or negligible, indicating no evidence for retail investors to trade more upon low opening prices.

To sum up, this evidence indicates that, during months when high opening prices occur more, there is a significant increase in retail trading activity that is driven by retail selling rather than retail buying. These are in line with our conjecture that daytime retail investors tend to trade against high opening prices by exerting too much selling pressure that drags stock prices away from their fair values after the market open.

Notably, Kang et al. (2022) propose an explanation for the intraday return reversal in China—that is, irrational daytime investors overly trading against previous price movements by providing excessive liquidity. However, they did not differentiate between negative and positive daytime reversals. We show that the contemporaneous abnormal total retail trading and retail selling volume is positively correlated with ABNR, but negatively correlated with ABPR. This suggests that daytime retail investors trade actively against high opening prices, but less actively when the market opens with low prices.

Next, we examine whether institutions also respond actively to the high opening prices. We first construct the monthly abnormal institutional trading volume (AB_INST) by calculating the ratio of aggregate trading volume from institutions in a month to its own moving average over the past 12 months. We also calculate abnormal selling and net buying measures and regress abnormal institution trading volume on ABNR, ABPR, ABNM, ABPM, and a set of controls, as before.

Interestingly, the coefficient signs for variables that are characterized by high opening prices as shown in columns (4) and (5), significantly reverse to negative compared with those presented in columns (1) and (2). This suggests that it is not due to the high opening price that attracts investors to trade, rather, retail investors trade more actively on positive overnight returns whereas institutions are less enthusiastic upon high opening prices.

Moreover, we take a further step to investigate the role of retail investors on the predictability of the intensity of a negative daytime reversal. If retail investors are attributable to the return reversals to some extent, we would see higher retail investor trading turnover for stocks that have larger magnitudes in daytime return reversals than those for stocks with a smaller degree of reversal. We conduct a double-sorting exercise by first sorting stocks into quintiles based on the overnight return component, and then on the daytime return component to control for different levels of overnight returns. By doing so, in each level of overnight returns, we distinguish among different levels of daytime reversals. Following the literature, we define retail investor orders as those below CNY 50,000. For each stock on each day, we calculate the retail trading turnover as the total trading volume from retail investors divided by the outstanding shares, after which the equal-and value-weighted portfolio retail investor trading turnovers are calculated.

Table 3.10 reports the retail trading turnover of each quintile and the differences between two extreme groups. Each row contains a set of stocks that differ in daytime returns but have similar overnight returns. For example, stocks with the largest magnitude in both overnight (high overnight return quintile) and daytime reversal (low day return quintile) have an equal-weighted average of the daily retail investor trading turnover of 0.75%.

As predicted, the rightmost column shows that stocks with more negative price movements during the daytime session (low daytime return quintile) have higher retail investor trading turnover than those with less negative intraday returns (high daytime return quintile), regardless of having equal or value weights. This indicates that the trading of retail investors contributes, at least partially to, negative daytime reversals.

Taken together, our evidence suggests that the positive overnight return, followed by negative daytime reversals, may not be explainable by compensations for liquidity provision. Instead, this evidence indicates that negative daytime reversals are likely to be induced by trades from retail investors in that they tend to overly trade against high opening prices.

### 3.5.3 Placebo test: An alternative sequence of day-to-night reversal

We have shown that ABNR can positively predict future returns, and it is possibly because daytime retail investors trade against high opening prices that essentially contain information, tending toward the wrong direction. Next, we conduct a placebo test that uses an alternative sequence that proceeds from a negative daytime return followed by a positive overnight return on the next day. Because this sequence of day-to-night reversals is unrelated to our economic interpretation of daytime retail investors responding to overnight returns, it should not predict future returns.

We construct a monthly frequency of trading days with negative daytime returns, followed by positive next day overnight returns (DOPR), for each stock. We then divide it by its moving average of the past 12 months and obtain the abnormal frequency of DOPR (ABDOPR). Panel A of Table 3.11 reports the summary statistics for DOPR and ABDOPR, and their correlations with NR and ABNR.

The results show that the DOPR and ABDOPR have similar distributions to our night-to-day return reversal measures, NR and ABNR, as shown in Table 3.1. The correlations between each of the two variables range from 0.521 to 0.632, suggesting that these alternative sequence measures capture similar but different information compared with the key variables of our interests.

We run similar Fama–Macbeth regressions as in Table 3.5, but replace ABPR with ABDOPR to see whether there is a significant coefficient for this alternative sequence measure. Because the sequence of consecutive days with negative daytime return, followed by positive overnight returns, is not characterized by daytime traders responding to overnight returns, there should be no predictive power of ABDOPR for future returns. Panel B reports the time-series averages of the cross-sectional Fama–Macbeth regression estimates. The coefficients of ABDOPR are never significant in all specifications, whereas those of ABNR are all positively significant, ranging from 0.14 to 0.22, with *t*-stat above 2.70. This indicates that the positive return predictability is only associated with return reversals, comprising sequences with negative overnight returns, followed by positive daytime returns, rather than those with alternative day-to-night sequences. In sum, our placebo test corroborates our argument that daytime investors trade against a high opening price and drive the daytime pricing errors.

### 3.5.4 Decomposing future returns: overnight and daytime components

In this subsection, we conduct our portfolio analyses by decomposing one-month ahead close-to-close returns into overnight and daytime components to observe the source of predictability. Each month, we sort stocks into quintiles based on ABNR and hold for one month. We then separate returns into overnight and daytime return. We report the value-weighted long–short portfolio component returns in Table 3.12. The result shows that the positive predictive power of ABNR for future monthly returns is revealed through the trades near or at market open, rather than the trades of daytime investors. In particular, the future monthly overnight FF-3 alpha of a long–short portfolio based on ABNR is 1.17%, with a *t*-stat of 18.44, whereas the future daytime component return is negative and smaller in magnitude at -0.76% (*t=-4.64*). The results are similar using raw returns and capital asset pricing model alphas. Overall, these findings are similar to those reported in Chapter 2—that is, most anomalous profits occur overnight and become negative in the daytime, except for the last half hour.

In sum, these results establish that the positive return prediction on ABNR mainly arises from investors trading at market open, whereas daytime traders tend to be on the wrong track in predicting future returns. This is consistent with our argument that daytime retail investors trade irrationally against opening prices and drag prices so as to deviate from fair values.

### 3.5.5 Negative daytime reversals and fundamentals

We now examine whether the main variable of our interest, the ABNR, conveys firms' fundamental information; we do so by conducting different specifications of Fama–Macbeth regressions, following Akbas et al. (2022). We first regress ABNR for stock $i$ in month $m$ on a dummy variable EA_Month(0), which equals to one if there is an earnings announcement during that month, and zero otherwise. This regression allows us to see whether negative daytime reversals tend to cluster around earnings release events.

$$ABNR_{im} = \alpha_0 + \alpha_1 EA\_Month(0)_{im} + Controls_{im} + \varepsilon_{im} \quad (3.8)$$

We also include another dummy variable EA_Month(-1) that equals to one for the previous month of earnings announcement, and zero otherwise, in columns (3) and (4), to control for the possible relationship between ABNR and the previous month of EA announcements. We use the same control variables as in Table 3.5 and report the coefficient estimate results in Panel A of Table 3.13. The coefficients of EA_Month(0) in all four specifications are significantly positive, indicating that ABNR is on average higher during months with earnings announcements compared with those without earnings announcements. To summarize, our evidence indicates that the abnormal intensity of return reversals tends to cluster around firm-specific information events that are likely to trigger daytime reversals.

Next, we examine whether our proxy for the intensity of negative daytime reversals, ABNR, can predict firms' future earnings surprises. If daytime retail investors trade against high opening prices that reflect positive information about firms' future fundamentals, we should see a higher level of ABNR associated with higher values of the subsequent earnings surprises. We construct two measures as our proxies for earnings surprises. The first one is the cumulative abnormal returns over the [-1, +1] daily window around the next earnings announcement events in the future. $CAR_{[-1,+1]}$ is estimated using the Fama–French three-factor model:

$$CAR^{i}_{[-1,+1]} = \sum_{d=-1}^{+1} (Ret^{ex}_{id} - \widehat{\beta_1} \times SMB_d - \widehat{\beta_2} \times HML_d - \widehat{\beta_3} \times MKT_d) \quad (3.9)$$

where d=0 indicates the next earnings release date. $\widehat{\beta_1}$, $\widehat{\beta_2}$, and $\widehat{\beta_3}$ are estimated using the previous 250 daily data by the Fama–French three-factor model for each stock. The second earnings surprise measure is accounting-based, namely, standard unexpected earnings (SUE), calculated as the difference between the actual and expected earnings per share (EPS) scaled by the standard deviation of the forecast errors over the previous five semi-annual intervals.[23]

$$SUE_{iq} = \frac{EPS_{iq} - EPS_{iq-2}}{\sigma_{i;q-6,q-1}}, \tag{3.10}$$

where $q$ represents next earnings announcement semi-annual. The expected EPS at each semi-annual $q$ is estimated by the actual EPS at semi-annual $q-2$ using the seasonal random walk assumption as in Foster et al. (1984). We also include the most recent lagged dependent variables along with other controls in the right-hand side in the form, as follows:

$$SURPRISE_{it} = \alpha_0 + \alpha_1 \times ABNR_{im} + \alpha_2 \times SURPRISE_{i,t-1} + Controls_{im} + \varepsilon_{im} \tag{3.11}$$

where $SURPPRISE_{it}$ indicates either cumulative abnormal returns over the [-1,+1] window ($CAR_{[-1,+1]}$) around the next earnings release date or standard unexpected earnings (SUE) in the next earnings announcement semi-annual. We report the coefficient estimate results in Panel B of Table 3.13. The results in column (2) show that a 1% increase in ABNR is associated with a 7.1 basis points increase in the three-day cumulative abnormal return around the next earnings release. The coefficients of ABNR on SUE are also significantly positive, regardless of whether we added the lagged term or not. This evidence shows that a higher level of ABNR indicates more positive earnings surprises around the next earnings announcement semi-annual.

In sum, our evidence shows that ABNR contains firms' positive information in the future, which reinforces the argument that high opening prices essentially contain valuable firm-specific information.

[23] We obtain the SUE measure directly from the CSMAR database.

## 3.6 Conclusion

The literature claims that return reversals occur when opposing investor clienteles trade at different times over a day. Accordingly, we investigate whether the presence and intensity of daily return reversals can predict future stock returns in China.

Our study complements the literature on overnight and intraday returns by showing that the abnormal frequency of positive overnight returns that are reversed during daytime has positive predictive power for returns in the following month. This predictive relationship remains when we consider various robustness tests; for example, when adjusting for common risk factors and using a large set of controls such as size, book-to-market ratio, contemporaneous returns, past returns, turnover rate, volatility, and illiquidity. Our results are also robust to transaction costs and different sequence of day-to-night return reversals.

We argue that this predictive relationship is due to daytime noise traders trading against a high opening price that indicates the presence of positive fundamental information. Traders thus overestimate their ability to process information, and are likely to drag prices, deviating from firms' fundamental values by trading too much. This interpretation is in line with Kang et al.'s (2022) excessive liquidity provision hypothesis in that they regard intraday return reversals as pricing errors, while they did not distinguish between positive and negative daytime reversals. We provide evidence that retail investors are likely to overly trade against high opening prices by showing that the abnormal trading volume from retail investors increases with the occurrence of positive overnight returns followed by negative daytime reversals. Hence, our findings are additional evidence for the role of retail investors on stock prices in China.

**Table 3.1**

**Summary statistics of return reversal intensity measures**

| Panel A: Summary Statistics | | | | | |
|---|---|---|---|---|---|
| | Mean | Median | Min | Max | SD |
| NR | 0.211 | 0.200 | 0 | 0.524 | 0.101 |
| ABNR | 1.045 | 0.997 | 0 | 3.571 | 0.509 |
| PR | 0.299 | 0.286 | 0.048 | 0.619 | 0.110 |
| ABPR | 1.002 | 0.972 | 0.173 | 2.189 | 0.382 |

| Panel B: Correlations | | | | | | | |
|---|---|---|---|---|---|---|---|
| | ABNR | PR | ABPR | Lead_ | Lead_ABN | Lead_PR | Lead_A |
| NR | 0.856 | -0.376 | -0.307 | 0.144 | -0.056 | -0.118 | -0.024 |
| ABNR | | -0.293 | -0.323 | 0.062 | 0.073 | -0.054 | -0.064 |
| PR | | | 0.880 | -0.108 | 0 | 0.138 | -0.049 |
| ABPR | | | | -0.056 | -0.053 | 0.066 | 0.072 |
| Lead_NR | | | | | 0.857 | -0.379 | -0.310 |
| Lead_AB | | | | | | -0.295 | -0.325 |
| Lead_PR | | | | | | | 0.881 |

This table reports the summary statistics and Pearson correlations of 4 monthly return-reversal intensity measures over the period from January 2009 to December 2020. NR and PR denote the level of return-reversal intensity, calculated as the ratio of the number of days with negative (positive) daytime reversals in a given month to the total number of trading days during that month, where negative daytime reversal is defined as if the overnight component return is positive and the daytime component return is negative, and vice versa. ABNR and ABPR denote the abnormal frequency of negative (positive) daytime reversal intensity, calculated as the ratio of NR (PR) in a month to the average NR(PR) over the past 12 months. LeadNR, LeadABNR, LeadPR, and LeadABPR represent NR, ABNR, PR and ABPR in the next calendar month, respectively. The statistics are calculated as the time-series average of the monthly cross-sectional statistics. All reported correlations are different from zero at $p < 0.10$.

**Table 3.2**

**Persistence of return reversal intensity measures**

| Panel A: Persistence of NR | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dept. Var. | $NR_{im+1}$ | $NR_{im+1}$ | $NR_{im+2}$ | $NR_{im+2}$ | $NR_{im+3}$ | $NR_{im+3}$ |
| NR | 0.146*** | 0.112*** | 0.109*** | 0.087*** | 0.096*** | 0.080*** |
| | (21.69) | (15.31) | (17.73) | (12.45) | (20.19) | (17.93) |
| Controls | No | Yes | No | Yes | No | Yes |
| Adj_$R^2$ | 2.27% | 6.30% | 1.28% | 5.04% | 0.96% | 4.45% |
| N | 317,050 | 317,050 | 313,505 | 313,505 | 309,962 | 309,962 |
| Panel B: Persistence of ABNR | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dept. Var. | $ABNR_{im+1}$ | $ABNR_{im+1}$ | $ABNR_{im+2}$ | $ABNR_{im+2}$ | $ABNR_{im+3}$ | $ABNR_{im+3}$ |
| ABNR | 0.072*** | 0.058*** | 0.022*** | 0.021*** | -0.002 | 0.003 |
| | (14.18) | (14.98) | (5.69) | (5.99) | (-0.99) | (1.35) |
| Controls | No | Yes | No | Yes | No | Yes |
| Adj_$R^2$ | 0.64% | 3.36% | 0.17% | 2.78% | 0.07% | 2.54% |
| N | 315,570 | 315,570 | 312,024 | 312,024 | 308,482 | 308,482 |
| Panel C: Persistence of PR | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dept. Var. | $PR_{im+1}$ | $PR_{im+1}$ | $PR_{im+2}$ | $PR_{im+2}$ | $PR_{im+3}$ | $PR_{im+3}$ |
| PR | 0.141*** | 0.099*** | 0.105*** | 0.077*** | 0.088*** | 0.063*** |
| | (30.19) | (23.48) | (22.12) | (21.34) | (19.34) | (19.87) |
| Controls | No | Yes | No | Yes | No | Yes |
| Adj_$R^2$ | 2.12% | 7.14% | 1.23% | 5.88% | 0.85% | 5.37% |
| N | 317,050 | 317,050 | 313,505 | 313,505 | 309,962 | 309,962 |
| Panel D: Persistence of ABPR | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dept. Var. | $ABPR_{im+1}$ | $ABPR_{im+1}$ | $ABPR_{im+2}$ | $ABPR_{im+2}$ | $ABPR_{im+3}$ | $ABPR_{im+3}$ |
| ABPR | 0.071*** | 0.059*** | 0.024*** | 0.025*** | -0.002 | 0.003 |
| | (18.32) | (19.37) | (6.34) | (6.74) | (-0.58) | (1.03) |
| Controls | No | Yes | No | Yes | No | Yes |
| Adj_$R^2$ | 0.66% | 3.91% | 0.26% | 3.08% | 0.10% | 2.78% |
| N | 315,652 | 315,652 | 312,107 | 312,107 | 308,565 | 308,565 |

This table presents evidence for the persistence of return-reversal intensity measures, using Fama-MacBeth regression where the dependent variable is the corresponding future value of each measure ($NR_{im+k}$, $ABNR_{im+k}$, $PR_{im+k}$, $ABPR_{im+k}$, k=1,2,3). For each panel, we report estimate results without controls in odd columns and results with controls in even columns. Controls include contemporaneous monthly returns, cumulative monthly returns over the past 6 months, logarithm of market capitalization in month *m*, monthly turnover in month *m*, monthly standard deviation of daily returns in month *m*, Amihud illiquidity in month *m*, logarithm of BM, return on equity, total asset growth rate and institutional ownership. The sample period spans from 2009 to 2020. The *t*-stat in parentheses is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.3**

**Summary statistics and correlations of main variables**

Panel A: Summary Statistics

| | RET_M | LNSIZE | LNBM | RET_6M | TOVR_M | SD_RET_M | ILLIQ_M | ROE | ASSET | IO |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.015 | 15.19 | 6.200 | 0.093 | 0.027 | 0.027 | 0.050 | 0.029 | 0.203 | 0.031 |
| Median | -0.001 | 15.14 | 6.256 | -0.001 | 0.017 | 0.024 | 0.030 | 0.025 | 0.097 | 0.011 |
| Min | -0.398 | 12.52 | 3.332 | -0.589 | 0.001 | 0.006 | 0.001 | -0.508 | -0.486 | 0 |
| Max | 0.726 | 19.04 | 8.273 | 2.592 | 0.156 | 0.084 | 0.616 | 0.287 | 5.100 | 0.282 |
| SD | 0.129 | 1.121 | 0.789 | 0.358 | 0.025 | 0.012 | 0.059 | 0.067 | 0.463 | 0.041 |

Panel B: Correlations

| | ABPR | NR | PR | RET_M | LNSIZE | LNBM | RET_6M | TOVR_M | SD_RET_M | ILLIQ_M | ROE | ASSET | IO |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ABNR | -0.323 | 0.856 | -0.293 | -0.195 | 0.000 | -0.029 | 0.048 | -0.090 | -0.126 | 0.009 | 0 | 0 | 0.012 |
| ABPR | | -0.307 | 0.880 | 0.234 | -0.024 | 0.035 | -0.029 | 0.092 | 0.042 | -0.052 | 0 | 0 | -0.034 |
| NR | | | -0.376 | -0.200 | 0.098 | -0.034 | 0.000 | -0.192 | -0.192 | 0 | 0.018 | 0.011 | 0.085 |
| PR | | | | 0.241 | -0.154 | -0.031 | 0.034 | 0.169 | 0.102 | 0.000 | -0.013 | -0.006 | -0.056 |
| RET_M | | | | | -0.045 | 0.018 | -0.030 | 0.242 | 0.329 | 0.000 | 0.000 | -0.007 | 0.000 |
| LNSIZE | | | | | | -0.091 | 0.095 | -0.374 | -0.184 | -0.377 | 0.046 | 0 | 0.264 |
| LNBM | | | | | | | -0.216 | 0.040 | -0.163 | 0 | 0.195 | 0.072 | -0.199 |
| RET_6M | | | | | | | | 0.188 | 0.215 | -0.085 | 0.014 | -0.010 | 0.090 |
| TOVR_M | | | | | | | | | 0.595 | -0.072 | -0.009 | 0.017 | -0.100 |
| SD_RET_M | | | | | | | | | | 0 | -0.017 | 0.010 | 0.018 |
| ILLIQ_M | | | | | | | | | | | -0.023 | -0.009 | -0.133 |
| ROE | | | | | | | | | | | | 0 | 0.058 |
| ASSET | | | | | | | | | | | | | 0.017 |

This table reports time-series averages of monthly cross-sectional summary statistics and Pearson correlations between various control variables. NR, ABNR, PR and ABPR are defined as above. RET_M is the standard monthly return in month *m*. RET_6M is the cumulative monthly return from month *m-6* to *m-1*. LNSIZE is the logarithm of market capitalization calculated as the number of shares outstanding times the month-end share price. LNBM is the logarithm of the ratio of book value to market value of equity. TOVR_M is the daily average turnover in month *m*, where daily turnover is the trading volume divided by the total number of shares outstanding on a given day. SD_RET_M is the standard deviation of daily returns in month *m*. ILLIQ_M is he Amihud (2002) measure of illiquidity in month *m*. ROE

**Table 3.3 - *Continued***

is the ratio of quarterly earnings to book equity from Hou et al. (2015). ASSET is the annual total asset growth from Fama & French (2015). IO is the proportion of stocks held by fund institutional investors. The sample consists of common A-share stocks on Shanghai and Shenzhen Stock Exchanges and spans from January 2009 to December 2020. The returns are in decimal points. All reported correlations are different from zero at $p < 0.10$.

**Table 3.4**

**Long-short portfolio returns based on intraday return intensity measures**

Panel A: Long-short portfolio returns based on ABNR and ABPR

| | Value weight | | | Equal weight | | | | Value weight | | | Equal weight | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ABNR | Excess | CAPM | FF-3 | Excess | CAPM | FF-3 | ABPR | Excess | CAPM | FF-3 | Excess | CAPM | FF-3 |
| Low | 0.93 | 0.74 | 0.80 | 0.95 | 0.76 | 0.83 | Low | 1.33* | 1.14* | 1.24* | 1.38* | 1.18* | 1.30* |
| | (1.16) | (1.10) | (1.11) | (1.18) | (1.11) | (1.13) | | (1.78) | (1.83) | (1.79) | (1.81) | (1.87) | (1.81) |
| 2 | 1.22 | 1.05 | 1.11 | 1.26 | 1.09 | 1.15 | 2 | 1.50* | 1.31* | 1.39* | 1.54 | 1.35** | 1.44* |
| | (1.61) | (1.63) | (1.61) | (1.63) | (1.65) | (1.62) | | (1.92) | (1.99) | (1.93) | (1.93) | (2.01) | (1.94) |
| 3 | 1.32* | 1.14* | 1.22* | 1.36* | 1.18* | 1.27* | 3 | 1.34* | 1.16* | 1.23* | 1.39* | 1.20* | 1.29* |
| | (1.75) | (1.80) | (1.76) | (1.77) | (1.82) | (1.77) | | (1.76) | (1.81) | (1.78) | (1.78) | (1.84) | (1.79) |
| 4 | 1.37* | 1.18* | 1.25* | 1.41* | 1.22* | 1.31* | 4 | 1.17 | 0.99 | 1.03 | 1.21 | 1.02 | 1.08 |
| | (1.83) | (1.88) | (1.84) | (1.85) | (1.91) | (1.85) | | (1.51) | (1.50) | (1.48) | (1.53) | (1.52) | (1.49) |
| High | 1.42* | 1.21* | 1.30* | 1.47* | 1.26* | 1.37* | High | 0.91 | 0.73 | 0.78 | 0.94 | 0.76 | 0.83 |
| | (1.82) | (1.89) | (1.85) | (1.85) | (1.92) | (1.87) | | (1.18) | (1.12) | (1.15) | (1.20) | (1.14) | (1.17) |
| H-L | 0.49*** | 0.46*** | 0.50*** | 0.51*** | 0.49*** | 0.53*** | H-L | -0.42*** | -0.41*** | -0.46*** | -0.43*** | -0.40*** | -0.48*** |
| | (4.34) | (3.90) | (4.27) | (4.63) | (4.19) | (4.76) | | (-4.20) | (-3.50) | (-3.71) | (-4.34) | (-3.39) | (-3.89) |

Panel B: Long-short portfolio returns based on ABNM and ABPM

| | Value weight | | | Equal weight | | | | Value weight | | | Equal weight | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ABN | Excess | CAPM | FF-3 | Excess | CAPM | FF-3 | ABPR | Excess | CAPM | FF-3 | Excess | CAPM | FF-3 |
| Low | 1.17 | 0.98 | 1.03 | 1.20 | 1.00 | 1.04 | Low | 1.18 | 0.97 | 1.01 | 1.20 | 1.00 | 1.04 |
| | (1.60) | (1.58) | (1.57) | (1.61) | (1.59) | (1.58) | | (1.50) | (1.50) | (1.48) | (1.61) | (1.59) | (1.58) |
| 2 | 1.22 | 1.04 | 1.08 | 1.25 | 1.06 | 1.10 | 2 | 1.26 | 1.06 | 1.08 | 1.25 | 1.06 | 1.10 |
| | (1.58) | (1.58) | (1.55) | (1.60) | (1.60) | (1.56) | | (1.61) | (1.63) | (1.59) | (1.60) | (1.60) | (1.56) |
| 3 | 1.23 | 1.03 | 1.07 | 1.25 | 1.05 | 1.09 | 3 | 1.27* | 1.08* | 1.13* | 1.25 | 1.05 | 1.09 |
| | (1.55) | (1.56) | (1.53) | (1.57) | (1.58) | (1.54) | | (1.69) | (1.71) | (1.67) | (1.57) | (1.58) | (1.54) |
| 4 | 1.36* | 1.18* | 1.23* | 1.39* | 1.21* | 1.25* | 4 | 1.36* | 1.18* | 1.22* | 1.39* | 1.21* | 1.25* |
| | (1.74) | (1.78) | (1.73) | (1.76) | (1.80) | (1.74) | | (1.78) | (1.82) | (1.78) | (1.76) | (1.80) | (1.74) |
| High | 1.32* | 1.11* | 1.15* | 1.34* | 1.13* | 1.17* | High | 1.22 | 1.04 | 1.09 | 1.34* | 1.13* | 1.17* |
| | (1.65) | (1.68) | (1.65) | (1.66) | (1.70) | (1.66) | | (1.57) | (1.56) | (1.53) | (1.66) | (1.70) | (1.66) |

**Table 3.4 - *Continued***

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| H-L | 0.14 | 0.13 | 0.12 | 0.14 | 0.13 | 0.13 | H-L | 0.03 | 0.07 | 0.08 | 0.14 | 0.13 | 0.13 |
| | (0.76) | (0.71) | (0.73) | (0.76) | (0.72) | (0.75) | | (0.33) | (0.72) | (0.74) | (0.76) | (0.72) | (0.75) |

This table reports long-short portfolio returns from one-way sorting analysis. Each month, we sort stocks into quintiles based on one particular measure, and we hold each portfolio for one month. Panel A presents both value- and equal-weighted average raw returns, one-factor alphas based on Market model and three-factor alphas based on Fama-French 3-factor model in the next calendar month for each portfolio and high-minus-low portfolio (H-L) that longs stocks with the top 20% ABNR or ABPR and shorts stocks with the bottom 20% ABNR or ABPR. ABNR and ABPR are defined as above. Panel B provides both value- and equal-weighted results sorted based on ABNM and ABPM. ABNM is the ratio of NM in month *m* to its moving average over the previous 12 months, where NM is the ratio of the number of days with negative overnight returns followed by negative daytime momentum to the number of total trading days in month *m*. ABPM is defined similarly except using days with positive overnight returns followed by positive daytime momentum. Returns are in percent. The sample period covers 2009–2020. The *t*-stat is based on Newey-West robust standard errors with 12 lags.

**Table 3.5**

**FM regressions of future returns on ABNR/ABPR**

| | $RET_{im+1}$ | | $RET_{im+1}$ | | $RET_{im+1}$ | | $RET_{im+2}$ | |
|---|---|---|---|---|---|---|---|---|
| $RET_{im+1}$ | Coef. | *t*-stat | Coef. | *t*-stat | Coef. | *t*-stat | Coef. | *t*-stat |
| ABNR | 0.18*** | (2.53) | 0.19*** | (2.62) | 0.13** | (2.27) | 0.03 | (0.34) |
| ABPR | -0.07 | (-0.94) | -0.07 | (-0.91) | 0.03 | (0.39) | 0.04 | (0.56) |
| RET_M | -4.41*** | (-4.62) | -4.45*** | (-4.68) | -2.65*** | (-2.61) | 0.16 | (0.19) |
| RET_6M | -0.02 | (-0.07) | -0.05 | (-0.16) | 0.61** | (1.99) | 0.80*** | (2.71) |
| LNSIZE | -0.42* | (-1.94) | -0.43** | (-1.98) | -0.58*** | (-2.84) | -0.52*** | (-2.83) |
| LNBM | 0.08 | (0.76) | 0.08 | (0.69) | 0.13 | (1.49) | 0.06 | (0.60) |
| ROE | | | 0.44 | (1.19) | 0.52* | (1.67) | -0.07 | (-0.18) |
| ASSET | | | -0.05** | (-2.25) | -0.05** | (-1.98) | -0.05** | (-2.16) |
| TOVR_M | | | | | -0.33*** | (-9.75) | -0.19*** | (-5.74) |
| SD_RET_M | | | | | 0.13 | (1.25) | -0.04 | (-0.60) |
| ILLIQ_M | | | | | 0.04** | (2.53) | 0.05*** | (3.37) |
| IO | | | | | 0.03 | (1.26) | 0.03 | (1.36) |
| Adj_R2 | 0.06 | | 0.06 | | 0.09 | | 0.07 | |
| N | 319,156 | | 319,156 | | 319,156 | | 319,119 | |

This table reports Fama-Macbeth (FM) regression estimates of regressing future returns on ABNR, ABPR and a series of other control variables listed in Table 3.3. The dependent variable of the first two specifications is the raw return for firm *i* in month *m+1*, while the dependent variable of the third specification is the raw return in month *m+2*. The main variables of interest are the monthly abnormal frequencies of negative and positive daytime reversals, respectively (ABNR and ABPR). The intercept for each specification is not shown below, for brevity. All variables are described in Appendix 3.1. The sample period covers 2009–2020. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.6**

**Firm characteristics based on ABNR and long-short portfolio returns across firm characteristics**

Panel A: Firm attributes sorted by ABNR

| ABNR | RET_M | LNSIZE | LNBM | RET_6M | TOVR_M | SD_RET_M | ILLIQ_M | ROE | ASSET | IO |
|---|---|---|---|---|---|---|---|---|---|---|
| Low | 0.043 | 15.14 | 6.218 | 0.087 | 0.031 | 0.029 | 0.048 | 0.026 | 0.200 | 0.028 |
| 2 | 0.024 | 15.23 | 6.211 | 0.081 | 0.027 | 0.028 | 0.049 | 0.029 | 0.209 | 0.030 |
| 3 | 0.012 | 15.26 | 6.194 | 0.087 | 0.025 | 0.027 | 0.049 | 0.030 | 0.210 | 0.032 |
| 4 | 0.002 | 15.25 | 6.181 | 0.097 | 0.024 | 0.026 | 0.050 | 0.030 | 0.205 | 0.032 |
| High | -0.013 | 15.17 | 6.150 | 0.126 | 0.024 | 0.026 | 0.052 | 0.027 | 0.190 | 0.030 |
| H-L | -0.056*** | 0.026 | -0.069*** | 0.039*** | -0.007*** | -0.003*** | 0.004** | 0.001 | -0.011* | 0.002*** |
| *t*-stat | (-25.02) | (0.95) | (-5.21) | (3.61) | (-13.33) | (-10.55) | (2.38) | (0.72) | (-1.71) | (2.64) |

Panel B: Long-short portfolio returns controlling firm characteristics

| H-L | ABNR | Excess | *t*-stat | CAPM | *t*-stat | FF-3 | *t*-stat | H-L | ABNR | Excess | *t*-stat | CAPM | *t*-stat | FF-3 | *t*-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LNSIZE | Small | 0.77*** | (3.76) | 0.78*** | (3.93) | 0.78*** | (4.13) | LNBM | Low | 0.55*** | (3.60) | 0.52*** | (3.29) | 0.60*** | (3.94) |
| | 2 | 0.83*** | (4.95) | 0.83*** | (5.01) | 0.81*** | (5.23) | | 2 | 0.39** | (2.53) | 0.40*** | (2.73) | 0.40*** | (2.71) |
| | 3 | 0.81*** | (4.62) | 0.77*** | (4.37) | 0.80*** | (4.65) | | 3 | 0.60*** | (4.17) | 0.55*** | (3.89) | 0.57*** | (4.23) |
| | 4 | 0.28* | (1.71) | 0.25 | (1.62) | 0.26 | (1.55) | | 4 | 0.54*** | (3.58) | 0.52*** | (3.50) | 0.50*** | (3.40) |
| | Big | 0.18 | (0.70) | 0.11 | (0.45) | 0.21 | (0.77) | | High | 0.31** | (2.02) | 0.27* | (1.81) | 0.34** | (2.05) |
| TOVR_M | Low | 0.30 | (1.51) | 0.27 | (1.37) | 0.33 | (1.49) | RET_6M | Low | 0.61*** | (2.84) | 0.58*** | (2.78) | 0.67*** | (3.83) |
| | 2 | 0.10 | (0.84) | 0.10 | (0.83) | 0.16 | (1.10) | | 2 | 0.37** | (2.32) | 0.34** | (2.03) | 0.40*** | (2.66) |
| | 3 | 0.34 | (1.60) | 0.29 | (1.50) | 0.29 | (1.55) | | 3 | 0.46** | (2.32) | 0.42** | (2.08) | 0.44** | (2.16) |
| | 4 | 0.32* | (1.91) | 0.33* | (1.91) | 0.36** | (2.20) | | 4 | 0.34** | (2.50) | 0.37*** | (2.76) | 0.39*** | (2.68) |
| | High | 0.88*** | (4.54) | 0.88*** | (4.50) | 0.93*** | (5.03) | | High | 0.51*** | (3.59) | 0.48*** | (3.11) | 0.47*** | (2.87) |
| ILLIQ_M | Low | 0.39 | (1.42) | 0.32 | (1.24) | 0.40 | (1.42) | SD_RET_M | Low | 0.22 | (1.34) | 0.20 | (1.28) | 0.22 | (1.32) |
| | 2 | 0.35*** | (2.90) | 0.31*** | (2.63) | 0.31*** | (3.00) | | 2 | 0.28 | (1.64) | 0.25 | (1.52) | 0.31 | (1.63) |
| | 3 | 0.51*** | (3.52) | 0.50*** | (3.32) | 0.49*** | (3.37) | | 3 | 0.27** | (2.37) | 0.30*** | (2.70) | 0.34*** | (2.83) |
| | 4 | 0.67*** | (3.74) | 0.64*** | (3.37) | 0.64*** | (3.68) | | 4 | 0.48*** | (2.90) | 0.44*** | (2.78) | 0.48*** | (2.85) |
| | High | 0.57*** | (3.60) | 0.55*** | (3.48) | 0.56*** | (3.80) | | High | 0.85*** | (5.01) | 0.83*** | (4.85) | 0.87*** | (5.74) |

**Table 3.6 - *Continued***

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ASSET | Low | 0.64*** | (3.69) | 0.59*** | (3.62) | 0.59*** | (3.81) | ROE | Low | 0.77*** | (3.74) | 0.71*** | (3.57) | 0.75*** | (4.09) |
| | 2 | 0.56*** | (3.95) | 0.54*** | (3.65) | 0.59*** | (3.89) | | 2 | 0.44*** | (2.77) | 0.40*** | (2.63) | 0.46*** | (3.27) |
| | 3 | 0.32** | (2.01) | 0.30* | (1.83) | 0.34** | (2.05) | | 3 | 0.43*** | (2.83) | 0.42 | (2.64) | 0.43 | (2.75) |
| | 4 | 0.55*** | (3.16) | 0.53*** | (3.24) | 0.55*** | (3.20) | | 4 | 0.45*** | (3.02) | 0.44*** | (3.00) | 0.45*** | (3.01) |
| | High | 0.62*** | (2.63) | 0.59** | (2.47) | 0.64*** | (2.80) | | High | 0.37* | (1.79) | 0.39* | (1.84) | 0.35* | (1.75) |
| IO | Low | 0.52*** | (3.13) | 0.52*** | (3.13) | 0.55*** | (3.28) | | | | | | | | |
| | 2 | 0.64*** | (5.40) | 0.60*** | (4.98) | 0.62*** | (5.22) | | | | | | | | |
| | 3 | 0.51*** | (3.50) | 0.49*** | (3.24) | 0.53*** | (3.74) | | | | | | | | |
| | 4 | 0.46*** | (3.48) | 0.43*** | (3.10) | 0.45*** | (3.77) | | | | | | | | |
| | High | 0.37* | (1.80) | 0.34* | (1.73) | 0.38 | (1.64) | | | | | | | | |

This table reports distributions of firm characteristics sorted by ABNR, as well as long-short portfolio returns by ABNR across different firm characteristics. Panel A presents time-series averages of cross-sectional summary statistics for different firm characteristics in 5 different ABNR groups. The bottom two rows display the differences and *t*-stat between stocks with the top 20% ABNR and those with the bottom 20% ABNR. Firm characteristic details are described in Appendix 3.1. Returns are in decimal points in Panel A. Panel B presents value-weighted long-short portfolio returns based on ABNR across different firm attributes. At the end of each month, we first sort stocks into quintiles based on different firm characteristics. Within each quintile, we then sort stocks into quintiles by ABNR and hold for one month. We present the results for the high-minus-low hedge portfolio (H - L) that is long stocks with a high value of ABNR and short stocks with a low ABNR, within each quintile by the firm attribute. The sample period covers 2009–2020. Returns are in percent in Panel B. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.7**

**Turnover rates and transaction costs of ABNR portfolios**

| | Turnover (%) | Break-even costs (%) | |
|---|---|---|---|
| | Mean | Zero Return | 5% Insignificance |
| Raw Return | 42.75 | 1.19 | 1.15 |
| CAPM Alpha | 42.75 | 1.14 | 1.10 |
| FF-3 Alpha | 42.75 | 1.05 | 0.99 |

This table presents the turnover of the strategy that longs high ABNR stocks and shorts low ABNR stocks and monthly break-even transaction costs. The long and short legs are weighted by market value. Zero return refers to the transaction costs that would offset the raw or risk-adjusted returns (CAPM and FF-3 alphas). 5% Insignificance refers to transaction costs that make the raw and risk-adjusted returns insignificant at 5% level. The sample period covers 2009–2020.

**Table 3.8**

**Monthly average ABNR based on four liquidity measures**

| (1) ILLIQ | | (2) SIZE | | (3) QSP | | (4) ESP | |
|---|---|---|---|---|---|---|---|
| Low | 1.051 | Small | 1.056 | Low | 1.074 | Low | 1.073 |
| 2 | 1.053 | 2 | 1.049 | 2 | 1.055 | 2 | 1.054 |
| 3 | 1.051 | 3 | 1.045 | 3 | 1.043 | 3 | 1.044 |
| 4 | 1.046 | 4 | 1.048 | 4 | 1.040 | 4 | 1.041 |
| High | 1.046 | Big | 1.050 | High | 1.035 | High | 1.036 |
| Diff | -0.006 | Diff | -0.006 | Diff | -0.038* | Diff | -0.037* |
| *t*-stat | (-0.27) | *t*-stat | (-0.27) | *t*-stat | (-1.70) | *t*-stat | (-1.65) |

This table reports monthly average ABNR based on a series of liquidity measures. We sort stocks into quintiles based on four liquidity measures at the end of each month and hold for one month. In each quintile, we report the monthly average of ABNR. ILLIQ is the monthly Amihud (2002) measure of illiquidity. SIZE is the logarithm of market capitalization calculated as the number of shares outstanding times month end's share price. QSP (Quote spread) is the daily average of the difference between bid price and ask price divided by the midquote price in a month. ESP (Effective spread) is the daily average of the twice the absolute value of the difference between execution price and midquote price divided by the midquote price in a month. The sample period covers 2009–2020. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.9**

**FM regressions of abnormal retail/institutional investor trading volume on ABNR**

| Dept.Var. | AB_RETAIL | | | AB_INST | | |
|---|---|---|---|---|---|---|
| | (1)B+S | (2)S | (3)B-S | (4)B+S | (5)S | (6)B-S |
| ABNR | 0.041*** | 0.039*** | -11.516** | -0.025*** | -0.013*** | 6.771 |
| | (4.11) | (4.03) | (-2.22) | (-4.97) | (-2.72) | (1.08) |
| ABPR | -0.048*** | -0.045*** | -7.166 | 0.018*** | -0.006 | 4.524 |
| | (-5.63) | (-5.23) | (-0.85) | (3.91) | (-1.05) | (0.78) |
| ABNM | -0.014*** | -0.012** | -11.828** | 0.023*** | 0.035*** | 6.227 |
| | (-2.85) | (-2.31) | (-2.19) | (5.07) | (7.36) | (1.47) |
| ABPM | 0.037*** | 0.035*** | -6.922 | -0.048*** | -0.053*** | 6.237 |
| | (3.12) | (2.79) | (-1.04) | (-10.97) | (-13.10) | (0.83) |
| RET_M | -0.770*** | -0.730*** | - | 0.725*** | 0.331*** | -7.341 |
| | (-9.64) | (-10.00) | (-2.70) | (11.06) | (4.18) | (-0.35) |
| RET_6M | -0.338*** | -0.355*** | 0.045 | 0.234*** | 0.239*** | -1.338 |
| | (-7.29) | (-7.31) | (0.02) | (7.75) | (7.84) | (-0.28) |
| LNSIZE | -0.000 | -0.002 | 0.108 | 0.013* | 0.011 | -1.287 |
| | (-0.02) | (-0.09) | (0.10) | (1.95) | (1.56) | (-1.44) |
| LNBM | -0.020** | -0.021** | -1.540 | 0.018*** | 0.014*** | -2.077 |
| | (-2.23) | (-2.27) | (-1.05) | (3.55) | (2.97) | (-0.90) |
| ROE | 0.004 | 0.003 | 2.904 | -0.013* | -0.014** | 2.177 |
| | (0.27) | (0.17) | (0.76) | (-1.93) | (-1.98) | (1.07) |
| ASSET | 0.002* | 0.003* | -0.199 | -0.002* | -0.002* | -0.082 |
| | (1.87) | (1.89) | (-0.89) | (-1.79) | (-1.84) | (-0.20) |
| TOVR_ | -0.024*** | -0.025*** | -0.016 | 0.028*** | 0.027*** | 0.367 |
| | (-7.61) | (-7.38) | (-0.03) | (7.80) | (8.73) | (0.37) |
| SD_RET | -0.120*** | -0.125*** | 1.949 | 0.079*** | 0.075*** | -1.702 |
| | (-10.17) | (-10.51) | (0.71) | (10.55) | (10.39) | (-0.66) |
| ILLIQ_ | 0.100 | 0.050 | 21.367 | -0.195 | -0.162 | -17.90 |
| | (1.17) | (0.64) | (0.56) | (-1.37) | (-1.23) | (-0.58) |
| IO | -0.002* | -0.002* | -0.338 | -0.002** | -0.002* | -0.458 |
| | (-1.81) | (-1.74) | (-1.49) | (-2.55) | (-1.87) | (-0.99) |
| Adj_$R^2$ | 0.47 | 0.46 | 0.01 | 0.45 | 0.39 | 0.01 |
| N | 318,214 | 318,214 | 318,214 | 318,214 | 318,214 | 318,214 |

This table reports Fama-Macbeth regression estimates of regressing abnormal trading volume on intensity of intraday return reversal measures. Columns (1) and (4) provide the results when the dependent variable is the abnormal total retail/institutions trading volume (B+S) for firm $i$ in month $m$. Columns (2) and (5) report results for abnormal retail/institutions sales (S) volume. Columns (3) and (6) present results for abnormal retail/institutions net buys (B-S) volume. We identify trades from retail/institutional investors as those with trade order size below CNY50,000/above CNY200,000. The main variable of interest is the monthly abnormal frequency of negative daytime reversals i.e., ABNR. All variables are described in Appendix 3.1. The sample period covers 2009–2020. The $t$-stat is based on Newey-West robust standard errors.

**Table 3.10**

**Daily average retail investor turnovers sequentially based on overnight and daytime returns**

| | Equal-weight | | | | | | Value-weight | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First sort: R_CO, Second sort: R_OC | | | | | | | | | | | |
| R_CO \ R_OC | Low | 2 | 3 | 4 | High | Diff | Low | 2 | 3 | 4 | High | Diff |
| Low | 0.57 | 0.46 | 0.41 | 0.37 | 0.37 | 0.20*** | 0.55 | 0.47 | 0.39 | 0.36 | 0.36 | 0.19*** |
| | | | | | | (29.12) | | | | | | (29.45) |
| 2 | 0.59 | 0.48 | 0.43 | 0.40 | 0.39 | 0.19*** | 0.57 | 0.46 | 0.41 | 0.38 | 0.38 | 0.19*** |
| | | | | | | (24.37) | | | | | | (24.57) |
| 3 | 0.57 | 0.46 | 0.42 | 0.39 | 0.40 | 0.18*** | 0.55 | 0.45 | 0.40 | 0.37 | 0.38 | 0.17*** |
| | | | | | | (25.79) | | | | | | (25.95) |
| 4 | 0.61 | 0.48 | 0.44 | 0.41 | 0.44 | 0.17*** | 0.58 | 0.47 | 0.43 | 0.40 | 0.42 | 0.16*** |
| | | | | | | (23.34) | | | | | | (23.26) |
| High | 0.75 | 0.59 | 0.54 | 0.52 | 0.54 | 0.21*** | 0.73 | 0.57 | 0.52 | 0.50 | 0.52 | 0.21*** |
| | | | | | | (23.76) | | | | | | (23.91) |

This table presents the equal- and value-weighted daily average retail investor turnover of quintile portfolios sorted sequentially based on overnight and the subsequent daytime returns. On each day, we only focus on the subset of stocks with a positive overnight return followed by a negative daytime reversal and sort these stocks into quintiles by their overnight returns. Within each quintile, we then sort stocks into quintiles based on the respective daytime returns. We identify trades from retail investors as those with trade order size below CNY50,000. The retail investor turnover is computed as the trading volume from retail investors divided by the total number of shares outstanding. The sample period covers 2009–2020. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.11**

**Placebo test: negative daytime returns followed by positive overnight returns**

| Panel A: Summary statistics for day-to-night positive reversals | | | | | |
|---|---|---|---|---|---|
| | Mean | Median | Min | Max | SD |
| DOPR | 0.202 | 0.190 | 0 | 0.524 | 0.101 |
| ABDOPR | 1.049 | 0.994 | 0 | 3.548 | 0.544 |
| | | | Correlation | | |
| | | NR | | ABNR | |
| DOPR | | 0.632 | | 0.521 | |
| ABDOPR | | 0.520 | | 0.586 | |

| Panel B: Fama-Macbeth Regression | | | | | | |
|---|---|---|---|---|---|---|
| $RET_{im+1}$ | Coef. | *t*-stat | Coef. | *t*-stat | Coef. | *t*-stat |
| ABNR | 0.22*** | (3.28) | 0.22*** | (3.33) | 0.14*** | (2.73) |
| ABDOPR | -0.05 | (-0.75) | -0.05 | (-0.75) | -0.05 | (-0.75) |
| RET_M | -4.37*** | (-4.63) | -4.41*** | (-4.68) | -2.56** | (-2.55) |
| RET_6M | -0.01 | (-0.04) | -0.04 | (-0.13) | 0.63** | (2.06) |
| LNSIZE | -0.42** | (-1.96) | -0.43** | (-1.99) | -0.58*** | (-2.85) |
| LNBM | 0.07 | (-0.74) | 0.07 | (0.67) | 0.13 | (1.48) |
| ROE | | | 0.42 | (1.12) | 0.49 | (1.55) |
| ASSET | | | -0.05** | (-2.23) | -0.05** | (-1.97) |
| TOVR_M | | | | | -0.33*** | (-9.78) |
| SD_RET_M | | | | | 0.13 | (1.26) |
| ILLIQ_M | | | | | 4.32*** | (2.56) |
| IO | | | | | 0.03 | (1.28) |
| Adj_R2 | 0.06 | | 0.06 | | 0.09 | |
| N | 319,070 | | 319,070 | | 319,070 | |

This table reports the results of placebo tests. That is, we replace the abnormal frequency of positive overnight return followed by negative daytime return (ABNR) with an alternative return reversal measure based on daytime-to-overnight positive reversals (ABDOPR). DOPR is the fraction of days with negative daytime returns followed by positive overnight returns in a month. ABDOPR measures the abnormal frequency of DOPR in a month compared with its moving average of the past 12 months. Panel A presents the time-series averages of cross-sectional summary statistics of DOPR and ABDOPR and their Pearson correlations with NR and ABNR. Panel B presents estimates of Fama-MacBeth regressions where we extend the analysis in Table 3.5, by including ABDOPR as an additional independent variable. The dependent variable is the one-month ahead return. All variables are described in Appendix 3.1. The sample period covers 2009–2020. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.12**

**Overnight/Intraday component returns of long-short portfolios based on ABNR**

| | Overnight return | | | | | | | Daytime return | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ABNR | Excess | *t*-stat | CAPM | *t*-stat | FF-3 | *t*-stat | ABN | Excess | *t*-stat | CAPM | *t*-stat | FF-3 | *t*-stat |
| Low | -3.47*** | (-9.73) | -3.61*** | (-10.81) | -3.58*** | (-11.42) | Low | 4.55*** | (6.21) | 4.53*** | (6.37) | 4.55*** | (6.25) |
| 2 | -2.77*** | (-8.13) | -2.90*** | (-9.11) | -2.87*** | (-9.37) | 2 | 4.09*** | (5.69) | 4.06*** | (5.83) | 4.09*** | (5.64) |
| 3 | -2.47*** | (-7.26) | -2.59*** | (-8.14) | -2.57*** | (-8.29) | 3 | 3.86*** | (5.43) | 3.82*** | (5.58) | 3.87*** | (5.31) |
| 4 | -2.32*** | (-6.67) | -2.45*** | (-7.32) | -2.43*** | (-7.45) | 4 | 3.74*** | (5.25) | 3.69*** | (5.44) | 3.75*** | (5.18) |
| High | -2.30*** | (-6.56) | -2.43*** | (-7.25) | -2.41*** | (-7.32) | High | 3.78*** | (5.02) | 3.72*** | (5.20) | 3.79*** | (4.93) |
| H-L | 1.16*** | (18.46) | 1.18*** | (19.64) | 1.17*** | (18.44) | H-L | -0.77*** | (-5.19) | -0.81*** | (-5.24) | -0.76*** | (-4.64) |

This table reports value-weighted raw return, one-factor and three-factor alphas for each portfolio and long-short portfolio returns that longs stocks with the top 20% ABNR and shorts stocks with the bottom 20% ABNR. Each month, we sort stocks into quintiles based on ABNR, and we hold each portfolio for one month. We decompose the next month return for each firm into its cumulative overnight and daytime components. The sample period covers 2009–2020. Returns are in percent. The *t*-statistics are based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

**Table 3.13**

**ABNR and fundamental news**

Panel A: Clustering of ABNR during months with earnings announcements

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| Dept. Var. | $ABNR_{im}$ | *t*-stat | $ABNR_{im}$ | *t*-stat | $ABNR_{im}$ | *t*-stat | $ABNR_{im}$ | *t*-stat |
| EA_Month(0) | 0.089*** | (5.14) | 0.049** | (2.42) | 0.095*** | (4.79) | 0.107** | (3.57) |
| EA_Month(-1) | | | | | 0.102*** | (4.74) | 0.153*** | (3.74) |
| RET_M | -0.988*** | (-15.17) | -0.777*** | (-15.51) | -0.988*** | (-15.17) | -0.777*** | (-15.53) |
| RET_6M | | | 0.101*** | (10.82) | | | 0.101*** | (10.84) |
| LNSIZE | | | -0.018*** | (-3.31) | | | -0.018*** | (-3.30) |
| LNBM | | | -0.021*** | (-7.99) | | | -0.021*** | (-7.93) |
| ROE | | | -0.016 | (-1.20) | | | -0.016 | (-1.18) |
| ASSET | | | -0.000 | (-0.01) | | | -0.000 | (-0.07) |
| TOVR_M | | | -0.010*** | (-6.00) | | | -0.010*** | (-5.98) |
| SD_RET_M | | | -4.748*** | (-7.06) | | | -4.750*** | (-7.05) |
| ILLIQ_M | | | 0.024 | (0.28) | | | 0.025 | (0.29) |
| IO | | | 0.001* | (1.80) | | | 0.001* | (1.77) |
| Adj_R2 | 0.044 | | 0.076 | | 0.044 | | 0.075 | |
| N | 319,170 | | 319,170 | | 319,170 | | 319,170 | |

Panel B: ABNR predicting earnings surprises

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| Dept. Var. | $CAR_{-1,+1}$ | *t*-stat | $CAR_{-1,+1}$ | *t*-stat | SUE | *t*-stat | SUE | *t*-stat |
| ABNR | 0.070** | (2.14) | 0.071** | (2.14) | 0.023* | (1.76) | 0.034*** | (6.99) |
| Lagged | | | 0.863** | (2.43) | | | 0.309*** | (23.96) |
| RET_M | 5.780*** | (12.80) | 5.790*** | (12.77) | 1.354*** | (10.21) | 1.220*** | (10.25) |
| RET_6M | 0.270** | (2.08) | 0.251* | (1.90) | 0.788*** | (6.42) | 0.656*** | (6.24) |
| LNSIZE | 0.039 | (1.09) | 0.036 | (1.01) | 0.057*** | (3.49) | 0.032** | (2.49) |
| LNBM | -0.001 | (0.02) | 0.000 | (0.01) | -0.062*** | (-3.99) | -0.041*** | (-2.96) |
| ROE | 0.098 | (0.90) | 0.094 | (0.86) | 0.248*** | (3.52) | 0.052 | (1.16) |
| ASSET | 0.014 | (1.14) | 0.014 | (1.13) | -0.000 | (-0.06) | -0.009 | (-1.32) |

**Table 3.13 - *Continued***

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| TOVR_M | -0.090*** | (-4.74) | -0.091*** | (-4.79) | -0.016*** | (-3.36) | -0.017*** | (-3.62) |
| SD_RET_M | -0.089* | (-1.68) | -0.090* | (-1.71) | -9.666*** | (-5.83) | -6.981*** | (-5.28) |
| ILLIQ_M | 2.045** | (2.04) | 2.009** | (2.02) | 0.063 | (0.43) | 0.237* | (1.90) |
| IO | 0.018** | (2.34) | 0.018** | (2.30) | 0.014*** | (7.57) | 0.009*** | (6.11) |
| Adj_R2 | 0.05 | | 0.05 | | 0.07 | | 0.17 | |
| N | 301,658 | | 301,658 | | 290,986 | | 290,986 | |

This table presents estimate results of Fama-Macbeth regressions that relate ABNR and fundamental information. Panel A examines whether days with positive overnight returns followed by negative daytime return tend to cluster during months with earnings announcement (EA) release. The dependent variable is ABNR for stock *i* in month *m*. The independent variable of interest is a dummy variable EA_Month(0) that equals to one if EA occurs during a month, and otherwise zero. EA_Month(-1) equals the value of one during the previous month of EA occurrence, and otherwise zero. Other controls are the same as in Table 3.5. Panel B reports the results that regress earnings surprise measures for the next EA release on monthly ABNR. We measure earnings surprises in two ways. The first one is market-based measure, defined as the cumulative abnormal return over the three days around the next earnings announcement release. The abnormal return is calculated using the Fama and French (1993) three-factor model using the previous 250 daily data to estimate factor loadings for each stock, $CAR^{i}_{[-1,+1]}=\sum_{d=-1}^{+1}(Ret^{ex}_{id} - \widehat{\beta_1} \times SMB_d - \widehat{\beta_2} \times HML_d - \widehat{\beta_3} \times MKT_d)$, where d=0 indicates EA release days. We require stocks to at least have 150 trading days to estimate factor loadings. The second measure SUE is based on accounting rule. Following Foster et al. (1984), the model is built on the assumption that earnings per share follow a seasonal random walk. The expected earnings per share EPS at each semi-annual $q$ is estimated by the actual EPS at semi-annual *q-2*. SUE is calculated as the difference between the actual and expected EPS scaled by the standard deviation of the forecast errors over the previous 5 semi-annual intervals $SUE_{iq} = \frac{EPS_{iq}-EPS_{iq-2}}{\sigma_{i;q-6,q-1}}$. We include the most recent (lagged) earnings surprise as an independent variable in columns (2) and (4). Other controls are the same as in Table 3.5. The *t*-stat is based on Newey-West robust standard errors.

**Appendix 3.1**

**Variable descriptions and constructions**

| Variable | Description & Construction |
|---|---|
| NR | NR is defined as the ratio of the number of trading days with positive overnight return followed by the negative daytime return to the total trading days in month *m* for firm *i*. We require at least 15 trading days in each month to calculate NR. |
| ABNR | ABNR for firm *i* is defined as the ratio of NR in month *m* to its moving average of NR over the past 12 months. |
| PR | PR is defined as the ratio of the number of trading days with negative overnight return followed by the positive daytime return to the total trading days in month *m* for firm *i*. We require at least 15 trading days in each month to calculate PR. |
| ABPR | ABPR for firm *i* is defined as the ratio of PR in month *m* to its moving average of PR over the past 12 months. |
| ABNM | ABNM is defined as the ratio of NM in month *m* divided by its moving average over the previous 12 months, where NM is defined as the ratio of the number of days with negative overnight returns followed by negative daytime momentum to the number of total trading days during month *m*. |
| ABPM | ABPM is defined as the ratio of PM in month *m* divided by its moving average over the previous 12 months, where PM is defined as the ratio of the number of days with positive overnight returns followed by positive daytime momentum to the number of total trading days during month *m*. |
| DOPR | DOPR is defined as the ratio of the number of trading days with the negative daytime return followed by the positive overnight return to the total trading days in month *m* for firm *i*. |
| ABDOPR | ABDOPR for firm *i* is defined as the ratio of NR in month *m* to its moving average of DOPR over the past 12 months. |
| RET_M | RET_M is the standard monthly return in month m, obtained from CSMAR monthly file. |
| RET_6M | RET_6M is the cumulative stock return over the past six months, from month *m-6* to month *m-1*. |
| LNSIZE | LNSIZE is calculated as the logarithm of the market capitalization, where market capitalization is defined as the total number of shares (in thousands) outstanding for a firm multiplied by the close price on the last day of month *m*. |
| LNBM | LNBM is calculated as the logarithm of the book-to-market (BM) ratio, where the BM ratio is defined as the total shareholders' equity minus the book value of preferred stocks for the most recent quarter after announcement date divided by the market equity. The market equity is unadjusted close price multiplying by total outstanding shares of month *m*. |
| TOVR_M | TOVR_M is defined as the daily average turnover in month *m*, where daily turnover is calculated as trading volume (i.e., the number of shares traded) divided by the total number of shares outstanding. |
| SD_RET_M | SD_RET_M is computed as the standard deviation of daily returns in month *m*. |

## Appendix 3.1 - *Continued*

| | |
|---|---|
| ILLIQ_M | The firm's monthly Amihud (2002) illiquidity measure: $ILLIQ\_M_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{\lvert R_{imd} \rvert}{VOLD_{imd}}$, where $R_{imt}$ is the stock return for firm $i$ on day $d$ of month $m$, $VOLD_{imd}$ is the corresponding Yuan daily volume (in million), and $D_{im}$ is the number of days in month $m$ for which data are available. |
| ROE | Following Hou et al. (2015), ROE is calculated as the ratio of quarterly earnings to book equity. Earnings is the quarterly net profit minus nonrecurrent gains/losses for the latest fiscal quarter after announcement date. The book equity equals the total shareholders' equity minus the book value of preferred stocks. |
| ASSET | Following Fama & French (2015), we define ASSET as total assets in the most recent annual report after announcement date divided by total assets in the previous annual report. |
| IO | Institutional ownership is defined as the number of shares of firm $i$ held by all fund institutional investors for the latest fiscal quarter after announcement date divided by the number of shares outstanding. |
| QSP | QSP is the daily average of the difference between bid price and ask price divided by the midquote price in a month. |
| ESP | ESP (Effective spread) is the daily average of the twice the absolute value of the difference between execution price and midquote price divided by the midquote price in a month. |
| AB_RETAIL/ AB_INST | AB_RETAIL/AB_INST is calculated as the fraction of retail trading volume in a month divided by the firm's moving average over previous 12 months. The fraction of retail/institutional trading volume is defined as the ratio of the aggregate daily retail/institutional trading volume to total trading volume in a month. We construct three measures that represent monthly retail trading volume comprised of (i) retail sales, (ii) the total of retail buys and sales, and (iii) the net of retail buys, i.e., retail buys minus retail sales. We identify trades from retail/institutional investors as those with trade order size below CNY50,000/above CNY200,000. |
| TOVR $_{retail}$ | The retail investor turnover is computed as the trading volume from retail investors divided by the total number of shares ou tstanding, where trades from retail investors are defined as those with trade order size below CNY50,000 |
| CAR$_{-1,+1}$ | CAR$_{-1,+1}$ is defined as the sum of abnormal returns over [-1,+1] window around earnings announcement. The abnormal return is calculated using the Fama and French (1993) three-factor model using the previous 250 daily data to estimate factor loadings. |
| SUE | SUE is calculated as the difference between the actual and expected EPS scaled by the standard deviation of the forecast erro rs over the previous 5 semi-annual intervals $SUE_{iq} = \frac{EPS_{iq} - EPS_{iq-2}}{\sigma_{i;q-6,q-1}}$. |

## Appendix 3.2

## Long-short portfolio returns based on NR and PR

Panel A: Long-short portfolio returns sorted by NR

| | Value weight | | | Equal weight | | |
|---|---|---|---|---|---|---|
| NR | Excess | CAPM alpha | FF-3 | Excess | CAPM alpha | FF-3 alpha |
| Low | 0.96 | 0.77 | 0.79 | 0.97 | 0.78 | 0.80 |
| | (1.17) | (1.10) | (1.08) | (1.18) | (1.10) | (1.09) |
| 2 | 1.21 | 1.01 | 1.03 | 1.23 | 1.03 | 1.05 |
| | (1.51) | (1.51) | (1.48) | (1.52) | (1.52) | (1.49) |
| 3 | 1.388* | 1.19* | 1.23* | 1.41* | 1.21* | 1.26* |
| | (1.81) | (1.88) | (1.83) | (1.83) | (1.90) | (1.85) |
| 4 | 1.37* | 1.17* | 1.23* | 1.40* | 1.20* | 1.25* |
| | (1.78) | (1.83) | (1.78) | (1.80) | (1.84) | (1.79) |
| High | 1.38* | 1.19** | 1.26* | 1.42* | 1.22** | 1.29* |
| | (1.91) | (1.97) | (1.91) | (1.94) | (2.00) | (1.94) |
| H-L | 0.43*** | 0.42** | 0.47*** | 0.44*** | 0.44*** | 0.49*** |
| | (2.63) | (2.52) | (3.15) | (2.74) | (2.64) | (3.27) |

Panel B: Long-short portfolio returns sorted by PR

| | Value weight | | | Equal weight | | |
|---|---|---|---|---|---|---|
| PR | Excess raw | CAPM alpha | FF-3 alpha | Excess raw | CAPM alpha | FF-3 alpha |
| Low | 1.28* | 1.09* | 1.17* | 1.31* | 1.12* | 1.20* |
| | (1.77) | (1.83) | (1.78) | (1.79) | (1.86) | (1.80) |
| 2 | 1.45* | 1.26* | 1.31* | 1.48* | 1.29* | 1.34* |
| | (1.86) | (1.93) | (1.88) | (1.88) | (1.95) | (1.90) |
| 3 | 1.36* | 1.17* | 1.21* | 1.39* | 1.19* | 1.23* |
| | (1.75) | (1.79) | (1.75) | (1.77) | (1.81) | (1.77) |
| 4 | 1.27 | 1.07 | 1.09 | 1.29 | 1.09 | 1.11 |
| | (1.58) | (1.58) | (1.55) | (1.60) | (1.59) | (1.56) |
| High | 0.94 | 0.74 | 0.76 | 0.96 | 0.76 | 0.77 |
| | (1.19) | (1.10) | (1.08) | (1.20) | (1.11) | (1.09) |
| H-L | -0.34*** | -0.35** | -0.41*** | -0.35*** | -0.37*** | -0.43*** |
| | (-2.58) | (-2.54) | (-3.28) | (-2.70) | (-2.66) | (-3.42) |

This table reports value-weighed hedge portfolio raw returns, CAPM alphas and FF-3 alphas sorted based on NR (Panel A) and PR (Panel B). Each month, we sort stocks into quintiles based on one particular measure, and we hold each portfolio for one month. NR (PR) is calculated as the ratio of the number of days with positive (negative) overnight returns followed by negative (positive) daytime returns to the number of total trading days. The sample period covers 2009–2020. Returns are in percent. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

## Appendix 3.3

### FM regressions of future returns on NR/PR

| | NR | PR | RET_M | RET_6 | LNSIZE | LNBM | TOVR_M | SD_RET | ILLIQ_ | ROE | ASSET | IO | Adj_R$^2$ | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $RET_{im+1}$ | 1.33*** | -0.54 | -4.76*** | -0.01 | -0.47** | 0.10 | | | | | | | 0.05 | 317,050 |
| | (3.26) | (-1.63) | (-4.62) | (-0.02) | (-2.23) | (0.98) | | | | | | | | |
| $RET_{im+1}$ | 0.78** | -0.24 | -3.21*** | 0.55* | -0.63*** | 0.15 | -0.33*** | 0.12 | 3.82** | 0.57 | -0.03** | 0.03 | 0.08 | 317,050 |
| | (2.35) | (-0.76) | (-3.05) | (1.77) | (-3.13) | (1.64) | (-10.10) | (1.21) | (2.51) | (1.61) | (-2.25) | (1.43) | | |
| $RET_{im+2}$ | 0.12 | -0.10 | -0.06 | 0.71** | -0.49*** | 0.07 | -0.19*** | -0.04 | 4.24** | 0.00 | -0.05** | 0.03 | 0.06 | 313,505 |
| | (0.36) | (-0.35) | (-0.07) | (2.38) | (-2.94) | (0.82) | (-5.95) | (-0.45) | (4.00) | (0.01) | (-2.23) | (1.49) | | |

This table reports Fama-Macbeth regression estimates of regressing future returns on NR, PR and a series of other control variables listed in Table 3.3. The dependent variable of the first two specifications is the raw return for firm i in month *m+1*, while the dependent variable of the third specification is the raw return in month *m+2*. The main variables of interest are the monthly frequencies of negative and positive daytime reversals, respectively (NR and PR). The intercept for each specification is not shown below, for brevity. All variables are described in Appendix 3.1. The sample period covers 2009–2020. The *t*-stat is based on Newey-West robust standard errors with 12 lags. *, **, *** indicate significance at the 0.10, 0.05 and the 0.01 level respectively.

# Chapter 4

# Short Selling, Margin Buying, and Stock Return Predictability

## 4.1 Introduction

The relationship between short selling and stock returns has been discussed for decades. Diamond and Verrecchia (1987) argue for a negative relationship between short selling activities and future stock returns. They point out while binding constraints such as high shorting transaction costs prevent uninformed short sellers from providing liquidity in the market, these constraints do not affect informed ones if they have strong beliefs on the future stock price decline. Thus, informed short sellers become relatively more active than those uninformed, leading to a predictive relationship between short-sales and future stock returns. Supportive evidence can be found in Boehmer et al (2008, 2020, 2021), Christopher et al. (2004, 2010) and Engelberg et al. (2012) Wang et al. (2020).

Stock return predictability of margin buying is more ambiguous. As indicated in the existing literature, margin traders in Asian financial markets are mostly retail investors who are often considered as less informed, unsophisticated and more affected by their sentiments (Hirose et al., 2009; Chang et al., 2014; Bian et al., 2021). Empirical evidence on the relationship between margin buying activities and future returns are mixed: Hirose et al. (2009) find that margin buying information can positively predict future stock returns at short horizon in the Japanese stock market while Lee and Ko (2016) find that Japanese margin buyers can neither exploit undervalued stocks nor anticipate future price increase when they use different sample period and methodology. Chang et al. (2014) also find no evidence that margin buying activities or the covering of margin buying positions can predict future stock returns in the Chinese stock market.

This chapter contributes to existing literature by investigating the impact of a policy change in August 2015 on the predictive power of short selling and margin buying for future returns in the Chinese stock market. We further examine whether short sellers and margin buyers take advantage of private information and/or expertise to profit from their trading.

China provides a unique setting to explore this. First, although qualified stocks have been simultaneously allowed to be sold short and bought on margin since March 31,2010 in China, short selling is far less prevalent than margin buying in terms of both trading volume and margin balance due to very restrictive regulations on short selling. On one hand, typical stock lending institutions in developed countries such as mutual funds, pension funds are not allowed to lend stocks in China. On the other hand, security companies are only allowed to lend out their proprietary stocks as stipulated by the Chinese Security Regulatory Commission (CSRC). Hence, they are more willing to lend out blue-chip stocks as these stocks tend to be less volatile and unlikely to incur dramatic price drop. Moreover, the loan fee of short selling in China is much higher than that in the US. Hence the thin trading compared to developed financial market questions Diamond and Verrecchia (1987)'s argument that informed short-seller's play render the predictability on stock returns. As the heavy restrictions prevent rational investors entering into the short selling and margin buying markets, hence the incremental information on future returns may not exist for China.

Second, according to the 2018 Yearbook of the Shanghai Stock Exchange (SSE), 82% trading volume comes from individual investors in China. Some prior studies have shown that individual investors tend to incur losses (Barber and Odean, 2000, 2009) due to biased behavior and poor skills relative to institutions. Jones et al. (2021) examines retail investors' trading behavior using comprehensive account-level data from the Shanghai Stock Exchange (SSE) over the period 2016 to 2019. Their result shows that retail investors with account sizes less than CNY 10 million tend to buy and sell in the opposite directions of future price movements, whereas those with larger account sizes exhibit different patterns. Under the assumption that most short selling/margin buying volumes come from individual investors, our concern is whether information from short selling and margin buying can predict future price movement in China. If short sellers or margin traders' activities contain information for future stock returns, whether they tend to be more informed or sophisticated.

Third, the Chinese stock market experiences a notorious price hike followed by a crash in 2015, resulting in losing almost one-third market value in just two months. Short sellers and margin buyers are blamed for this stock crash and CSRC has imposed a series of constraints on short selling and margin trading since August 2015. Hence it is a nature setting to test the impact of the policy. We separate the whole sample into two subsamples using August 3,2015 as the breakpoint to investigate whether the tightening policy changes the return predictability and investor' behavior. Taken together, the unique institutional setting in China, provides us an opportunity to investigate the predictability of short selling/margin trading from multiple perspectives.

The sample consists of common A-share stocks that can be sold short and bought on margin over the period from December 5,2011 through November 29,2019. We exclude stocks from Growth Enterprise Market and Scientific Innovation Board for consistency of trading rules. We also eliminate stocks that have been special treated. We start from December 5,2011 when CSRC first expanded its list of eligible stocks. We discard the initial period from the launch day of March 31,2010 to December 4,2011 due to the thin trading volume.

We follow the methodology of Boehmer et al (2008) and form quintiles each day based on previous 5-day short selling/margin buying activity (SFR/MTR) and use calendar-time approach (Jegadeesh and Titman, 1993) to calculate future daily returns of portfolios and return differences between high and low SFR/MTR portfolios. Our baseline results show that before August 2015, short selling has negative predictive power for future stock returns and margin trading has positive predictive power for returns in the following week/month, while after August 2015, short selling has no predictive power for future stock returns and the sign of the predicted return of margin buying reverses to negative. Moreover, double sort analyses show that the predictive power of previous short selling activity is more pronounced among stocks with relatively small size, low volatility and low turnover ratio before 2015. In contrast, margin buying activity can predict future returns across all quintiles of firm characteristics such as size, book-to-market, volatility and turnover ratio before the policy change.

To explore potential explanations for the predictive power of short selling and margin buying, we examine whether the short sellers/margin buyers are informed or possess sophisticated skills of processing available information. We use earnings surprises and media corporate news to facilitate our investigation. Our results show that short sellers do take advantage of forthcoming earnings surprises and have superior skills to process firms' fundamental information before 2015 but not for second sub-period. For corporate news, we don't find any evidence that short sellers possess any private information or sophisticated skills. This suggests that short sellers mainly dig firms' fundamental information for their profits. In addition, our evidence suggest that margin buyers do not possess private information for the long period 2011-2019. The results also show that margin buyers are inferior to deal with publicly available information, especially with that contained in good news after the policy change in 2015.

Furthermore, we use daily transaction data to examine the impact of the ban on T+0 on the trading behavior of short sellers and margin buyers. Specifically, we follow Diether et al. (2009) and Chang et al. (2014) to regress daily short selling/margin buying activity on the contemporaneous stock return, past 5-day return, sell- (buy-) order imbalance, effective spread and intraday volatility. The results show that short sellers trade on temporary price rebound following low returns in the past week, and they provide liquidity in high contemporaneous buying pressure both before and after 2015. Positive coefficient of contemporaneous volatility and the negative coefficient of spread, suggest that short sellers trade as risk-bearers during periods of differences of opinions before August 2015, while it is not the case after 2015. For margin buyers, positive coefficients of past 5-day return in both samples suggest that margin buyers trade on momentum. However, different signs of coefficients on contemporaneous return in the two samples indicate that margin buyers seem better at identifying potentially underpriced stocks before August 2015. Our evidence also supports liquidity provision hypothesis by margin trading in both samples.

In summary, our results show that after the policy tightening, the short sellers/margin buyers could not predict future returns or predict correctly and they do not possess private information or have professional information-processing skills. These indicate that mainly irrational investors exist in the market due to heavy restrictions.

One relevant paper to ours is Chang et al. (2014), in which they mainly examine the impact of short-sale pilot scheme implementation on price efficiency and volatility whereas we focus on how the short-selling restriction influences the predictive power of short-selling/margin-buying on future stock returns. Ours differs from theirs in several ways. First, due to the data availability, their study only covers a two-year period (2010-2012) immediately following the allowance of short selling and margin trading. As indicated in Figure 4.1, the trading during the earlier part of their sample period is very thin. In addition, the sample size of eligible companies is small. Our sample period is much longer (2011-2019) and our sample size is much larger as many more stocks have been allowed for short selling and margin trading after December 5, 2011. This makes our results more representative and more reliable. Second, during our sample period, there is a significant policy change in 2015, which allows us to investigate the impact of the policy change. Third, using earnings surprises, media covered corporate news and transaction data, we further provide a batch of comprehensive analyses on the short-seller and margin trader's motivation, behavior and role in the overall stock market trading.

Another recent paper that is relevant to ours is Jones et al. (2021). They investigate the trading behavior and return performance of Chinese retail investors, whose trades account for over 80 percent of the total trading volume in the market. In comparison, our study mainly focuses on the leverage market where retail investors also take the dominance. In particular, we examine return predictability by short sellers and margin buyers. Our study differs theirs in the following way. First, their main target is the SHSE retail investors identified by the account indicator while ours mainly focus on short sellers and margin buyers. The scope of these investors provides a complement to their study as investigating the predictive power for future price movement of a specific group of investors with higher net wealth and better trading experience. Second, their sample only covers relatively tranquil periods after 2015 stock crisis while we go through both before and after crisis periods. We believe our study facilitates to see the consequence of policy interventions of Chinese authorities responding to crisis.

This chapter contributes to the literature in several ways. First, we implement additional evidence for the relationship between short selling/margin buying and stock returns of the Chinese stock market, which is the second largest in the world. Second, we examine the predictive power on stock returns in the presence of earning surprises and corporate news to see whether short sellers and margin traders are more sophisticated or trade on inside information. Third, we further examine how tightening of the restrictions on short selling and margin trading in August 2015 affects their predictive power on stock returns. Overall, our results provide asset pricing implications and are of interest to both policy makers and investors.

The rest of chapter is structured as follows. Section 4.2 discusses the related literature. Section 4.3 describes institutional backgrounds and data. Section 4.4 examines the return predictability of short selling/margin buying in general. Section 4.5 investigates return predictability around the news release. Section 4.6 explores trading behaviors of short sellers and margin buyers, and Section 4.7 concludes.

## 4.2 Related literature

We review the literature along three lines: (1) the predictive power of short selling on the future stock returns; (2) the predictive power of margin trading on the future stock returns; and (3) whether short sellers trade on insider information or sophisticated skills.

### 4.2.1 Short selling predictability on stock returns

One of the main streams of explanations for predictability of short selling on stock returns advanced by Diamond and Verrecchia (1987) is that short-sale constraints will prevent uninformed investors from providing liquidity thus relatively increasing the proportion of informed participants in the short-sale market, and ultimately leading to a negative relationship between shorting activities and stock returns.

The empirical literature examining the relationship between short-sales and future stock returns is voluminous. Earlier studies find mixed results by using monthly short interest as a proxy for shorting demand. Figlewski (1981), Brent et al. (1990) fails to document a significant relationship between the short interest and stock returns, whereas Desai et al. (2002) and Cohen et al. (2007) find a negative relationship between the two.

More recently, many studies employ short flow ratio as shorting selling activity measure. The negative relation between shorting volume and future stock returns is well reported. For example, Boehmer et al. (2008) show that heavily shorted stocks underperform lightly shorted stocks by an annual risk-adjusted average of 15.6% in the following 20 trading days after portfolio formation for NYSE stocks during the period 2000-2004. Using the similar proxy, Diether et al. (2009) document a negative relationship between short selling and future stock returns using the SEC-mandated short selling data for 2005. Takahashi (2010) documents the predictive power of short selling in Japanese market using the flow-based measure for shorting demand. Wang et al. (2020) find the negative return prediction on short selling in NYSE market using daily short volumes.

Chang et al. (2014) comprehensively studies on the leveraged trading in China. They find that short selling activities marginally predict future returns over five trading days and the covering activities of short positions has predictive power on stock returns over the next 20 trading days in Chinese stock market. However, their sample is small and only covers a short period of the short-selling activities when the market for these activities was less mature, and there was no short-selling restriction imposed.

Boehmer et al. (2021) provide a global perspective on the predictability of eight different short sale measures for future returns across 38 countries between 2006 and 2014. They conclude that the predictive powers of shorting measures are stronger in countries with more binding short-sale regulations, less market development, higher shorting costs, lower liquidity and lower market efficiency. Their findings are basically consistent with Diamond and Verrecchia (1987)'s theory that higher costs of short selling prevent uninformed short sellers from the market thus enhancing the informativeness in the short selling market.

### 4.2.2 Margin buying predictability on stock returns

It is evidenced that margin buyers in Asian financial markets are mostly retail investors whose transactions are often regarded as unsophisticated, speculative and easily affected by sentiments (Hirose, 2009; Bian et al., 2021). On one hand, as retail investors have long been considered as noise traders who are less informed and rational, there might be no predictive power of margin buying for future returns. On the other hand, it could also be possible that margin buyers' predicted returns move in the opposite direction of stock price movements in the future, as they are inferior to process firms' public information and displaying more behavioral biases (Jones et al., 2021). Furthermore, noise traders may further push prices away from their fundamental values if they follow herding behavior in a highly correlated manner (Delong et al., 1990) in a context of limits to arbitrage, thus resulting in a positive return prediction.

The empirical evidence on the relationship between margin trading and future stock returns are also mixed. Hirose et al. (2009) report that margin buying information can positively predict future stock returns for small firms at short horizon in the Japanese stock market. By contrast, Lee and Ko (2016) find that Japanese margin buyers can neither exploit undervalued stocks nor anticipate the future price increase. Although Chang et al. (2014) find evidence for the return prediction of short-selling activities, as mentioned above, they report no return predictability of either margin buying activities or the covering of margin buying positions in the Chinese stock market for the period 2010-2012.

### 4.2.3 Informed short selling around the information release

Since short sellers are generally regarded as more sophisticated or informed investors.

To determine whether the short selling predictability comes from their better skills to process public information or private information is of interest among academicians. On one hand, Christopher et al. (2004) uncovers a significant negative relationship between abnormal levels of short selling five days leading up to earnings announcement and post-announcement change in stock prices for 913 Nasdaq-listed firms, indicating large proportion of short sellers are informed. Christopher et al. (2010) further examine short selling prior to analyst downgrades and consequent stock price movements, and their results also show that short sellers can anticipate the magnitude of downgrades and take profitable positions in advance. They additionally show that the informed trading arises mainly because short sellers receive tips from insiders about firm's downgrade rather than they have superior analytical skills. More recently, Boehmer et al. (2020) find a large portion of short sellers' information incorporated into prices on days with fundamental events such as earnings announcements or the release of analyst reports. They also find that short sellers not only respond to public information but also have private information to enhance their performance.

On the other hand, Engelberg et al. (2012) examine daily short selling and stock price movements based on a large archive of corporate news release events for NYSE firms. They find weak evidence that short sellers can anticipate the news and trade before the news release but strong evidence that short sellers trade right after the news release and the prediction power for the future return is twice as strong upon the positive news release and four time as strong on negative news release. As such, they conclude that a substantial portion of short sellers' information advantage comes from their superior skills to process publicly available information, rather than they have private information regarding the forthcoming news. Wang et al. (2020) document a negative relationship between long-term shorting flows and future returns up to one year in NYSE over the period 2010-2015, but the abnormal short-term shorting flows can neither predict future returns, nor predict negative news. Their results also support the conjecture that short sellers are sophisticated.

Using Chinese data, Chen et al. (2016) report evidence that short selling/margin buying activities significantly escalates five days prior to the release of negative/positive information, indicating that Chinese short sellers/margin traders might have inside information.

To summarize, extant literature generally establishes that short sellers can predict future returns while the margin traders may not. Our study contributes to the literature by answering whether short selling/margin buying has predictive powers for future returns in the Chinese stock market. Specifically, we examine whether the restrictions imposed on short selling and margin trading in August 2015 changes the predictability. Furthermore, this study sheds lights on the debate by investigating whether short sellers/margin traders are informed or sophisticated in the Chinese stock market.

## 4.3 Institutional background and data

### 4.3.1 Institutional background

On March 31,2010, China launched a pilot scheme that allows designated stocks to be contemporaneously sold short and bought on margin. Qualified stocks should satisfy: 1) a minimum of 200 million tradable shares, 2) a public float of no less than RMB800 million, 3) more than 4000 shareholders, 4) on a three-month rolling basis, the daily turnover ratio more than 15% of benchmark index, 5) daily trading volume no less than RMB50 million, 6) daily returns deviation less than 4% from the benchmark index return.

Initially only 90 stocks were on the eligible list, after several rounds of expansions (see Panel C of Table 4.1), 1600 stocks were allowed to be sold short/bought on margin by 29 November 2019, accounting for 42.03% of the total number of A-share stocks and 84.57% of the market value of A-share stocks. The most recent major expansion occurs on 19 August 2019, with eligible stocks increasing from 950 to 1600 excluding stocks from Sci-Tech Innovative Board.

China's institutional setting is quite different from other countries in following ways. First, only qualified investors with minimum trading history of 20 days and minimum daily account balance of RMB500,000 for the recent 20 trading days are allowed to participate in short selling/margin buying. Second, transaction costs of short selling/margin buying are quite high. Normally security brokerages charge an annualized 7-9% short selling/margin buying loan fee plus transaction commission depending on investors' account size. However, in terms of trading convenience, margin buying is much easier than short selling since stock supply for lending is often scarce. Third, short selling volume is far less than margin trading volume. According to Development Report of China's Security Industry (2020), the average daily short selling volume (in CNY) accounts for 2.87% of average margin buying volume over 2019 and the daily average stock lending balance accounts for 1.15% of financing balance during the same period.

Furthermore, there is a structural change in terms of short-selling policy. Chinese stock market experiences a stock market crash from June 15 to August 26, 2015, with the China Securities Index (CSI300) plummeting from 5362 to 2952, a drop of 45%. To prevent markets from further declining, CSRC urgently came out with the T+1 trading rule on 3 August 2015 that prohibits short sellers paying back stocks borrowed on the same day. This modification largely reduces short selling trading volume. Shortly after the releasing of the T+1 trading rule, China Financial Futures Exchange (CFFX) imposed more restrictions such as largely reducing daily open positions of index futures to 10 lots per contract, dramatically increasing transaction commissions from 0.015% to 0.23% and margin requirement from 10% to 40%. These restrictions greatly discourage brokerage firms to lend stocks out given the fact that they have more difficulties in hedging their price risks. Hence, this policy change offers us an ideal opportunity to investigate its impact on the return predictability of short selling and margin buying.

### 4.3.2 Data and summary statistics

Our initial sample consists of common A-share stocks that can be sold short and bought on margin from December 5,2011 to November 29,2019. We exclude stocks from Growth Enterprise Market and Scientific Innovation Board for consistency of trading rules. We omit data records of 90 eligible stocks before the first expansion on December 5,2011 due to the thin trading volume. Data retrieved from China Stock Market Trading Research (CSMAR) include daily short selling volume, margin buying value, stock return and trading volume, market capitalization of each stock, and the company financial reporting data. We further exclude financial stocks indicated based on Guidelines for the industry classification of listed companies (2012 revision) by CSRC and stocks with trading days less than 10 in a calendar month. Our final sample consists of 811,407 firm-day observations for short selling and 1,258,819 for margin trading.

Figure 4.1 presents time-series data of short selling/margin buying for A-share stocks from 2010 to 2019. Short Flow Ratio (SFR) is measured as shorting volume divided by the total trading volume (in shares) of the stock and Margin Trading Ratio (MTR) is measured as margin buying volume divided by trading volume (in CNY).[24] Daily SFR/MTR are aggregated into monthly data. At the initial stage from April 2010 to April 2011, the proportion of short selling/margin buying of total trading is close to zero. Also, there is a sharp decrease in SFR after August 2015 while margin trading ratio only experiences a moderate decline around August 2015.

Table 4.1 reports summary statistics. As shown in Panel A, the magnitude of margin buying is much larger than short selling over the whole sample period, with MTR over 22 times of SFR. This discrepancy increases to 55 times after the harsh restrictions imposed on August 3,2015. Shorting activities sharply decrease, with shorting flow ratio being averaged 1.24% before August 2015 versus 0.31% after that. On the contrary, the time-series mean of margin buying ratio is slightly higher in the in the post August 2015 period than in the pre-August 2015 period (17.03 vs. 16.72).

Panel B presents firm characteristics of portfolios sorted based on short selling/margin buying activities. Following Boehmer et al. (2008), on each day, stocks are sorted into quintiles based on previous 5-day SFR/MTR and time-series averages of cross-sectional firm characteristics are reported. Firm size is measured as floating

[24] Due to data accessibility, we use volume in share to calculate SFR and value in CNY to calculate MTR.

market value in billion Yuan. Book-to-Market is defined as shareholders' equity scaled by the market capitalization. Volatility (Vol) is measured as high-minus-low price scaled by high price. Turnover ratio is measured as trading volume divided by floating number of shares.

As shown from Panel B, shorting activities of A-share stocks are strongly positively correlated with firm size measured by the firm's market capitalization. In addition, volatility and turnover ratio are both negatively correlated with shorting activities while book-to-market ratio is monotonically increasing in shorting activities. Recall security companies can only lend their proprietary stocks out in China and hedging tools are not widely available, therefore they are more willing to lend large and less volatile blue-chip stocks.

In sharp contrast, margin buying activities are largely negatively correlated with firm size but not correlated with BM ratio. Also, margin buyers like to trade stocks that have higher turnover and higher volatility. In short, short sellers and margin buyers seem to target stocks with different characteristics.

### 4.4 Empirical analyses

If short sellers/margin traders can predict future returns, the stocks heavily sold short/bought on margin should under-/outperform those lightly traded. On each day, we sort stocks into quintiles based on previous 5-day's SFR/MTR, equal-weighted portfolios are then held for 5 (a week) and 20 (roughly a month) trading days after skipping the first day of the portfolio formation to eliminate the possible interference of bid and ask bounce. Since portfolios are adjusted each day, there are overlapping holding day returns. To deal with this issue, we use calendar-time approach (Jegadeesh and Titman, 1993) to calculate average daily returns. Specifically, the portfolio holding period return is the simple average of the next 5 (or 20) daily portfolio returns, and one of the 5 (or 20) daily portfolios is rebalanced every day.

#### 4.4.1 Analyses based on univariate sorts

All stocks are sorted into 5 quintiles based on previous week SFR or MTR and hold for a week/month skipping one day after the portfolio formation. Table 4.2 presents equal-weighted portfolio returns and risk adjusted returns obtained from Fama-French 3-factor model for each quintile based on SFR, while Table 4.3 reports the results based on MTR. It is clear that before August 2015, the portfolio returns are largely decreasing with SFR. Table 4.2 shows that the average daily return for the 5-day holding period is 5.95 basis points (bps) with a $t$-value of 2.56 on most heavily shorted portfolio and 9.78 bps ($t=3.25$) on most lightly shorted portfolio, and the high-minus-low return difference being -3.83 bp ($t=-2.89$) or −9.58% per annum.[25] For the risk adjusted return, the high-minus-low is also negative, −2.17 bps, but it is statistically insignificant. However, on a monthly horizon, the average equal-weighted and risk-adjusted daily return differences are −3.26 and −2.86 bps (or −8.15% and −7.15% per annum) with $t$-values equal to −4.95 and −3.44, respectively. The results are largely consistent with the prior literature that finds a negative relationship between short selling and future stock returns (Boehmer et al., 2008, Diether et al., 2009, Wang et al., 2020).

As mentioned earlier, to prevent stock prices from further declining during the 2015 market crash, regulators imposed a series of bans to restrain short selling such as T+1 settlement, increasing transaction cost, and downsizing the index futures trading volumes. The result, as indicated in Table 4.1, is that SFR on average decreases by 75% from the pre-August 2015 period to the post-August 2015 period. Evidence from right part of Table 4.2 suggest that short selling has almost no information about future stock returns given positive and insignificant risk adjusted return differences between most heavily and most lightly shorted stocks after 2015.[26]

Why the 2015 policy on tightening short selling greatly impacts the predictability of short selling? In 2015, Chinese stock market loses almost two-thirds market value in just two months. To prevent the market further declining, Chinese authority imposes a series of strict policies respondingly. These constraints largely restrict short-selling activities and make the stock price less likely to reflect pessimistic information. As a

[25] Annualized return equals to daily return multiplying 250.
[26] To save space, we focus on risk-adjusted return.

result, short-selling will become less attractive in general, especially for sophisticated investors who expect to profit from short-selling. In addition, short constraints will limit day-traders to cover their positions on the same day and thus reduce their incentives to engage in the short selling as they may multi-day traders as well. These day traders are likely informed investor. Moreover, short-selling ban would worsen market quality, which is likely to make the signal generated form short-selling less convincing. These effects will all reduce the expected profitability from short selling such that more sophisticated short sellers may leave the market and return prediction will be weakened or even reversed. Our results show that heavy restrictions on short selling might not be an effective policy to incorporate news into stock prices and improve price efficiency.

For margin trading, Table 4.3 shows that before August 2015 the highest MTR stocks outperform the lowest MTR stocks by an average daily return of 6.09 bps ($t=7.19$) for equal-weighted portfolio and 5.24 bps ($t=5.27$) on a risk-adjusted basis in the following week, respectively; and 4.38 bps ($t=5.27$) for the equal-weighted portfolio and 4.15 bps ($t=7.86$) on the risk-adjusted basis in the following month, indicating that margin buying can positively predict future stock returns. In addition, portfolio returns are generally increasing in MTR. However, results exhibit somewhat different pattern after the August 2015 stock price crash. Specifically, stocks heavily bought on margin underperform those lightly bought on margin by a risk-adjusted daily return of 2.05 bps or −5.13% per annum ($t=-1.88$) on a weekly horizon and −1.95 bps or−4.88% per annum ($t=-3.23$) on a monthly horizon. The results show that margin traders predict stock returns in the wrong direction after the policy tighten.

The opposite return predictability pattern on MTR after August 2015 is somewhat in line with the results in Jones et al. (2021), in which they show that Chinese retail investors with small account balance (less unsophisticated) trade in the opposite direction of future price movements for the period 2016-2019. Based on their interpretation, the differences in return predictability of margin-buying may be because during pre-crisis period, relatively large proportion of retail investors with large account balance and institutions take participation in margin trading whereas after stock crisis, more retail investors with relatively small account size involve in the market.

It is also likely that most sophisticated investors do both margin trading and short selling to make profit. Once the short selling is restricted, they may also do less margin trading. This argument could be formally tested if the account type data for short selling/margin buying is available, as in Jones et al. (2021).

Notably, it is possible that the different return predictability between the two sub-samples is caused by stocks that are added to the eligible list after August 2015. It is reported that stocks are gradually added in the eligible trading list according to their past earnings performance, past volatility and liquidity since the pilot scheme launch. At the initial stage, only blue-chip stocks are allowed for this list. Over several rounds of expansion, the number has climbed to 1600, meaning that smaller and less well performed stocks are in the trading list. We report the timeline of expanding history in Panel C of Table 4.1. As can be seen, two more additions occur after August 2015 and the total number of eligible stocks increases from 900 to 1600.

This natural experiment enables us to roughly treat our separated samples as one containing relatively large and better performed stocks and the other with relatively small and worse performed stocks. Barber and Odean (2008) propose that retail investors are net buyers of attention-grabbing stocks, and they tend to pay more attention to non-essential information rather than fundamental information. The small, more volatile stocks have the attributes of being more attention-grabbing and thus attracting more unsophisticated retail investors. Therefore, it could be that more unsophisticated investors are attracted by those small and volatile stocks added in the trading list in our later period sample and caused counter intuitive predictability. To account for this possibility, we exclude stocks that are not in the eligible list in the earlier sample and obtain similar results as shown in Table 4.4.[27] The result shows that our findings of differences in return prediction patterns over two periods are not driven by stocks that are lately added into the trading list.

[27] For the sake of brevity, we only report high-low portfolio returns.

### 4.4.2 Double sort analyses

Prior literature has found several characteristics that relate to the cross-sectional differences in average returns. To examine whether these characteristics have impacts on short selling/margin buying predictability, we conduct double sorts based on both SFR/MTR and market capitalization, book-to-market ratio, volatility and turnover ratio, respectively.

We first sort stocks into quintiles based on these characteristics for the previous month. Size and book-to-market ratio are the values taken at the end of the previous month. Turnover is the average daily turnover in the previous month, while volatility is the daily average of high-minus-low price scaled by the high price in the previous month. Within a characteristic quintile, we then sort stocks into quintiles based on past 5-day short selling/margin buying activities and rebalance each day. Similarly, we follow Boehmer et al. (2008) to calculate portfolio returns in the following 20 trading days skipping the first trading day after the portfolio formation.[28] We report FF 3-factor risk adjusted return differences between heavily and lightly shorted/margin bought portfolios within a specific characteristic group.

Table 4.5 and 4.6 present the double sorting results for short selling and margin buying, respectively. Begin with firm size or market capitalization in Panel A Table 4.5, for the subsample before August 2015, the following 20-day risk-adjusted portfolio return differences between heavily and lightly shorted stocks (high-minus-low) are negatively significant for the two smallest quintiles and statistically insignificant for the rest 3 quintiles, indicating that the return predictability on SFR mainly exists among small size stocks. For the subsample period after August 2015, we see no clear patterns across the size quintiles: the hedge strategy generates significant negative returns for the 2nd and 3rd size quintiles while positive returns for the rest quintiles. The high-minus-low return differences are negatively significant for the second and third smallest size quintiles and positively significant for the rest 3 quintiles.

[28] We report double sorting results for holding 5 trading days in the Appendix 4.1 and 4.2. Results are qualitatively the same.

In Table 4.6, we see that in the first subsample the high-minus-low returns based on margin trading are positive and significant across all size quintiles which echoes the finding in Table 4.3 that margin traders can predict future returns before August 2015. In the second subsample period after August 2015, margin trading affects the high-minus-low return in the wrong direction across four out of five size quintiles, indicating the predictability of margin trading is generally not affected by size.

Short sellers seem to be able to predict negative returns for all but the third quintile portfolios sorted on BM in the first subsample period. The prediction is poor in the second subsample, i.e., they can only predict negative high-minus-low return for the fourth quintile (see Table 4.5 Panel B). Similarly, margin trading can predict positive high-minus-low return for all quintiles in the first subsample period but have wrong prediction in the second subsample period for 3 out of 5 quintiles (see Table 4.6 Panel B). Hence, the SFR and MTR prediction power seems not dependent too much on BM.

It is well known that more volatile stocks underperform less volatile stocks (Ang et al., 2006). One might consider that volatile stocks may be those that are heavily shorted if the volatility reflects severe divergence of opinion. To account for this effect, we control for volatility. As seen, return differences between heavily shorted stocks and lightly shorted stocks are negative for four quintiles in the first subsample period, although only significant in the lowest volatile quintile, with risk adjusted returns being −4.02 basis points ($t=-3.02$) per day (see Table 4.5 Panel A). In the second subsample, short selling is associated with the negative high-minus-low return of quintiles 2 and 3 but the positive return of quintile 5 (see Table 4.5 Panel B). Table 4.6 shows that stocks heavily bought on margin outperform those lightly bought on margin across all quintiles in the first subsample period, with risk adjusted returns ranging from 3.87 to 8.95 bps (all are statistically significant at the 1% level) per day before 2015. The signs of the predicted return of margin buying are significantly negative in quintiles 1, 3, and 5 after August 2015, suggesting that margin buying return predictability is robust across different volatile groups, even they are in wrong sign.

Brennan et al. (1998) find that firms with high trading volume underperform those with low trading volume. To rule out the possibility that the predictive power of shorting is driven by trading volume, we control for trading volume. The result shows that stocks with heavy shorting activity significantly underperform those with light shorting activity across quintiles 1, 2, and 4 in the following month before the policy tightening in August 2015. For the period after the policy tightening, SFR predicts the negative and significant high-minus-low return for quintiles 2 and 3. However, for the most heavily traded quintile, the high-minus-low return is significantly positive. Overall, the short selling predictive power is more pronounced in relatively low trading volume quintiles, which is consistent with the notion that mispricing of stocks with low trading volume is more difficult to be arbitraged away. Therefore, we infer that trading volume can explain short-selling return prediction at most partially. For margin trading, the results are similar to that of volatility. MTR can still predict positive high-minus-low return controlling for trading volume in the first subperiod while the prediction has a wrong sign for most quintiles in the second subsample.

In sum, we find that the previous 5-day short selling and margin-buying activities remain predictive power on future returns after controlling size, BM ratio, volatility and trading volume, return predictors that well documented in the literature. In addition, short selling has predictability among stocks with relatively small size, low volatility and trading volume before 2015. In contrast, margin buying activity can predict significant positive future returns in the following month among stocks with different firm characteristics before the policy change and this return predictability goes to opposite direction after August 2015 in most quintiles. The possible reason may be that a too restrictive policy on short selling and margin trading lead to fewer informed traders participating in the short selling/margin buying activities. The remainder are noise traders that are less informed, more irrational and less sophisticated.

### 4.4.3 Fama-Macbeth regressions

To provide more evidence on the predictability of short selling/margin buying activities on future returns with controlling past returns, size, BM, volatility and turnover ratio simultaneously, we run Fama-MacBeth (1973) regressions on the form:

$$Ret_{i;t+2,t+m} = \alpha + \beta_1 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) + controls + \varepsilon_{it} \qquad (4.1)$$

where $m$ equals to 6 or 21. For day $t$, the dependent variable is rolling stock return in 5-, 20-days (i.e.$t+2$ to $t+6$ and $t+2$ to $t+21$) over December 5,2011 through November 29,2019 and the explanatory variable is shorting flow/margin buying ratio five days prior to day $t$. For each day $t$, we run cross-sectional regressions on above variables controlling for firm characteristics, including previous month of size, BM ratio, volatility, turnover, and last month return. Then we calculate time-series average of coefficients to make inferences.

The results reported in Table 4.7 are consistent with portfolio analysis in Table 4.2 and 4.3. Specifically, 10% increase in SFR results in daily average return over the next 20 trading days of 0.077% (*t=3.15*) lower after controlling firm characteristics before August 2015, while no return predictability can be observed for the second subsample. The coefficient of SFR on future returns in shorter horizon (i.e., in a week) is significant at 10% level with a set of controls before August 2015 while becomes negligible in the more recent sample. Results for margin buying show that when there is 10% increase in margin buying ratio, future returns over next 5- and 20-trading days are 0.032% and 0.030% (*t=2.84 and 4.82*) higher on a daily basis after controlling for variables mentioned above before the T+0 ban was imposed. However, the signs of the coefficients both reverse to negative (*t=−1.71 and −2.96*) after 2015. These results support that the predictive power of short-selling and margin-buying on stock returns before 2015, and the reversed predictability of margin-buying after 2015, are robust to past month returns, size, BM, volatility and turnover ratio.

### 4.5 Return predictability and information advantage

There is overwhelming evidence that short sellers have information advantage over other traders. One common claim refers to short sellers taking advantage of their private information before it is released to public, to make profits (Christopher et al., 2004, 2010; Boehmer et al., 2020). For example, Christopher et al. (2004) report evidence of informed trading 5 days prior to earnings announcement release. Another possible explanation for short sellers' information advantage relates to short sellers' ability to process public information. Engelberg et al. (2012) argue that a substantial portion of short sellers' information advantage comes from their superior skills to process publicly available information, rather than they have private information regarding the forthcoming news.

Therefore, in this subsection, we investigate whether the return predictability we report is due to sellers/margin buyers trade against forthcoming news or their superior information processing skills. We argue that if short sellers/margin buyers can anticipate forthcoming news, their trading activities just before news events release would indicate more negative/positive future returns per unit increase in trading activity. Alternatively, if they have superior skills to process publicly released information, their trading activities on news arrival days are likely to have stronger predictive power for future returns compared with those on non-news-arrival days.

We test these hypotheses by using two types of news elements, the earnings surprise and media corporate news. In particular, we run cross-sectional Fama-Macbeth regressions by adding dummies that indicate the occurrence of different types of news, and their interactions with short selling/margin buying activities to see whether the return predictability is enhanced in different cases.

### 4.5.1 Return predictability and informed trading

We begin by exploring whether short sellers/margin buyers trade on information of earnings releases (Christopher et al., 2004, 2010). In the spirit of Akbas et al. (2017), we classify the earnings announcements into negative and positive news events (POS_EA and NEG_EA) based on their cumulative abnormal returns over [−1,+1] daily window around earnings release events. $CAR_{[-1,+1]}$ is estimated using Fama-French 3-factor model:

$$CAR^{i}_{[-1,+1]}=\sum_{t=-1}^{+1}(Ret^{ex}_{it} - \widehat{\beta_1} \times SMB_t - \widehat{\beta_2} \times HML_t - \widehat{\beta_3} \times MKT_t) \quad (4.2)$$

where $t$=0 indicates each earnings release date. $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$ are estimated using previous 250 daily data by Fama-French three factor model for each stock. We define the dummy variable $POS\_EA_{it}$/$NEG\_EA_{it}$ that equals to one if the firm $i$ has positive/negative $CAR_{[-1,+1]}$ on day $t$, and zero otherwise.

We run Fama-Macbeth regressions of daily average returns in the subsequent week/month on the previous week SFR/MTR and interactions with POS_EA and NEG_EA in the form of:

$$Ret_{i;t+2,t+m} = \alpha + \beta_1 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) + \beta_2 POS\_EA_{it}$$
$$+\beta_3 NEG\_EA_{it} + \beta_4 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) \times POS\_EA_{it}$$
$$+\beta_5 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) \times NEG\_EA_{it} + controls + \varepsilon_{it} \quad (4.3)$$

where $m$=6 or 21. We hypothesis that if short sellers/margin traders trade against earnings surprises in the right direction, the coefficients of the interaction terms are expected to be significantly negative with respect to SFR and significantly positive to MTR. For example, the negative coefficient of SFR interacted with NEG_EA suggest that one unit increase in SFR one week prior to negative earnings events would result in more declines in future returns. This enhanced return predictability may be because short sellers can anticipate forthcoming earnings news in advance. As firms mostly announce their earnings within a short period in China, there would be zero announcements outside these periods.[29] To make sure we have enough observations to estimate Fama-Macben coefficients in equation (4.3), we only include days with at least 3% of total number of firms with earnings announcements. We also control size, BM, turnover ratio, volatility and returns of previous month, as previously.

Table 4.8 Panel A shows results for the short sellers. For the earlier sample period, the coefficient of the interaction term of NEG_EA and SFR is −9.33 with significant $t$-statistics of −2.00 for the period [t+2, t+6], while that of the term interacted with

[29] In China, firms are required to report their financial statements to regulators before four preset deadline dates each year.

POS_EA is insignificant. This finding indicates that the return predictability of SFR is strengthened for the following week in the case of negative earnings surprise, indicating that short sellers can anticipate a series of, especially, pessimistic earnings release events. By contrast, the coefficients of the interaction term for the later sample period are insignificantly negative, consistent with our prior finding that short selling has no predictive power for future returns.

Panel B reports results for margin traders. As can be seen from all columns, the coefficients of terms that are interacted with MTR are never significant regardless of earnings event type and holding period length, both before and after the policy change. Therefore, we conclude that margin buyers do not take advantage of forthcoming earnings news.

Next, we use corporate news as an alternative information source to test the informed trading hypothesis. We obtain corporate news information from CSMAR database. This database contains corporate news from mainstream media in China such as cninfo, Security Newspaper etc. Each observation in the database has a unique identifier and represents a piece of news occurrence for a stock. If the news releases occur at non-trading hours, we treat the release day as the next available trading day. We use the unique identifier to match the news data with the short selling/margin trading database. The sample contains matched 193,764 firm-day news observations over the sample period from December 5,2011 to November 29,2019. For each day, we assign stocks into *with* and *without* news announcement portfolios. Average returns, trading value, volatility and other firm characteristics are then calculated for the two portfolios accordingly.

Table 4.9 provides summary statistics for news release data and the corresponding average daily trading data of with (without) news release portfolios, in which stocks are eligible for short selling and margin trading during the whole sample period. As shown in Panel A, news release mostly occurs on non-trading sessions with 171,888 out of 193,764 cases. There is roughly 46.3% news released on weekends which is defined as Saturday and Sunday. This is a common practice to avoid excess market volatility caused by news announcement. Panel B reports the mean stock return, volatility, trading value, and turnover ratio for *with* and *without* news portfolios across the sample period. It is obvious that the average stock return tends to be much higher when there is news announcement comparing to that *without* news release. Also, trading volume in CNY, volatility and turnover ratio are all higher for stocks during the days with news release than those of without.

As it could be the case that investors respond differently to different types of news, we use the sign of the cumulative abnormal returns over [-1,+1] window around news release events as a proxy for news type (positive vs negative news) following Akbas et al. (2017). $CAR_{[-1,+1]}$ is calculated as the same method mentioned in Equation (4.3). We define GOODNEWS/BADNEWS for stock *i* on day *t* that equals to one if they have positive/negative $CAR_{[-1,+1]}$ around news release day *t*, and zero otherwise. We report day-firm observations for two types of news in Panel C of Table 4.9. As can be seen, news release occurrence is more frequent during our earlier period sample, with the percentage of 25.67% (108,399/422,141) in first sample period versus that of 10.14% after 2015. Good news occurrence accounts for 11.38% of total day-firm sample before August 2015 while it accounts only 4.75% in our later period sample. Similar result is for bad news occurrence (14.30 vs 5.40).

To test whether the predictability derived from short selling and margin buying before 2015 takes information advantage from private information, we add GOODNEWS (BADNEWS) indicator variables and interaction terms SFR (MTR)× GOODNEWS (BADNEWS) into Equation (4.1). The indicator variable GOODNEWS(BADNEWS) takes value one if a stock is covered by positive (negative) news on day *t*, zero otherwise. To ensure enough observations, we only include days with at least 3% of total number of firms with news releases.

$$Ret_{i;t+2,t+m} = \alpha + \beta_1 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) + \beta_2 GOODNEWS_{it} + \beta_3 BADNEWS_{it} + \beta_4 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) \times GOODNEWS_{it} + \beta_5 SFR_{i;t-5,t-1}(MTR_{i;t-5,t-1}) \times BADNEWS_{it} + controls + \varepsilon_{it}$$

(4.4)

where $m$=6 or 21. Control variables include firm size, book-to-market, volatility, trading volume and previous month returns. If the coefficient of the interaction term is significant with the "right" predicted sign (i.e., positive for MTR×GOODNEWS and negative for SFR×BADNEWS), then we argue that it is likely that short sellers/margin buyers make use of their private information ahead of news and can better predict the future returns.

Table 4.10 presents the results. Panel A shows that the coefficients of interaction terms are either not statistically significant or positive for short sellers, indicating no evidence that short sellers possess private information about corporate news. For margin buyers, the coefficients of the interaction terms are significantly negative after August 2015, indicating that margin buyers do not correctly trade on the forthcoming news information. This is consistent with our baseline results that margin traders wrongly predict future returns for that period. We also show weak evidence that margin traders exploit information before 2015, as the coefficients of the interaction terms exhibit different signs in case of good and bad news. The differences in return prediction pattern between using earnings announcements and corporate news before 2015 suggest that the content of media news stories may contain information beyond firms' fundamental values.

### 4.5.2 Return predictability and information-processing ability

In this subsection, we seek to examine whether the return predictability can be explained by another hypothesis that short sellers/margin buyers have superior capability in dealing with information contained in publicly available earnings and corporate news rather than private information.

To answer this question, we run Fama-Macbeth regressions in the forms of:

$$Ret_{i;t+m} = \alpha + \beta_1 SFR_{it}(MTR_{it}) + \beta_2 GOOD\_EA_{it} + \beta_3 BAD\_EA_{it}$$
$$+\beta_4 SFR_{it}(MTR_{it}) \times GOOD\_EA_{it} + \beta_5 SFR_{it}(MTR_{it}) \times$$
$$BAD\_EA_{it} + controls + \varepsilon_{it} \quad (4.5)$$

$$Ret_{i;t+m} = \alpha + \beta_1 SFR_{it}(MTR_{it}) + \beta_2 GOODNEWS_{it} + \beta_3 BADNEWS_{it}$$
$$+\beta_4 SFR_{it}(MTR_{it}) \times GOODNEWS_{it} + \beta_5 SFR_{it}(MTR_{it}) \times BADNEWS_{it} + controls + \varepsilon_{it} \quad (4.6)$$

where *m*=6 or 21. The independent variables are SFR or MTR for firm $i$ on day *t*, earnings/news indicators and their interactions with SFR or MTR. GOOD_EA/BAD_EA is the dummy variable that equals to one if the firm $i$ has positive/negative $CAR_{[-1,+1]}$ on day $t$ around earnings announcement events, and zero otherwise. GOODNEWS/BADNEWS is set to equal one if the cumulative abnormal return around news release events for firm $i$ is positive/negative, and otherwise zero.

To make sure there are enough observations to run FM regressions, we include days with earnings/news release events at least 3% of the total firm-day observations. If the coefficients of the interaction terms are significantly negative for news indicators interacted with SFR, and are significantly positive for indicators interacted with MTR, we can make inference that these traders perform well at processing public information.

The results regarding earnings announcements are reported in Table 4.11 and those regarding corporate news are reported in Table 4.12. The coefficient of the term NEG_EA interacted with contemporaneous SFR on future returns in the [2,6] daily window is significantly negative at 7.54 (*t=-2.09*), as shown in the first column of Panel A, Table 4.11. This suggests that short sellers are good at dealing with information that conveys firms' less than expected earnings performance before August 2015. By contrast, there is no evidence showing that short sellers can analyze public earnings information properly after 2015, indicating that sophisticated investors may leave the market owing to the shorting ban policy. For margin buyers, the coefficients of the interaction terms are never significant regardless of the earnings surprise type and the sample period, indicating that margin buyers do not well process firms' fundamental information for their profits.

In addition, results in Table 4.12 show no supportive evidence for short sellers having superior ability to deal with information contained in public news, as the coefficients of the interaction terms are insignificant regardless of time period and holding length. For margin trading, the coefficients of the term interacted with the indicator of negative $CAR_{[-1,+1]}$ around news release (i.e., bad news) are all negligible for four specifications, indicating that margin buyers are no good at dealing with information in the case of bad news. It is also worth mentioning that the coefficients of MTR interacted with good news events are all negative and most (3 out of 4) are significant at least 5% level, suggesting that margin buyers perform worse when there is positive news release. This result is consistent with our baseline results showing that margin traders wrongly predict future returns after August 2015 and echoes the findings in Jones et al. (2021) that Chinese retail investors are inferior to dealing with public information and generate "wrong" predicted returns.

In sum, our results in this section evidence that short sellers possess private information about firms' earnings surprises, especially negative surprises, and have superior skills to process firm-specific information related to their fundamental values before August 2015, while these informational advantages do not exist after the policy change. For margin buyers, the wrongly predicted sign of their trades on future returns after 2015 is probably owing to their inferiority to deal with publicly available information contained in good news. Also, our evidence show that they could not anticipate the forthcoming corporate news.

### 4.6 Impacts of policy tightening on trading behavior

Our results have shown that the shorting ban on T+0 in August 2015 affects the return predictability on short selling and margin buying. In this section, we make a comparison of trading behavior of short sellers and margin buyers before and after this shorting ban implementation to see whether policy changes leveraged investors' trading. In particular, we run Fama-MacBeth regressions following Chang et al. (2014) separately before and after the policy change in the form of:

$$SFR_{it}(MTR_{it}) = \alpha + \beta_1 Ret_{it} + \beta_2 Ret_{i;t-5,t-1} + \beta_3 buy\_oib_{it} + \beta_4 sell\_oib_{it}$$

$$+Vol_{it} + Spread_{it} + controls + \varepsilon_{it} \qquad (4.7)$$

where the coefficients of contemporaneous ($\beta_1$) and past 5-day returns ($\beta_2$) reveal how short sellers/margin buyers respond to historical and contemporaneous stock prices respectively.

In addition, to examine whether short sellers/margin buyers provide liquidity to stocks under high buying/selling pressure, we add contemporaneous buy- (sell-) order imbalance (Lee and Ready, 1991). If short sellers/margin buyers provide liquidity in high buying/selling pressure, their increased trading volume would be accompanied by higher buying/selling order imbalance (or equivalently lower selling-/buying-OIB). Diether et al. (2009) propose that short sellers benefit from providing liquidity on days with high buying pressure when the buying pressure subsidies and stock prices converge to their fundamentals among US stocks. However, Chang et al. (2014) do not find any supporting evidence during 2010 and 2012 in Chinese stock market.

Moreover, we follow Diether et al. (2009) to add contemporaneous volatility (Vol) and information asymmetry (Spread) measures to examine whether short sellers/margin buyers act as opportunistic risk bearers during periods of increased uncertainty. If the uncertainty is caused by asymmetric information, then their increased shorting activity would coincide with higher information asymmetry and higher volatility. If the uncertainty is caused by increased divergence of opinions, then their increased volume would coincide with lower information asymmetry and higher volatility. Following them, we use intraday volatility calculated as high price minus low price divided by high price to measure uncertainty and use volume-weighted average of the effective spread to measure information asymmetry and divergence of opinions (Diether et al., 2009; Chang et al., 2014), where the effective spread is calculated as the twice the absolute value of the difference between execution price and midquote price divided by the midquote price.

We run cross-sectional Fama-Macbeth regression of Equation (4.7) and report results in Table 4.13. Column (1) and (2) present results before August 2015 while column (3) and (4) report those for the later period. We use control variables such as past 5-day dependent variables, past 5-day buy (sell) order imbalance, past 5-day volatility, past

5-day trading volume, past-5-day firm size and past 5-day BM, following Chang et al. (2014). We argue that if they trade differently over different sample periods, we would see different coefficients of interest.

### 4.6.1 Trading patterns of short sellers

The results of short sellers are reported in column (1) and (3) of Table 4.13. As can be seen, the magnitudes of all coefficients are mostly much smaller after 2015, which is reasonable as SFR drops to a large extent in the second period sample. The coefficient of the past 5-day return is significantly negative and the coefficient of contemporaneous return is significantly positive for both samples, indicating that short sellers trade against temporal price rebound after experiencing several days' price drop. Our result is similar to that of Chang et al. (2014) on China.

In addition, the result shows that in both period sample, SFR is positively related to contemporaneous buying pressure and negatively related to contemporaneous selling pressure, consistent with liquidity provision hypothesis. Our result is different from Chang et al. (2014) in that they do not find any significant relation between buying pressure and short selling activity whereas we do. We attribute it to the difference in the sample period we use.

The negative coefficient of spread for short selling in our earlier sample period suggests no worsening of information asymmetry is associated with SFR, consistent with our earlier evidence that short sellers do not derive their information advantage from media news before August 2015, while not align with our findings of their exploiting earnings announcements as their informational source. The positive coefficient of contemporaneous volatility 4.31($t=11.52$) and the negative coefficient of spread −0.13 ($t=-3.07$) suggest that short sellers trade as risk-bearers in periods of high divergent opinions before August 2015. By contrast, the insignificance of the coefficient of volatility after 2015 reveals no evidence for short sellers as risk bearers.

### 4.6.2 Trading patterns of margin buyers

The results for margin buyers are presented in column (2) and (4) of Table 4.13. The coefficients of past 5-day return are significantly positive for both samples, indicating that margin buyers trade on momentum and they expect price continuation in the future. However, the coefficients of contemporaneous return exhibit different patterns over two periods. Specifically, the coefficient of contemporaneous return on MTR reveals that 10% increase in stock return is associated with 0.03% decrease in MTR before 2015, suggesting that margin buyers are likely to identify temporary underpricing stocks. By contrast, there is 0.13% increase in MTR associating with 10% increase in contemporaneous return after stock crisis, indicating that margin traders seem more irrational in picking stocks in our later period sample, given the reversed predictive sign after 15 August 2015.

The coefficients of order imbalance in both samples suggest that increased margin buying is associated with higher selling pressure as well as lower buying pressure which is consistent with the notion that margin buyers act as liquidity providers in higher selling pressure. There is no evidence that margin buyers trade as risk bearers when there is high uncertainty as their trading activity is negatively related with intraday volatility.

To conclude, our results in this section show that Chinese margin buyers trade on momentum but respond differently to contemporaneous return under different policy environment. They trade more irrationally in our later period sample. In contrast, Chinese short sellers relatively more irrational, as they trade on temporary price rebound following low returns in the past week for both sample periods, although the coefficients are much smaller in magnitudes after August 2015. Both of them seem to provide liquidity on days with high buying or selling pressure and short sellers also act as risk-bearers during periods of differences of opinions before policy change.

### 4.7 Conclusion

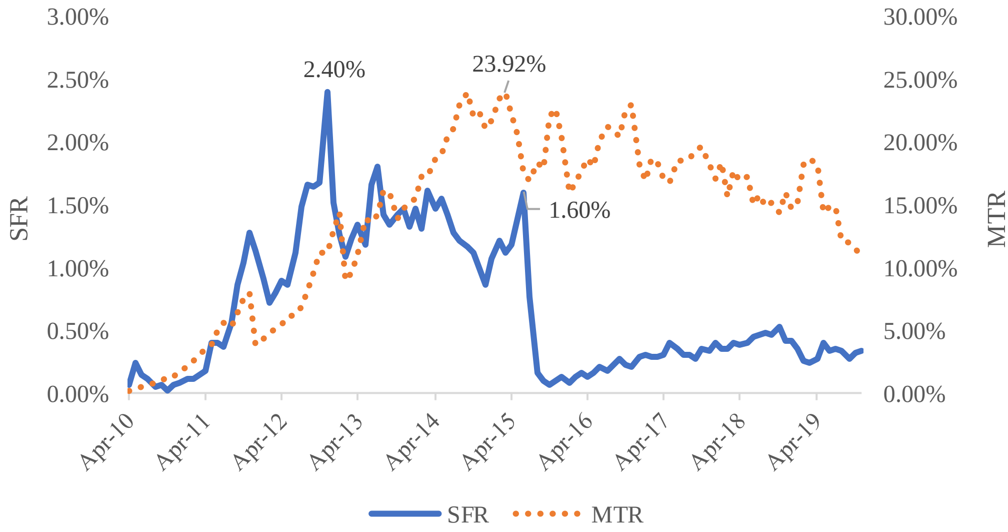
In this study, we comprehensively examine the predictive power of short-selling and margin-buying activities for future returns using the daily frequency data in the Chinese market for the period of 2011–2019. We also investigate the impact of the ban on T+0 in August 2015 on the return prediction of short selling/margin buying. Both portfolio analyses and Fama-Macbeth regressions support the hypothesis that short selling and margin buying can predict future returns before policy tightening in 2015 while this predictability becomes negligible for short selling after August 2015 and even in the opposite direction for margin buying.

We explore how short seller/margin buyers derive their information advantages by examining the return predictability in the presence of earnings surprise and corporate news. Our results suggest that short sellers can anticipate the forthcoming earnings announcements and have superior earnings-information-processing skills before August 2015 but not after the shorting ban. By contrast, there is no evidence showing that margin buyers trade on their private information on earnings surprises. We also show evidence that the “wrong” predicted returns generated by margin buyers after 2015 are related to their poor skills to process publicly available information, especially in the case of good news.

Finally, the results of short sellers/margin buyers’ trading behavior before and after the shorting ban suggest that short sellers tend to trade against temporary price increase while margin buyers seem to be able to detect temporary underpricing stocks before 2015. However, the coefficient of the contemporaneous return against SFR becomes much smaller in magnitudes and the sign against MTR turns to opposite after the shorting ban on T+0 was imposed, indicating that the policy change may be the reason that prevents relatively more informed and sophisticated investors from trading in the market, hence the trading behavior becomes more irrational after 2015.

**Figure 4.1**

**Time-series trends of the shorting flow ratio (SFR) and margin trading ratio (MTR)**




The sample consists of all eligible common A-share stocks excluding financial firms from 31 March 2010 to 29 November 2019. SFR is defined as shorting volume divided by trading volume (in shares). MTR is defined as margin buying volume divided by trading volume (in CNY). Daily SFR/MTR are aggregated into monthly data.

**Table 4.1**

**Summary statistics of main variables**

| Panel A: Summary statistics of SFR/MTR (in percent) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Obs (firm- | Mean | Median | Min | Max | SD |
| Full Period: | SFR | 811,407 | 0.75 | 0.27 | 0.00 | 6.10 | 1.14 |
| 05/12/2011-29/11/2019 | MTR | 1,258,819 | 16.93 | 16.68 | 2.23 | 37.22 | 7.37 |
| Sub-period 1: | SFR | 371,100 | 1.24 | 0.67 | 0.00 | 6.10 | 1.44 |
| 05/12/2011- | MTR | 416,438 | 16.72 | 16.63 | 2.23 | 37.22 | 8.08 |
| Sub-period 2: | SFR | 440,307 | 0.31 | 0.16 | 0.00 | 0.26 | 0.43 |
| 03/08/2015- | MTR | 842,381 | 17.03 | 16.70 | 3.28 | 36.64 | 6.96 |

| Panel B: Portfolio Characteristics based on SFR/MTR Sorting | | | | | |
|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High |
| SFR (%) | 0.08 | 0.21 | 0.42 | 0.84 | 1.87 |
| Firm Size | 15.80 | 20.90 | 25.40 | 32.80 | 39.50 |
| Vol (%) | 3.72 | 3.55 | 3.48 | 3.38 | 3.24 |
| Turnover ratio (%) | 2.29 | 1.94 | 1.79 | 1.56 | 1.25 |
| BM ratio | 0.66 | 0.67 | 0.72 | 0.73 | 0.74 |
| MTR (%) | 10.58 | 14.55 | 17.03 | 19.53 | 24.12 |
| Firm Size | 41.50 | 28.20 | 20.50 | 16.20 | 11.80 |
| Vol (%) | 3.45 | 3.48 | 3.54 | 3.59 | 3.56 |
| Turnover ratio (%) | 1.35 | 1.70 | 1.91 | 2.09 | 2.11 |
| BM ratio | 0.65 | 0.71 | 0.70 | 0.70 | 0.69 |

| Panel C: Expansion process | | | |
|---|---|---|---|
| Addition before August 2015 | | Addition after August 2015 | |
| 31/03/2010 | Initially 90 stocks are added | 12/12/2016 | No. of eligible stocks: 950 |
| 05/12/2011 | No. of eligible stocks: 285 | 18/08/2019 | No. of eligible stocks: 1600 |
| 31/01/2013 | No. of eligible stocks: 494 | | |
| 16/09/2013 | No. of eligible stocks: 700 | | |
| 22/09/2014 | No. of eligible stocks: 900 | | |

This table reports summary statistics of short selling/margin buying activities and firm characteristics for common A-share stocks that are allowed to be sold short/bought on margin from December 5,2011 through November 29,2019. Panel A reports time-series averages of cross-sectional shorting flow/margin trading ratio for different periods. SFR is defined as shorting volume scaled by trading volume in shares. MTR is defined as margin buying volume scaled by trading volume in CNY. Panel B reports portfolio characteristics based on previous five-day SFR/MTR for eligible stocks over the same period. Firm size is measured as floating market value in billion yuan. Book-to-market is measured as shareholders' equity scaled by the market capitalization. Volatility (Vol) is measured as high-minus-low price scaled by high price. Turnover ratio is measured as trading volume divided by floating number of shares. Panel C reports the date and numbers of eligible stocks since the pilot scheme takes into effect on March 31,2010.

**Table 4.2**

**Long-short portfolio returns based on SFR**

| | 05/12/2011-31/07/2015 | | | | 3/8/2015-29/11/2019 | | | |
|---|---|---|---|---|---|---|---|---|
| | [2,6] Raw | [2,6] Alpha | [2,21] Raw | [2,21] Alpha | [2,6] Raw | [2,6] Alpha | [2,21] Raw | [2,21] Alpha |
| Low | 9.78*** | 5.68* | 9.60*** | 8.54*** | -2.40 | -2.23 | -2.07** | -2.02 |
| | (3.25) | (1.89) | (6.31) | (4.53) | (-1.10) | (-0.99) | (-2.01) | (-1.56) |
| 2 | 9.18*** | 5.46* | 9.93*** | 8.94*** | -1.60 | -1.45 | -1.83* | -1.78 |
| | (3.20) | (1.89) | (6.96) | (5.07) | (-0.79) | (-0.70) | (-1.91) | (-1.48) |
| 3 | 8.23*** | 4.69* | 8.96*** | 8.03*** | -0.53 | -0.39 | -1.30 | -1.26 |
| | (2.96) | (1.66) | (6.44) | (4.67) | (-0.26) | (-0.19) | (-1.45) | (-1.11) |
| 4 | 7.11*** | 4.03 | 7.41*** | 6.60*** | -0.70 | -0.57 | -1.38 | -1.34 |
| | (2.80) | (1.54) | (5.83) | (4.14) | (-0.36) | (-0.29) | (-1.58) | (-1.21) |
| High | 5.95*** | 3.50 | 6.34*** | 5.68*** | -1.71 | -1.60 | -1.42* | -1.38 |
| | (2.56) | (1.42) | (5.21) | (3.69) | (-0.90) | (-0.81) | (-1.65) | (-1.27) |
| H-L | -3.83*** | -2.17 | -3.26*** | -2.86*** | 0.70 | 0.63 | 0.65** | 0.64 |
| | (-2.89) | (-1.53) | (-4.95) | (-3.44) | (0.93) | (0.69) | (1.96) | (1.48) |

This table reports the average daily equal-weighted raw excess returns and Fama-French 3-factor alpha of quintile portfolios over two different periods. The first subsample period spans from December 5,2011 to July 31,2015 and the second spans from August 3,2015 to November 29,2019. Each day, stocks are sorted into quintiles based on the previous 5-day SFR and hold for the following 5 and 20 trading days after skipping one day. This process is repeated for each trading day. For portfolios with holding period for 5 (20) trading days, its daily return is an average of 5 (20) different daily portfolios returns with 1/5 (1/20) of the portfolio rebalanced each day. We present daily calendar-time returns in bps. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 4.3**

**Long-short portfolio returns based on MTR**

| | 05/12/2011-31/07/2015 | | | | 3/8/2015-29/11/2019 | | | |
|---|---|---|---|---|---|---|---|---|
| | [2,6] Raw | [2,6] Alpha alpha | [2,21] Raw | [2,21] Alpha alpha | [2,6] Raw | [2,6] Alpha alpha | [2,21] Raw | [2,21] Alpha alpha |
| Low | 5.42** | 2.53 | 6.93*** | 6.18*** | 1.57 | 1.70 | 1.14 | 1.18 |
| | (2.23) | (1.00) | (5.74) | (4.07) | (0.87) | (0.92) | (1.31) | (1.08) |
| 2 | 6.31** | 3.05 | 6.86*** | 6.01*** | -1.18 | -1.03 | -1.11 | -1.06 |
| | (2.36) | (1.11) | (5.19) | (3.64) | (-0.58) | (-0.49) | (-1.14) | (-0.87) |
| 3 | 8.44*** | 4.98* | 8.41*** | 7.49*** | -1.62 | -1.43 | -1.43 | -1.38 |
| | (3.08) | (1.78) | (6.12) | (4.38) | (-0.74) | (-0.64) | (-1.36) | (-1.04) |
| 4 | 8.91*** | 5.32* | 8.76*** | 7.81*** | -1.80 | -1.59 | -1.91* | -1.85 |
| | (3.21) | (1.90) | (6.11) | (4.39) | (-0.78) | (-0.68) | (-1.72) | (-1.33) |
| High | 11.51*** | 7.77*** | 11.30*** | 10.33*** | -0.59** | -0.35 | -0.84 | -0.77 |
| | (4.08) | (2.77) | (7.85) | (5.80) | (-0.24) | (-0.14) | (-0.72) | (-0.53) |
| H-L | 6.09*** | 5.24*** | 4.38*** | 4.15*** | -2.16** | -2.05* | -1.98*** | -1.95*** |
| | (7.19) | (5.27) | (10.45) | (7.86) | (-2.19) | (-1.88) | (-4.18) | (-3.23) |

This table reports the average daily equal-weighted raw excess returns and Fama-French 3-factor alpha of quintile portfolios over two different periods. The first subsample period spans from December 5,2011 to July 31,2015 and the second spans from August 3,2015 to November 29,2019. Each day, stocks are sorted into quintiles based on the previous 5-day MTR and hold for the following 5 and 20 trading days after skipping one day. This process is repeated for each trading day. For portfolios with holding period for 5 (20) trading days, its daily return is an average of 5 (20) different daily portfolios returns with 1/5 (1/20) of the portfolio rebalanced each day. We present daily calendar-time returns in bps. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 4.4**

**Long-short portfolio returns for samples excluding stocks not on the list before August 2015**

| | | [2,6] | [2,6] | [2,21] | [2,21] |
|---|---|---|---|---|---|
| | | Excess | FF-3 alpha | Excess | FF-3 alpha |
| $SFR_{-5,-1}$ | H-L | 0.62 | 0.55 | 0.68** | 0.67 |
| | *t*-stat | (0.82) | (0.60) | (2.05) | (1.55) |
| $MTR_{-5,-1}$ | H-L | -1.72* | -1.61 | -1.80*** | -1.77*** |
| | *t*-stat | (-1.77) | (-1.50) | (-3.82) | (-2.95) |

This table presents long-short raw return and FF 3-factor alpha differences between stocks with top 20% SFR/MTR and those with bottom 20% SFR/MTR over August 2015 through November 2019. Each day, stocks are sorted into quintiles based on the previous 5-day SFR/MTR and hold for the following 5 and 20 trading days skipping one day after portfolio formation. We exclude stocks that are not in the trading list before August 2015, i.e., those that become eligible after August 2015 are eliminated. We present daily equal-weighted calendar-time returns in bps. Newey-west adjusted *t*-statistics are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 4.5**

**Monthly long-short portfolio returns based on SFR across firm characteristics**

| Panel A: 05/12/2011--31/07/2015 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | -1.81** | Low | -3.87*** | Low | -4.02*** | Low | -4.69*** |
| | (-2.51) | | (-3.47) | | (-3.02) | | (-4.09) |
| 2 | -2.57** | 2 | -6.41*** | 2 | -1.69 | 2 | -6.24*** |
| | (-2.40) | | (-5.73) | | (-1.57) | | (-5.78) |
| 3 | -1.41 | 3 | -1.25 | 3 | 0.67 | 3 | -0.36 |
| | (-1.39) | | (-1.00) | | (0.62) | | (-0.32) |
| 4 | -0.98 | 4 | -1.99* | 4 | -1.54 | 4 | -1.83* |
| | (-0.96) | | (-1.67) | | (-0.99) | | (-1.77) |
| Big | 0.36 | High | -1.96* | High | -1.60 | High | -1.16 |
| | (0.55) | | (-1.72) | | (-1.37) | | (-1.01) |
| Panel B: 03/08/2015--29/11/2019 | | | | | | | |
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | 2.14*** | Low | -1.07 | Low | -0.18 | Low | -0.33 |
| | (4.13) | | (-1.56) | | (-0.61) | | (-0.92) |
| 2 | -1.27*** | 2 | 0.00 | 2 | -2.41*** | 2 | -1.12*** |
| | (-3.02) | | (0.11) | | (-5.88) | | (-2.73) |
| 3 | -1.06*** | 3 | -0.16 | 3 | -1.83*** | 3 | -2.05*** |
| | (-2.84) | | (-0.30) | | (-4.20) | | (-4.64) |
| 4 | 1.45*** | 4 | -1.64*** | 4 | 0.14 | 4 | -0.14 |
| | (3.22) | | (-3.76) | | (0.33) | | (-0.29) |
| Big | 1.19** | High | 1.25*** | High | 3.56*** | High | 1.87*** |
| | (2.36) | | (2.95) | | (7.12) | | (4.00) |

This table reports the long-short portfolio alphas based on double sorting. Panel A reports the results for the period from December 5,2011 to July 31,2015 and the Panel B for the period from August 3,2015 to November 29,2019. Firms are first sorted into quintiles based on a given characteristic at previous month end. Within each quintile, firms are then sorted into quintiles based on the SFR. See notes in Table 4.1 for the description of firm characteristics. Daily equal-weighted returns in basis points are calculated using a calendar-time approach with a holding period of 20-trading days, in which the Fama-French alpha is an average of 20 different daily portfolio returns rebalanced each day. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 4.6**

**Monthly long-short portfolio returns based on MTR across firm characteristics**

| Panel A: 05/12/2011--31/07/2015 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | 8.50*** | Low | 5.01*** | Low | 8.26*** | Low | 9.57*** |
| | (13.24) | | (5.71) | | (12.55) | | (9.32) |
| 2 | 7.57*** | 2 | 8.88*** | 2 | 8.95*** | 2 | 5.60*** |
| | (10.01) | | (12.28) | | (11.87) | | (6.49) |
| 3 | 3.26*** | 3 | 8.87*** | 3 | 4.20*** | 3 | 5.96*** |
| | (4.94) | | (11.09) | | (4.52) | | (6.48) |
| 4 | 6.65*** | 4 | 7.98*** | 4 | 4.15*** | 4 | 6.44*** |
| | (8.48) | | (10.44) | | (4.69) | | (12.52) |
| Big | 3.08*** | High | 4.06*** | High | 3.87*** | High | 7.40*** |
| | (3.55) | | (5.78) | | (4.83) | | (7.82) |
| Panel B: 03/08/2015--29/11/2019 | | | | | | | |
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | 3.87*** | Low | -5.02*** | Low | -2.40*** | Low | -2.78*** |
| | (8.99) | | (-5.58) | | (-4.99) | | (-5.06) |
| 2 | 0.58 | 2 | -1.60** | 2 | -0.69 | 2 | -3.29*** |
| | (1.31) | | (-2.22) | | (-1.38) | | (-5.27) |
| 3 | -3.55*** | 3 | 0.19 | 3 | -1.86*** | 3 | -2.08*** |
| | (-7.59) | | (0.27) | | (-2.74) | | (-3.72) |
| 4 | -6.60*** | 4 | 0.49 | 4 | -0.64 | 4 | 0.59 |
| | (-12.59) | | (0.79) | | (-0.78) | | (0.93) |
| Big | -7.67*** | High | -2.33*** | High | -3.01*** | High | 4.97*** |
| | (-11.84) | | (-5.13) | | (-4.41) | | (7.11) |

This table reports the high-minus-low portfolio alphas based on double sorting. Panel A reports the results for the period from December 5,2011 to July 31,2015 and the Panel B for the period from August 3,2015 to November 29,2019. Firms are first sorted into quintiles based on a given characteristic at previous month end. Within each quintile, firms are then sorted into quintiles based on the MTR. See notes in Table 4.1 for the description of firm characteristics. Daily equal-weighted returns in basis points are calculated using a calendar-time approach with a holding period of 20-trading days, in which the Fama-French alpha is an average of 20 different daily portfolio returns rebalanced each day. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

## Table 4.7

## FM regressions of future returns on SFR/MTR

| Panel A: SFR | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 05/12/2011-31/07/2015 | | | | 3/8/2015-29/11/2019 | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | [2,6] | [2,6] | [2,21] | [2,21] | [2,6] | [2,6] | [2,21] | [2,21] |
| $SFR_{-5,-1}$ | -1.56** | -0.80* | -1.31*** | -0.77*** | -0.53 | -1.39 | -0.38 | -0.76 |
| | (2.39) | (-1.65) | (-3.37) | (-3.15) | (-0.27) | (-1.16) | (-0.37) | (-1.26) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| TS obs | 888 | 888 | 888 | 888 | 1033 | 1033 | 1033 | 1033 |
| N | 402,897 | 401,270 | 402,897 | 401,270 | 588,041 | 574,008 | 588,041 | 574,008 |
| Adj_$R^2$ | 0.01 | 0.08 | 0.01 | 0.08 | 0.01 | 0.09 | 0.01 | 0.09 |
| Panel B: MTR | | | | | | | | |
| $MTR_{-5,-1}$ | 0.51*** | 0.32*** | 0.39*** | 0.30*** | -0.16 | -0.16* | -0.17** | -0.14*** |
| | (3.54) | (2.84) | (5.30) | (4.82) | (-1.07) | (-1.71) | (-2.10) | (-2.96) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| TS obs | 888 | 888 | 888 | 888 | 1033 | 1033 | 1033 | 1033 |
| N | 412,849 | 411,157 | 412,849 | 411,157 | 809,776 | 790,367 | 809,776 | 790,367 |
| Adj_$R^2$ | 0.01 | 0.08 | 0.01 | 0.09 | 0.02 | 0.08 | 0.02 | 0.09 |

This table reports the daily Fama-Macbeth (FM) regressions of future excess returns on previous 5-day short selling/margin buying activities over two different periods over two sample periods. The dependent variable is the average daily excess return in percent for the next week [2, 6] or for the next month [2, 21]. The independent variable in Panel A is SFR and that in Panel B is MTR. The control variables include past month return, market capitalization, book-to-market ratio, volatility, turnover of previous month. See notes in Table 4.1 for the description of firm characteristics. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 4.8**

**FM regressions of future returns on previous week SFR/MTR, earnings surprises, and their interactions**

| Panel A: SFR | | | | |
|---|---|---|---|---|
| | 5/12/2011-31/7/2015 | | 3/8/2015-29/11/2019 | |
| | (1) | (2) | (3) | (4) |
| LHS variable | [2,6] | [2,21] | [2,6] | [2,21] |
| $SFR_{-5,-1}$ | 3.90** | 0.68 | -7.45 | -5.37 |
| | (2.31) | (1.50) | (-0.85) | (-1.46) |
| NEG_EA | 0.14** | -0.01 | -0.02 | 0.00 |
| | (2.47) | (-0.73) | (-0.48) | (0.03) |
| POS_EA | 0.01 | 0.02 | 0.10*** | 0.02 |
| | (0.12) | (1.45) | (4.17) | (1.24) |
| NEG_EA × $SFR_{-5,-1}$ | -9.33** | -0.14 | -8.98 | -4.63 |
| | (-2.00) | (-0.09) | (-0.38) | (-0.47) |
| POS_EA × $SFR_{-5,-1}$ | -1.14 | 1.02 | -7.22 | 5.95 |
| | (-0.38) | (0.83) | (-0.55) | (0.59) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 51 | 51 | 65 | 65 |
| N | 23,330 | 23,330 | 35,711 | 35,711 |
| Adj-$R^2$ | 0.06 | 0.05 | 0.05 | 0.06 |
| Panel B: MTR | | | | |
| $MTR_{-5,-1}$ | 0.92*** | 0.57** | 0.31 | 0.07 |
| | (2.57) | (1.98) | (0.84) | (0.49) |
| NEG_EA | 0.01 | -0.05 | 0.01 | -0.05* |
| | (0.06) | (-0.17) | (0.09) | (-1.71) |
| POS_EA | -0.09 | -0.01 | 0.09 | 0.01 |
| | (-0.64) | (-0.17) | (1.43) | (0.35) |
| NEG_EA × $MTR_{-5,-1}$ | 0.78 | 0.56 | -0.27 | 0.12 |
| | (0.88) | (1.19) | (-0.76) | (0.78) |
| POS_EA × $MTR_{-5,-1}$ | 0.63 | 0.34 | -0.33 | -0.04 |
| | (0.77) | (0.89) | (-0.87) | (-0.22) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 51 | 51 | 72 | 72 |
| N | 23,884 | 23,884 | 55,838 | 55,838 |
| Adj-$R^2$ | 0.06 | 0.07 | 0.07 | 0.07 |

This table presents Fama-MacBeth (FM) regression results examining the relation between future returns, previous week short selling/margin buying activities and earnings news over two sample periods. Panel A reports results for short selling while Panel B for margin trading. The dependent variable is the average daily excess return in percent for the next week [2, 6] or month [2, 21]. The independent variables include SFR/MTR, positive/negative earnings surprise indicators, and their interactions with SFR/MTR. We use POS_SUE and NEG_SUE dummies to proxy for positive and negative earnings surprises, where POS_SUE/NEG_SUE for firm *i* on day *t* is equal 1 if its $CAR_{[-1,+1]}$ around earnings release is positive/negative, otherwise zero. $CAR_{[-1,+1]}$ is estimated using FF-3-factor model. We control for firm size, BM, volatility, trading volume and return of last month. *t*-statistics are reported using Newey-West standard errors. *, **, ***denote the 10%, 5%, 1% significance level.

**Table 4.9**

**The distribution of news releases and the associated trading data**

Panel A: Firm-day observations

| By release day | Firm-day obs | % | By trading session | Firm-day obs | % |
|---|---|---|---|---|---|
| Weekday | 140,051 | 53.70 | Trading session | 21,875 | 11.29 |
| Weekend | 89,712 | 46.30 | Non-trading session | 171,888 | 88.71 |
| Total | 193,764 | 100 | Total | 193,764 | 100 |

Panel B: Trading data of stock portfolios based on news release

| | Mean Daily Return (bps) | Mean Trading value (Million Yuan) | Volatility (%) | Turnover ratio (%) |
|---|---|---|---|---|
| News Release | 32.56 | 708 | 3.86 | 2.10 |
| No News Release | 2.85 | 261 | 3.43 | 1.71 |

Panel C: Firm-day obs of good/bad news

| | 5/12/2011-31/7/2015 | | 3/8/2015-29/11/2019 | |
|---|---|---|---|---|
| | Number | % | Number | % |
| Firm-day obs with news release | 108,399 | 25.67 | 85,365 | 10.14 |
| Firm-day obs with good news release | 48,033 | 11.38 | 39,953 | 4.75 |
| Firm-day obs with bad news release | 60,377 | 14.30 | 45,412 | 5.40 |
| Total firm-day obs | 422,141 | 100 | 841,663 | 100 |

This table presents summary statistics of media corporate news release over the period 05/12/2011 through 29/11/2019. Panel A displays the distribution of news release by release day and by trading session. Weekend refers to Saturday and Sunday while weekdays are the rest days. The trading session is from 9:30 to 11:30am and 13:00 to 15:00 of weekdays when stocks are allowed to trade in the market while non-trading session is all the rest of time. Panel B displays portfolio characteristics such as daily raw return, trading value, volatility and turnover ratio for stocks with and without news. News release information is obtained from CSMAR. We use the unique identifier to match news release information with daily stock trading database and short selling/margin buying database. We adjust news release days as follows: 1) If news release occurs after 15:00 on Monday, Tuesday, Wednesday and Thursday or at any time on Sunday, we match them to the next calendar day; 2) If news release occurs on Saturday, we match them to the next two calendar days; 3) If news release occurs after 15:00 on Friday, we match them to next three calendar days. We drop all financial stocks and the stocks with missing data. Panel C reports the distribution of good and bad corporate news over two periods, where the news type is measured by the sign of the cumulative abnormal return over [-1,+1] window around news release events. The news for stock *i* is considered as good/bad if CAR is positive/negative.

**Table 4.10**

**FM regressions of future returns on previous week SFR/MTR, news type, and their interactions**

| Panel A: SFR | | | | |
|---|---|---|---|---|
| | 05/12/2011-31/07/2015 | | 3/8/2015-29/11/2019 | |
| | (1) | (2) | (3) | (4) |
| | [2,6] | [2,21] | [2,6] | [2,21] |
| $SFR_{-5,-1}$ | -1.70** | -0.92** | 3.48 | -0.60 |
| | (-1.93) | (-2.16) | (0.89) | (-0.62) |
| GOODNEWS | 0.07 | 0.15*** | 0.05 | 0.04** |
| | (-0.85) | (3.10) | (1.30) | (2.09) |
| BADNEWS | 0.03 | 0.12*** | 0.03 | 0.01 |
| | (0.29) | (2.56) | (0.88) | (0.62) |
| GOODNEWS × $SFR_{-5,-1}$ | 1.47 | 0.38 | -43.62 | -10.56 |
| | (0.94) | (0.55) | (-1.44) | (-1.19) |
| BADNEWS × $SFR_{-5,-1}$ | -0.11 | 1.11 | -6.35 | 4.88* |
| | (-0.06) | (1.46) | (-1.04) | (1.78) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 410 | 410 | 466 | 466 |
| N | 143,665 | 143,665 | 291,771 | 291,771 |
| Adj_$R^2$ | 0.09 | 0.09 | 0.08 | 0.08 |
| Panel B: MTR | | | | |
| $MTR_{-5,-1}$ | 0.26 | 0.28** | -0.11 | -0.14* |
| | (1.30) | (2.38) | (-0.79) | (-1.95) |
| GOODNEWS | 0.27** | 0.19 | 0.12*** | 0.09*** |
| | (2.52) | (2.83) | (3.00) | (3.80) |
| BADNEWS | 0.13 | 0.14** | 0.13*** | 0.09*** |
| | (1.27) | (2.18) | (2.83) | (3.62) |
| GOODNEWS × $MTR_{-5,-1}$ | -0.51* | -0.11 | -0.40** | -0.20** |
| | (-1.71) | (-0.77) | (-2.30) | (-2.36) |
| BADNEWS × $MTR_{-5,-1}$ | 0.61** | 0.13 | -0.56*** | -0.36*** |
| | (2.00) | (0.88) | (-2.68) | (-4.09) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 409 | 409 | 411 | 411 |
| N | 146,280 | 146,280 | 328,332 | 328,332 |
| Adj_$R^2$ | 0.09 | 0.09 | 0.08 | 0.08 |

This table presents Fama-MacBeth (FM) regression results examining the relation between future returns, previous week short selling/margin buying activities and news over two sample periods. Panel A reports results for short sellers while Panel B for margin buyers. The dependent variable is the average daily excess return in percent for the next week [2, 6] or month [2, 21]. The independent variables include SFR/MTR, good /bad news indicators, and their interactions with SFR/MTR. GOODNEWS/BADNEWS for firm $i$ on day $t$ is a dummy variable that equals to 1 if its $CAR_{[-1,+1]}$ around earnings release is positive/negative, otherwise zero. $CAR_{[-1,+1]}$ is estimated using FF-3-factor model. We control for firm size, BM, volatility, trading volume and return of last month. $t$-statistics are reported using Newey-West standard errors. *, **, ***denote the 10%, 5%, 1% significance level, respectively.

**Table 4.11**

**FM regressions of future returns on contemporaneous SFR/MTR, earnings surprises, and their interactions**

| | 05/12/2011-31/07/2015 | | 3/8/2015-29/11/2019 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | [2,6] | [2,21] | [2,6] | [2,21] |
| Panel A: SFR | | | | |
| $SFR_t$ | 1.67* | 0.33 | 1.26 | -3.39** |
| | (1.67) | (0.68) | (0.28) | (-2.42) |
| NEG_EA | 0.13*** | -0.03* | -0.09** | -0.04* |
| | (2.82) | (-1.99) | (-2.18) | (-1.69) |
| GOOD_EA | 0.01 | 0.03* | 0.07** | 0.01 |
| | (0.22) | (1.73) | (2.24) | (0.56) |
| NEG_EA×$SFR_t$ | -7.54** | 0.80 | 60.52 | 16.33 |
| | (-2.09) | (0.87) | (1.50) | (0.94) |
| GOOD_EA×$SFR_t$ | 0.33 | 1.04 | -33.06 | 6.18 |
| | (0.13) | (1.02) | (-0.99) | (0.66) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 51 | 51 | 65 | 65 |
| N | 21,442 | 21,442 | 25,281 | 25,281 |
| Adj_$R^2$ | 0.06 | 0.05 | 0.06 | 0.07 |
| Panel B: MTR | | | | |
| $MTR_t$ | 0.90*** | 0.46*** | 0.06 | 0.07 |
| | (3.88) | (3.34) | (0.24) | (0.72) |
| NEG_EA | -0.05 | -0.09 | 0.24 | -0.04 |
| | (-0.51) | (-1.59) | (0.59) | (-1.55) |
| GOOD_EA | -0.03 | -0.01 | 0.07 | 0.04 |
| | (-0.31) | (-0.10) | (1.41) | (1.43) |
| NEG_EA×$MTR_t$ | 0.65 | 0.69 | 0.24 | 0.03 |
| | (0.75) | (1.54) | (0.59) | (0.20) |
| GOOD_EA×$MTR_t$ | 0.03 | 0.02 | 0.05 | -0.18 |
| | (0.05) | (0.06) | (0.15) | (-1.28) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 51 | 51 | 65 | 65 |
| N | 23,318 | 23,318 | 35,698 | 35,698 |
| Adj_$R^2$ | 0.06 | 0.06 | 0.06 | 0.07 |

This table presents Fama-MacBeth regression results examining the relation between future returns, contemporaneous short selling/margin buying activities and earnings news. Panel A reports results for short selling while Panel B for margin trading. The dependent variable is the daily excess return in percent for the next week or month. The independent variables include SFR/MTR, positive/negative earnings surprise indicators, and their interactions with SFR/MTR. We use POS_SUE and NEG_SUE dummy to proxy for positive and negative earnings surprise, where POS_SUE/NEG_SUE for firm $i$ on day $t$ is equal 1 if its $CAR_{[-1,+1]}$ around earnings release is positive/negative, otherwise zero. $CAR_{[-1,+1]}$ is estimated using FF-3-factor model. We control for firm size, BM, volatility, trading volume and return of last month. $t$-statistics are reported using Newey-West standard errors.

**Table 4.12**

**FM regressions of future returns on contemporaneous SFR/MTR, news type, and their interactions**

| | 05/12/2011-31/07/2015 | | 3/8/2015-29/11/2019 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | [2,6] | [2,21] | [2,6] | [2,21] |
| **Panel A: SFR** | | | | |
| $SFR_t$ | -1.69 | -0.66 | 3.75 | -1.37 |
| | (-0.79) | (-0.81) | (1.13) | (-1.62) |
| GOODNEWS | 0.11 | 0.10** | 0.00 | -0.01 |
| | (1.34) | (2.09) | (0.20) | (-1.04) |
| BADNEWS | 0.18** | 0.12*** | 0.03 | 0.02 |
| | (2.24) | (2.63) | (1.08) | (1.80) |
| GOODNEWS × $SFR_t$ | -0.03 | 0.63 | 27.66 | -0.18 |
| | (-0.01) | (0.70) | (0.58) | (-0.01) |
| BADNEWS × $SFR_t$ | 1.03 | 0.62 | -75.81 | -15.99 |
| | (0.41) | (0.62) | (-1.30) | (-1.07) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 419 | 419 | 570 | 556 |
| N | 135,436 | 135,333 | 263,118 | 259,072 |
| Adj_$R^2$ | 0.08 | 0.08 | 0.09 | 0.09 |
| **Panel B: MTR** | | | | |
| $MTR_t$ | 0.07 | 0.08 | -0.14 | -0.09** |
| | (0.54) | (1.36) | (-1.52) | (-2.16) |
| GOODNEWS | 0.18*** | 0.09* | 0.10*** | 0.05** |
| | (2.56) | (1.79) | (2.82) | (2.44) |
| BADNEWS | 0.20*** | 0.09* | 0.05 | 0.05*** |
| | (2.66) | (1.82) | (1.28) | (2.62) |
| GOODNEWS × $MTR_t$ | -0.49 | -0.34** | -0.39** | -0.19*** |
| | (-1.22) | (-1.96) | (-2.39) | (-2.67) |
| BADNEWS × $MTR_t$ | -0.18 | -0.07 | 0.08 | -0.05 |
| | (-0.61) | (-0.49) | (0.53) | (-0.75) |
| Controls | Yes | Yes | Yes | Yes |
| TS obs | 408 | 408 | 421 | 409 |
| N | 146,176 | 146,072 | 332,740 | 326,603 |
| Adj_$R^2$ | 0.09 | 0.09 | 0.08 | 0.08 |

This table presents Fama-MacBeth (FM) regression results examining the relation between future returns, contemporaneous short selling/margin buying activities and news over two sample periods. Panel A reports results for short sellers while Panel B for margin buyers. The dependent variable is the average daily excess return in percent for the next week [2, 6] or month [2, 21]. The independent variables include contemporaneous SFR/MTR, good/bad news indicators, and their interactions with SFR/MTR. GOODNEWS/BADNEWS for firm *i* is a dummy variable that equals to 1 if its $CAR_{[-1,+1]}$ around earnings release is positive/negative, otherwise zero. $CAR_{[-1,+1]}$ is estimated using FF-3-factor model. We control for firm size, BM, volatility, trading volume and return of last month. *t*-statistics are reported using Newey-West standard errors.

**Table 4.13**

**Trading behavior patterns of short sellers and margin buyers**

| | 05/12/2011-31/07/2015 | | 03/08/2015-29/11/2019 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| RHS | $SFR_t$ | $MTR_t$ | $SFR_t$ | $MTR_t$ |
| Returnt | 4.06*** | -3.36*** | 0.64*** | 13.41*** |
| | (16.70) | (3.18) | (9.39) | (17.02) |
| $Return_{-5,-1}$ | -7.19*** | 14.35*** | -1.46*** | 16.76*** |
| | (18.30) | (7.56) | (12.34) | (11.42) |
| $sell\_oib_t$ | 1.07*** | -2.41*** | 0.32*** | -3.96*** |
| | (22.28) | (9.00) | (17.66) | (28.26) |
| $buy\_oib_t$ | 0.39*** | -3.90*** | 0.10*** | -5.98*** |
| | (5.94) | (15.97) | (4.75) | (32.39) |
| $Volatility_t$ | 4.31*** | -26.87*** | 0.04 | -13.36*** |
| | (11.52) | (23.61) | (0.56) | (12.22) |
| $Spread_t$ | -0.13*** | -0.99*** | 0.24*** | -1.76*** |
| | (3.07) | (5.30) | (8.45) | (11.09) |
| Controls | YES | YES | YES | YES |
| TS obs | 888 | 888 | 1055 | 1055 |
| Adj-R2 | 0.56 | 0.36 | 0.30 | 0.43 |

This table presents Fama-MacBeth regression results examining the determinants of short selling and margin buying over two sub-periods, i.e., from December 5,2011 through July 31,2015, from August 3,2015 through November 29, 2019. The dependent variable is daily SFR and MTR for stock *i* on day *t* in percent. The regressors include contemporaneous stock return, past 5-day return, contemporaneous sell- (buy-) order imbalance, volatility and spread. Control variables include past 5-day dependent variables, past 5-day buy (sell) order imbalance, past 5-day volatility, past 5-day trading volume, past-5day firm size and past 5-day BM. Order imbalance is calculated as the difference between buy trades volume and sell trades volume divided by the sum of these two. We use Lee and Ready (1991) algorithm to identify buy trades and sell trades. Buy order imbalance equals to order imbalance if order imbalance is positive and zero otherwise. Similarly, sell order imbalance equals to order imbalance if order imbalance is negative and zero otherwise. Intraday volatility is calculated as high price minus low price divided by high price. Spread is calculated as volume-weighted average of the effective spread. *t*-statistics are reported using Newey-West standard errors with 5 lags. *, **, ***denotes 10%, 5%, 1% significance level respectively.

## Appendix 4.1

**Weekly long-short portfolio returns based on SFR across firm characteristics**

| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
|---|---|---|---|---|---|---|---|
| Panel A: 05/12/2011--31/07/2015 | | | | | | | |
| Small | -0.00 | Low | -1.81 | Low | -0.57 | Low | -1.82 |
| | (-0.04) | | (-0.81) | | (-0.24) | | (-0.78) |
| 2 | -1.92 | 2 | -2.71 | 2 | 0.43 | 2 | -7.36*** |
| | (-1.28) | | (-1.28) | | (0.21) | | (-3.93) |
| 3 | -1.24 | 3 | 1.28 | 3 | -2.43 | 3 | -1.19 |
| | (-0.62) | | (0.53) | | (-1.11) | | (-0.56) |
| 4 | -3.51 | 4 | -3.38 | 4 | -1.30 | 4 | -3.16 |
| | (-1.61) | | (-1.39) | | (-0.49) | | (-1.48) |
| Big | 2.62 | High | -2.32 | High | 1.06 | High | 0.74 |
| | (1.33) | | (-0.98) | | (0.44) | | (0.34) |
| Panel B: 03/08/2015--29/11/2019 | | | | | | | |
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | 0.37 | Low | -0.88 | Low | 0.24 | Low | 0.17 |
| | (0.34) | | (-0.75) | | (0.29) | | (0.21) |
| 2 | -1.26 | 2 | -0.61 | 2 | -0.74 | 2 | -1.34 |
| | (-1.36) | | (-0.55) | | (-0.73) | | (-1.39) |
| 3 | -0.70 | 3 | -0.48 | 3 | -3.57*** | 3 | -0.82 |
| | (-0.85) | | (-0.48) | | (-4.02) | | (-0.89) |
| 4 | 0.79 | 4 | -2.14* | 4 | 1.30 | 4 | -0.73 |
| | (0.76) | | (-1.84) | | (1.17) | | (-0.70) |
| Big | 1.96* | High | -0.00 | High | 3.46** | High | 0.58 |
| | (1.81) | | (-0.05) | | (2.46) | | (0.44) |

This table reports the high-minus-low portfolio alphas based on double sorting. Panel A reports the results for the period from December 5,2011 to July 31,2015 and the Panel B for the period from August 3,2015 to November 29,2019. Firms are first sorted into quintiles based on a given characteristic at previous month end. Within each quintile, firms are then sorted into quintiles based on the SFR. See notes in Table 4.1 for the description of firm characteristics. Daily equal-weighted returns in basis points are calculated using a calendar-time approach with a holding period of 5-trading days, in which the Fama-French alpha is an average of 5 different daily portfolio returns rebalanced each day. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

## Appendix 4.2

**Weekly long-short portfolio returns based on MTR across firm characteristics**

| Panel A: 05/12/2011--31/07/2015 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | 8.79*** | Low | 6.94*** | Low | 8.06*** | Low | 7.56*** |
| | (5.72) | | (3.70) | | (4.56) | | (3.64) |
| 2 | 9.16*** | 2 | 9.66*** | 2 | 6.27*** | 2 | 5.07*** |
| | (4.83) | | (5.97) | | (4.13) | | (2.80) |
| 3 | 5.62*** | 3 | 8.40*** | 3 | 3.31 | 3 | 5.30*** |
| | (3.53) | | (4.85) | | (1.60) | | (3.08) |
| 4 | 10.55*** | 4 | 0.93*** | 4 | 5.34*** | 4 | 8.56*** |
| | (6.13) | | (5.51) | | (2.75) | | (5.11) |
| Big | -0.54 | High | 3.76** | High | 7.59*** | High | 10.54*** |
| | (-0.27) | | (2.37) | | (3.30) | | (5.38) |

| Panel B: 03/08/2015--29/11/2019 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Size | B-S | BM | H-L | Vol | H-L | Turnover | H-L |
| Small | 3.47*** | Low | -4.20** | Low | -2.97*** | Low | -3.51*** |
| | (3.68) | | (-2.24) | | (-2.94) | | (-3.20) |
| 2 | 0.39 | 2 | -2.95** | 2 | -1.71* | 2 | -4.29*** |
| | (0.38) | | (-1.98) | | (-1.66) | | (-3.59) |
| 3 | -5.00*** | 3 | 0.24 | 3 | -1.88 | 3 | -0.87 |
| | (-4.92) | | (0.18) | | (-1.38) | | (-0.73) |
| 4 | -5.70*** | 4 | 0.69 | 4 | -0.20 | 4 | -0.52 |
| | (-4.68) | | (0.53) | | (-0.13) | | (-0.41) |
| Big | -8.59*** | High | -2.05** | High | -3.74** | High | 3.34** |
| | (-6.42) | | (-2.18) | | (-2.39) | | (2.42) |

This table reports the high-minus-low portfolio alphas based on double sorting. Panel A reports the results for the period from December 5,2011 to July 31,2015 and the Panel B for the period from August 3,2015 to November 29,2019. Firms are first sorted into quintiles based on a given characteristic at previous month end. Within each quintile, firms are then sorted into quintiles based on the MTR. See notes in Table 4.1 for the description of firm characteristics. Daily equal-weighted returns in basis points are calculated using a calendar-time approach with a holding period of 5-trading days, in which the Fama-French alpha is an average of 5 different daily portfolio returns rebalanced each day. Newey-west adjusted *t*-statistics with 5 legs are reported in parentheses. *, **, ***denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

# Chapter 5

# Conclusion

A large number of variables have been reported as predictors of cross-sectional stock returns, but there is little consensus in the source of these anomalies. This thesis examines this issue in the Chinese stock market, which has unique regulatory settings of trading rules, such as the T+1 arrangement, as well as short-selling policy.

In this study, Chapter 2 provides a comprehensive analysis of the component return pattern of a trading day. In particular, we adopt the investor heterogeneity assumption to explain intraday return pattern differences between the US and Chinese stock market. By using the trade order size and institutional ownership change for the investor type, we show that institutional investors tend to trade actively near or at market open and close, whereas retail investors are more likely to initiate trades during the remaining daytime periods. We document a pronounced U-shape pattern of long–short portfolio profits of a trading day for trading-related variables. By establishing a link between the U-shape pattern and investors' trade directions, we confirm the relatively important role played by the trades of institutions on stock prices for the market opening and closing sessions. We also document an enhancement effect on the return prediction for institutions at market open and close, and a deteriorating effect for retail investors over these two periods. Finally, we consider institutions' early trades at market open as seeking mispricing profits, presumably caused by the unique T+1 trading rule as well as a sequence of overnight news.

Chapter 3 documents the positive relationship between the negative daytime reversal intensity and returns in the following month. The result remains after controlling for return predictors that correlate with future stock returns and various risk factors. We consider the results as the tendency of overconfident daytime retail investors to trade against high opening prices that essentially convey fundamental values. Because these investors overestimate their own ability to process information or the precision of their private information, they may trade into wrong directions by exerting too much selling pressure and even drag prices below firms' fair values. Consequently, overtrades against opening prices by daytime noise traders leads to a predictive relationship, as stock prices eventually converge to their fundamental values. This way, Chapter 3 sheds light on the role of retail investors on stock returns in the cross section.

Chapter 4 compares the before and after of the short-selling policy change in August 2015—that is, the implementation of the T+1 trading rule that prohibits short sellers paying back shares they borrowed earlier in the same day. Before the new policy was implemented, short selling was shown to have negative predictive power for future returns, and margin buying could positively predict subsequent month returns. However, after August 2015, short selling shows no predictive power and the sign of the predicted return of margin buying reverses to negative. Our interpretation is that the heavy short restriction drives out many informed leveraged traders. With mainly irrational investors left in the market for short selling and margin buying, the incremental information for future returns may not exist. These results have economic implications for investors and policy implications for regulators. Despite the interesting results on stock returns in the cross section, this thesis has some limitations. For example, we show in Chapter 2 that the tendency of institutions to trade early at market open, and seeking for mispricing profits, is probably caused by the T+1 rule and a series of overnight information releases. However, what causes investors to trade heavily for the last half hour before market closure needs to be explored. Indeed, many institutions rely on closing prices as benchmarks for their investment. Further analyses are necessary to understand the intention of institutions' trades toward market closure. In addition, as institutional investors account for more roles in trading activities with the rise of high-frequency trading over recent decades, it is also of interest to investigate how the time-of-the-day effects change according to the time.[30]

[30] Trading volume from mutual, private fund, and foreign capital in total accounts for 34.9% of the total A-share trading volume for the first half year of 2021—this figure being 6.5% in 2015 (see https://cj.sina.com.cn/articles/view/1704103183/65928d0f02002ovlm?cref=cj).

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