Retail and Institutional Investor Trading Behaviors: Evidence from China

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Abstract

We study two important questions regarding trading dynamics in China: how do retail and institutional investors trade, and what are the underlying factors for these behaviors? Different from the U.S., China's stock market has two prominent features: dominance of retail investors, and active participation by the government. After reviewing nearly 100 previous studies, we reach three conclusions. First, there are substantial heterogeneity in retail investors. Small retail investors have low financial literacy, exhibit behavioral biases, and not surprisingly, negatively predict future returns; whereas large retail investors and institutions are capable of processing information, and they positively predict future returns. Second, the macro- and firm-level information environment in China is slowly but gradually improving, which greatly affects trading behaviors of different investors, especially the more sophisticated institutional investors and large retail investors. Finally, the Chinese government actively adjusts their regulations on the stock market to serve the dual goals of growth and stability. Many regulations are effective, while some may generate unintended consequences.

Keywords: retail investors, institutional investors, government regulation, information efficiency, Chinese stock market
JEL codes: G11, G12, G14, G18, G23.

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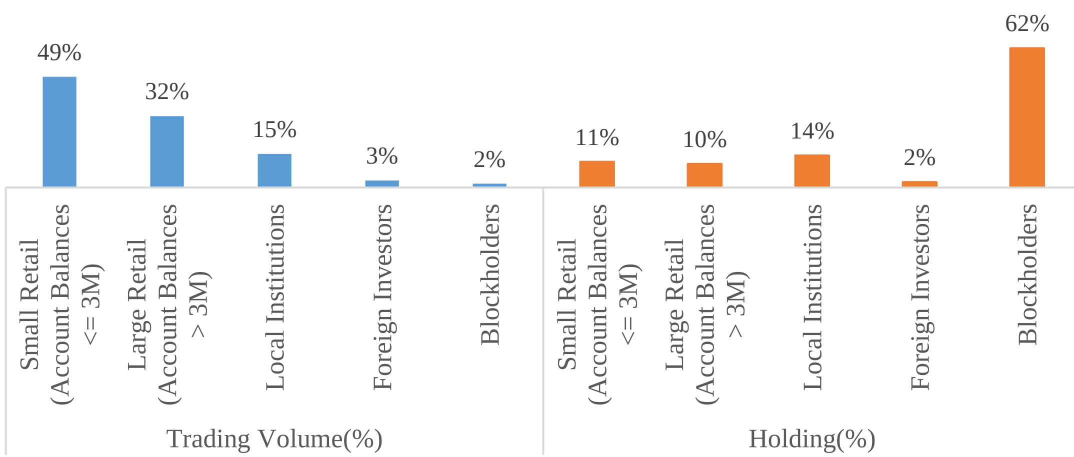
1. Introduction

There are three major types of investors in China: retail investors, institutions, and blockholders. Retail investors, also known as individual investors, register their accounts with personal IDs. Institutions are professional investors who register their accounts with government-issued permits and licenses, and institutions can be further divided into domestic institutions and foreign institutions. Finally, block shareholders or major share-holders hold large chunks of shares for strategic reasons, and they can be individuals, corporations, the central and/or local government. To illustrate the investor compositions in Chinese stock market, we use the summary statistics from Table 1 of Jones, Shi, Zhang and Zhang (2024), based on proprietary data from one major stock exchange in China over January 2016 to June 2019, to create Figure 1. For the thousands of A-share stocks listed on this exchange, Jones et al. (2024) first aggregate daily account-level trading and holding information for each stock, and then average them over all stocks and all trading days to obtain these summary statistics. Two clear patterns emerge from Figure 1. First, for trading in the left half panel, retail investors, especially the smaller ones, contribute the most to the daily trading volumes, accounting for 80% of total volumes. Institutions account for less than 20%, while block-holders barely trade. Second, for holding in the right half panel and in sharp contrast with trading, retail investors (small or large) hold only 20% of all shares despite their dominance in trading. Institutions hold close to 20% of all shares, and block-holders hold about 60%.

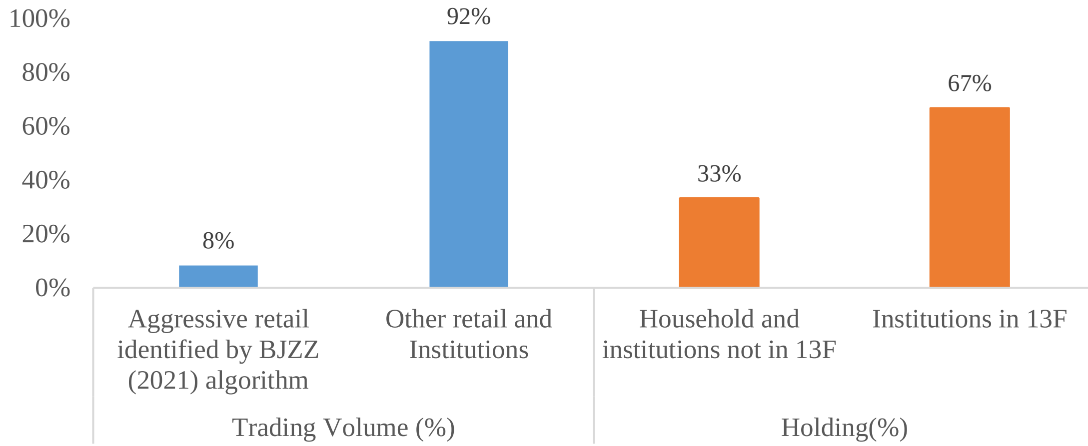
To have a heuristic understanding of these magnitudes in the Chinese stock market, we present in Figure 2 the trading and holding summary statistics in the U.S. stock market. Here we don’t have access to exchange proprietary data, so we compute trading and holding statistics based on best known public data and methods in the literature. For trading, we rely on the Boehmer, Jones, Zhang, and Zhang (2021, therefore BJZZ) subpenny algorithm to identify aggressive retail trades using marketable orders. The less aggressive orders, mainly limit orders, normally have similar magnitude.[1] Since the U.S. government doesn't directly trade or hold stock shares, we assume the rest of trading come from institutions. From the left half panel of Figure 2, 8% of daily trading volume in the U.S. are marketable retail orders. Under the assumption of retail limit orders are with similar magnitude, roughly 16% of daily volume are from retail investors. For holding, we follow Koijen and Yogo (2019) and obtain data from 13F, which contains quarterly holding data of institutions with more than $100 million in 13F securities. We attribute the rest of holding to household and other institutions. From the right side of Figure 2, 13F institutions hold 67% of all shares in the U.S., while households and other institutions hold 33%. Compared with China, institutions, rather than the retail investors or block holders, are the most important trading and holding entities in the U.S.

Figure1. Trading and Holding of Various Investors in China



[1] For instance, the Charles Schwab brokerage firm reports that in the second quarter of 2016, market orders account for 50.0% of its customers' nondirected orders in NYSE-listed securities, while limit orders account for 45.1% and other orders account for the remainder. Other examples are further discussed in Boehmer et al. (2021).

Figure 2 Trading and Holding of Various Investors in the U.S.



The comparison of the two figures clearly illustrates the drastic differences between the Chinese and the U.S. stock market, suggesting that theories and empirical evidence based on the U.S. setup may not be readily applicable to the Chinese market. Meanwhile, the differences and richness of data in the Chinese market attracts substantial interests from many scholars, which potentially explains the rapid increase in academic studies on Chinese investors in recent years, which inspires the current review.

To better understand the driving forces for the trading behaviors of Chinese investors, we provide a brief overview on important features of the Chinese financial system. The foremost feature is that the country is a large and quickly developing economy. According to a World Bank report published in 2022, countries with Gross National Income (GNI) per capita higher than \$13,845 are developed markets, and those below are developing markets.[2] When the stock market was established in 1990, China's GNI per capita was \$330. As of 2023 (when this paper was written), China's GNI per capita increases to \$12,850. These numbers show that China's economy experiences rapid and tremendous growth over the past 30 years, making it the second-largest

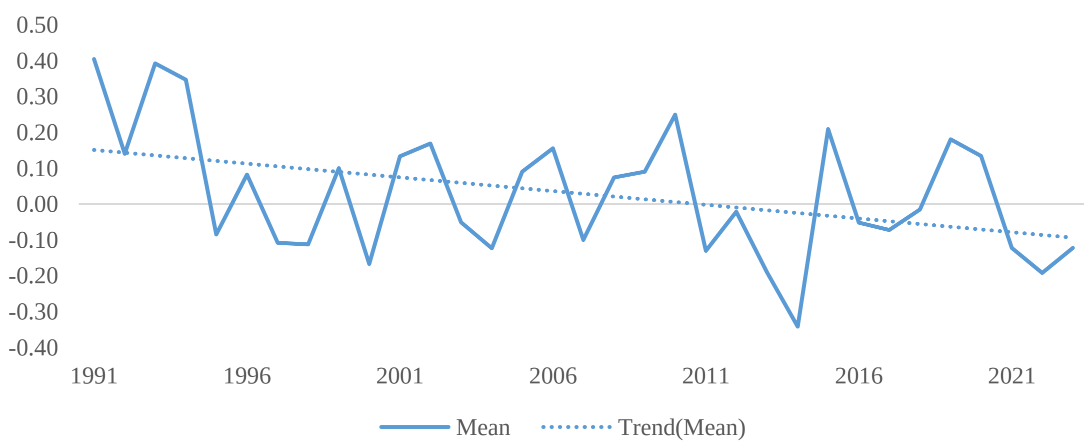
[2] The officially defined threshold is obtained from https://datahelpdesk.worldbank.org/knowledgebase/articles/378834-how-does-the-world-bank-classify-countries.

economy in the world. Meanwhile, given the thresholds from World Bank, the Chinese economy is close to but still not a developed market, and its economy might be more comparable to that of an emerging market rather than a developed market. According to Karolyi (2015), emerging markets are normally disadvantaged with constrained market capacity, inefficient operational trading systems, less corporate opacity, and limited legal protections. In fact, the dominance of retail investors in trading can be found in many other developing markets, such as India (Balasubramaniam, Ramadorai, Campbell, and Ranish, 2023), Korea (Choe, Kho, and Stulz, 2005), and Indonesia (Dvořák, 2005). With these commonalities between China and other developing markets, our study of Chinese investors' trading behaviors might shed light on other emerging markets.

Given its current developing market status, the Chinese government strongly believes that growth and stability are the two most important goals. To achieve these two goals, the government and its regulators provide regular guidance for the capital market, and they actively participate in the financial system when deemed necessary. Brunnermeier, Sockin and Xiong (2022) propose both theoretical framework and empirical evidence to understand the optimal design of government intervention, which depends on the properties of individual economies and the goals of the governments. Theoretically, Brunnermerier et al. (2022) find that when financial stability is prioritized, a government-centric financial system would be the optimal solution. Empirically, they find that the Chinese government uses a wide array of policy tools to maintain stability and guard against market cyclical fluctuations. Some interventions may help improve market efficiency, whereas others may not.

Another key element for a capital market is its information efficiency. Being a developing economy, the overall information efficiency in China is still relatively low. But with the market's rapid growth and government guidance, it gradually and significantly improves. Here we follow Saffi and Sigurdsson (2011) and construct a price inefficiency measure, the cross correlations between current and last week's stock weekly returns. As market efficiency improves, the cross correlations would decrease. Figure 3 presents the cross correlations over 1991 to 2021, averaged over all Chinese firms. The time-series plot clearly shows a decrease from 0.40 to -0.12 over the past 30 years, indicating that the market efficiency is gradually improving. This is consistent with the findings in Carpenter, Lu and Whitelaw (2021), which also states that stock prices are more informative about future profits after decades of development in China. Needless to say, the development could be unbalanced. For instance, information efficiency is likely higher for privately owned firms than for state-owned firms, perhaps because the state subsidies make earnings harder to predict and state-directed investment policy decreases the efficiency of capital allocation.[3]

Figure 3. Price Inefficiency in the Chinese Stock Market



[3] In fact, the cost of equity is still higher for a typical Chinese firm than for a typical U.S. firm. Bekaert, Ke, Wang, and Zhang (2023) examine the valuation differential between firms in China and the U.S., and find that investor composition is the most important determinant. Firms with more foreign accessibility have more comparable valuations to U.S. benchmark firms, firms with more retail investors have higher valuations due to potential speculative trading, while firms with more state ownerships have lower valuations related to potential operational (in)efficiencies.

So far, we show that the Chinese capital market exhibits critical differences from developed markets in aspects including the dominance of retail investors in trading, active government participation, and gradually improved information efficiency. Highlighting the distinct characteristics of the Chinese equity market, this review focuses on the trading behaviors of different investor types. We investigate their trading motives and their roles in price discovery and information efficiency, and study the influence of the evolution of government regulations and information environment on trading behaviors. By analyzing the investment decisions of different groups of investors in the Chinese capital market, we present the latest evidence, economic mechanisms, and practical implications for academia, practitioners, and policymakers to facilitate their understanding of the Chinese capital market, and shed lights on developments of other emerging countries with similar features, such as large quantity of retail investors and low market efficiency.

There are multiple recent reviews on the Chinese capital market. For instance, Allen, Qian and Gu (2017) discuss the overall Chinese financial system; Carpenter and Whitelaw (2017) examine the development of China's stock market; Hachem (2018) investigates Chinese shadow banking; Song and Xiong (2018) look into financial risks; Allen, Qian and Qian (2019) describe the framework of financial institutions; Hu, Pan and Wang (2021) provide an empirical overview of the development and characteristics of Chinese capital market; and Hu and Wang (2022) work on the development of China's financial markets, including bonds, stocks, asset-backed securities, financial derivatives, and currency.

Compared to these insightful reviews, this review focuses on studies examining the trading behaviors of different investors in China, investigating their trading motives and their impacts on price discovery process and information efficiency. Readers might be curious: why study trading behaviors in China in particular? All papers in this review are motivated along two perspectives. First, Chinese investors display different trading behaviors and/or biases than investors from other markets, and thus these studies provide new insights on these topics. Second, the Chinese data is unique, and can be used to examine certain theories or predictions that so far couldn't be tested in other markets, and thus these studies provide unique opportunities to complete our understanding of markets and trading behaviors. [4] Either perspective provides new insights to the existing literature, and our review helps to organize these studies and provides three conclusions. First, for the large population of retail investors in China, there are substantial heterogeneity. Small retail investors have low financial literacy, exhibit behavioral biases, and not surprisingly, negatively predict future returns; whereas large retail investors and institutions are capable of processing information, and they positively predict future returns. Second, the trading of institutional investors and large retail investors in China benefit from and contribute to the improving macro- and firm-level information environment. Finally, the Chinese government actively adjusts their regulations on the stock market to serve the dual goals of growth and stability. While many of them are effective, some generate unintended consequences.

2. Trading Dynamics and Return Predictability

One heuristic way to understand investors trading dynamics is through the relation between their trading and the subsequent returns. Therefore, we start from trading's return predictability in this section. To have a better understanding of these patterns in the Chinese stock market, in each subsection, we compare findings in China with those in the U.S.

2.1 Retail Investors vs. Institutional Investors

[4] We categorize all studies reviewed in this paper into these two broad perspectives in the appendix.

Following studies on U.S. retail investors (Kelley and Tetlock, 2013; Boehmer et al., 2021), Jones et al. (2024) take a direct way to establish the relations between investor trading and future returns with the following simple specification:

$$Ret_{i,d} = a0_d + a1_d Oib_{i,d-1} + a2'_d Controls_{i,d-1} + u1_{i,d}. \quad (1)$$

Here, the dependent variable is the return on day d for stock i, and the main independent variable is the order imbalance from a particular investor group on the previous day for this particular stock, and it is computed as $Oib_{i,d-1} = \frac{buy\_volume_{i,d-1} - sell\_volume_{i,d-1}}{buy\_volume_{i,d-1} + sell\_volume_{i,d-1}}$. Since the study focuses on different groups of retail and institutional investors, the order imbalance measure is separately computed for different groups of retail investors and institutional investors, which requires account-level trading details and a clear classification of each account. This is one of the advantages of Jones et al. (2024), which has access to a proprietary dataset directly from a major exchange, with allows account level classifications and trading and holding details for listed stocks. If the coefficient $a1$ is positive, then the trading from a particular group of investors can predict returns in the future. That is, the stocks they buy more have higher returns the next day, indicating a correct predictive direction. However, if coefficient $a1$ is negative, then the trading from this particular group of investors predicts future returns in the wrong direction, because the stocks they buy more actually have lower returns the next day.

Jones et al. (2024) show distinctive predictive patterns for various investors: retail investors with smaller accounts, with values less than 3 million RMBs, have significant and negative $a1$ coefficients, indicating that their orders are in the wrong direction for future price movements; retail investors with larger accounts, with values higher than 3 million RMBs, together with institutional investors, have significant and positive $a1$ coefficients, suggesting that their orders are in the right directions. Clearly, different investors have different predictive power for future stock returns. Jones et al. (2024) further examine how retail and institutional order flows are related to past returns, and find that small retail investors pursue a momentum trading style, i.e., buying high and selling low, which demands liquidity and potentially leads to lower future returns. In contrast, large retail investors and institutional investors follow a contrarian pattern, that is, buying low and selling high, which literally provides liquidity to the market and is likely compensated positively.

Several studies on U.S. retail investors, such as Kaniel, Saar, and Titman (2008), Kelley and Tetlock (2013), Boehmer et al. (2021), use retail order data from proprietary datasets or identified from public trade-by-trade data and find retail investors are contrarian investors and their trading could positively predict future returns in the U.S. stock markets. Clearly, Chinese retail investors have critical differences from U.S. markets, in the sense that small Chinese retail investors are momentum investors, and negatively associated with future returns, while large Chinese retail investors are contrarian investors, and positively predict future returns. For institutional investors, Puckett and Yan (2011) use the proprietary ANcerno data and find U.S. institutional investors earn significant abnormal returns on their trades, which is consistent with positive predictive power of institutional order flows for future returns.

Do the different trading patterns of these heterogeneous investors lead to account performances? An, Lou and Shi (2022) use the same proprietary data set and focus on the 2014-2015 bubble-crash period to examine the wealth redistribution effect among investors. The Chinese market index, CSI300 (a capitalization-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Chinese A-share markets) increases from 2321.98 (2014/1/2) to 5335.12 (2015/6/12, the highest point in 2015), which resembles a sizeable bubble, while then it quickly drops to 3025.69 (2015/8/26, the lowest point in 2015), which constitutes a large crash. Over this volatile period of price movement, An et al. (2022) find that the largest 0.5% households (with account balances higher than 10 million RMBs) generally profit, while the smallest 85% households (with account balances lower than 0.5 million RMBs) incur losses, representing a wealth transfer from the poor to the rich in the amount of 250B RMB.

Both above studies focus on the trading dynamics among different types of investors. One earlier study, Choi, Jin, and Yan (2013) use holding data from the Shanghai Stock Exchange to examine how ownership breadth predicts future returns. The ownership breadth is the proportion of market participants with a long position in a given stock. Their results provide another interesting perspective. Higher retail ownership, especially of small retail investors, is associated with lower future returns, indicating that higher small retail ownership is likely related to over-pricing. In contrast, higher institutional ownership leads to higher future returns, suggesting that institutional investors might have predictive power for future returns. This study echoes the findings of An et al. (2022) and Jones et al. (2024).

Another earlier study, Pan, Tang, and Xu (2016), make use of publicly available data, and examine how general trading, without account level information, is related to future stock returns. They use a regression method to decompose the firm-level turnover ratios (share volumes divided by total shares) into two components. The first component is a linear combination of market level turnover and firm level important events, which is considered as "predicted turnover". The second component or the residual component is the abnormal turnover (ATR), designed to represent trading for speculative demands unrelated to market-level or firm-level important information, and is therefore "speculative". The authors document strong and negative relations between ATR and future stock returns, which suggests that higher speculative demand leads to lower future returns.

If the retail investors are the main drivers behind these speculative demands, these results are consistent with the three earlier mentioned studies. [5]

2.2 Foreign Investors vs. Domestic Investors

Other than the separation into retail and institutional investors, another interesting division of investors is domestic vs. foreign investors. For foreigners in the U.S. market, Forbes (2010) uses the official data compiled by the U.S. Department of the Treasury and the Federal Reserve Bank, and finds foreigners are willing to invest over $2 trillion per year in the U.S. and their average equity returns are 7.6% from 2000 to 2006, which are less than the 17.4% that U.S. investors earn on their foreign investments.

To study foreign investors in the Chinese stock market, Chui, Subrahmanyam, and Titman (2022) use the multiple share class structure in China to directly compare the trading dynamics of domestic and foreign investors for the same set of stocks. There are three important share classes for a Chinese stock: A shares, B shares and H shares. The A shares are issued for domestic investors, and are traded in either Shanghai or Shenzhen Stock Exchanges. The B-shares are offered to foreign investors, and they are also traded in Shanghai or Shenzhen Stock Exchanges. Unlike A and B shares, the H-shares are traded in Hong Kong Stock Exchange, and can be owned by anybody with legal status in Hong Kong Stock Exchange. Note that one stock can have both A and B shares listed in mainland China, as well as H shares in Hong Kong. Now, do domestic investors trading A shares and foreign investors trading B shares behave alike? Chui et al. (2022) directly compare their trading patterns, namely the momentum and reversal (contrarian) return patterns. In most markets, momentum indicates that prices follow lasting trends, and high past returns indicate higher future returns, while reversal (contrarian) indicates reversals in the price

[5] More studies on heterogeneous investor trading dynamics and return predictability include Ng and Wu (2007), Chen, Yuan, and He (2013), and Li, Geng, Subrahmanyam, and Yu (2017).

trends, and high past returns implies lower future returns. An earlier study, Chui, Titman, and Wei (2010) document the existence of momentum patterns in most countries worldwide. Interestingly, Chui et al. (2022) find strong momentum patterns in the B shares market, which serves foreign investors, but not in the A share market, where local retail investors dominate. The authors state that the existence of momentum in B shares is consistent with a market dominated by informed investors, who underreact to information, while the reversal pattern in A shares is more consistent with a market dominated by noise traders, where trading is more motivated by liquidity and speculative demands.

Benefitting from the government campaigns on openness, foreign investors can directly invest in A-shares through three different channels: Qualified Foreign Institutional Investors program (QFII), RMB Qualified Foreign Institutional Investors program (RQFII) and Hong Kong Connect program (HKC). According to official statements, all participants in the QFII and RQFII, as the names indicate, are institutional investors, while most HKC investors are institutional investors. As shown in Figure 1, foreign investors account for 2.38% of the holdings and 3.11% of the trades. Lundblad, Shi, Zhang, and Zhang (2023) use proprietary exchange data to directly examine the return predictability and trading dynamics of foreign investors in China and compare their behaviors with those of domestic institutional investors. Earlier studies comparing domestic and foreign investors generally find that the former performs better than the latter owing to the local information advantage. Interestingly, Lundblad et al. (2023) find that foreign investors positively predict future returns, and their return predictive power is comparable to domestic institutional investors, indicating that foreigners do not have an information disadvantage. They also find that foreign investors, similar to local institutional investors, are mostly contrarian traders who buy low and sell high, potentially providing liquidity to the market.[6]

In this section, we compare the return predictive power and trading patterns of retail, institutional, and foreign investors in the Chinese stock market. The general empirical pattern is that smaller retail investors are momentum traders and predict returns incorrectly, whereas larger retail and institutional investors (local or foreign) are contrarian traders and predict returns correctly.

3. Why Investors Trade: The Information Channel

Investors trade for many different reasons, and the usual suspects include information, behavioral properties, and liquidity. In this section, we focus on the information channel. Investors can be classified into two categories: informed and uninformed. "Informed investors" have information advantages, either because they have private access to valuable information, or because they have better skills in processing public information. Typically, neither information acquisition nor processing is free, thus informed investors tend to have resources and sophistication, and many view institutional and large retail investors as sophisticated and resourceful investors. Given their information advantages, informed investors typically have stronger return predictive power and make more money in the stock market than do uninformed investors. Using U.S. data, Hendershoot, Livdan, and Schurhoff (2015) find U.S. institutional order flow are informed about macro and firm-level news, and Kelley and Tetlock (2013) and Boehmer et al. (2021) provide evidence that U.S. retail investors might be informed of firm-level information.

[6] Other studies on foreign investors' role in market quality include Chen, Du, Li, and Ouyang (2013), etc.

3.1 Information at the Macro Level

Given the prominent role that the government plays in the Chinese stock market and the important role that the macroeconomy plays in the stock market in general, we start our discussion on macro level information. In the model of Brunnermeirer et al. (2022), for a government-centric economy with frequent government interventions to maintain financial stability, investors would pay substantial attention to obtaining regulation related information, such as policy changes or announcements of important macroeconomic measures.

Guo, Jia, and Sun (2023) is one of the first studies on information dissemination of the central bank announcements on monetary policies. To be specific, they study an interesting case of the pre-announcement premium for central bank unscheduled public announcements on monetary policies, especially the M2 (broad measure of monetary aggregates) growth statistics. As these announcements are not pre-scheduled, they provide interesting settings for studying information acquisition and the corresponding risk premiums. They first document a sizable pre-announcement premium of 25 basis points over a three-day window (20.83% annualized) before the real announcements using data from January 2010 to December 2019. The authors also document a significant drop in uncertainty before the announcement, and argue that the uncertainty resolution is probably the reason for the pre-announcement premium. Next, they directly link the decrease in uncertainty to the Baidu search on the M2 keyword right before announcements, and find that many uninformed investors, typical users of the Baidu search engine, engage in information acquisition before announcements.

Ammer, Rogers, Wang, and Yu (2023) provide direct evidence that fund managers are among those who paid for macroeconomic information acquisition and are later rewarded. During the sample period from 2008 to 2020, all mutual fund managers are asked by the China Securities

Regulatory Commission (CSRC) to provide their views and forecasts on short-term economic and financial conditions, and these discussions are collected and published periodically on the China Securities Journal. Ammer et al. (2023) implement textual analysis tools on the quarterly reports of China's fund managers, including their forecasts of future Chinese monetary policy. The first finding is that the consensus of these fund managers serves as an excellent predictor of future monetary policies, better than alternatives such as forward rates and the PBOC (People's Bank of China)'s survey of Commercial Bankers, suggesting that fund managers, being skillful and sophisticated, are likely informed about future policy changes through their efforts in information collection and processing. As one might expect, fund managers adjust their investments based on their forecasts, such as buying long-term assets when expecting a more relaxing monetary policy and vice versa. More importantly, these adjustments significantly improve fund performances by higher alphas and better market timing, and induce more inflows. These results are consistent with the prior that macro information is important for asset returns, and manager's superior skills in collecting and processing this information is an important channel for fund performances. Ammer et al. (2023) also provide direct evidence that manager's forecast is better when the fund spends more resources in acquiring and processing related information. [7]

3.2 Information at the Firm Level

3.2.1 Information Efficiency at the Beginning of the 2000s

There are more studies on firm-level information in the Chinese capital market than on macro-level information. As a starting point, we first review two papers on the general issue of firm-level information quality, to get an idea of the level of information efficiency at early stage

[7] More studies on macro-level information include Han and Hong (2014), He, Wang and Zhu (2023), etc.

of China's capital market development. We mention in earlier discussions that A-share stocks are traded by domestic investors, and B-share stocks by foreign investors. The A-B premium refers to the empirical observation that A shares are traded at premiums compared to the same firm's B-share stocks. Chan, Menkveld, and Yang (2008) studies the A-B share premium from 2000 to 2001, and find that 46% of the premium variation can be explained by information asymmetry, measured by adverse selection estimated from a microstructure model. This finding has two implications: information environment plays a significant role in pricing of both A and B share stocks, and A share market is relatively more opaque and less efficient than the B share market.

Gul, Kim, and Qiu (2010) directly examine the issue of market information efficiency, namely how fast firm-level information gets into price, by linking ownership concentration, foreign shareholding, and audit quality with synchronicity (an efficiency measure). Higher synchronicity normally indicates lower information efficiency. Using data over 1996 to 2003, the authors find that higher foreign ownership and audit quality both contribute to better efficiency, whereas higher state ownership does the opposite. [8]

The above two studies indicate that at least over the decade around the 2000s, the level of information efficiency is low in the A-share market. Over the decades after the early 2000s, many efforts, by regulators, professionals and general investors, are devoted to improve the information efficiency and have profound impacts on trading dynamics. In the discussion below, we separate previous studies on firm-level information in China into three subsections according to the order of the information environment evolution: professional information providers, information

[8] More early studies related to information efficiency in Chinese stock markets include Chan, Menkveld, and Yang (2007), Yan, Xu, Shi, and Wang (2012), etc.

disclosure regulations, and the latest developments in information acquisition related to physical visits and online searches.

3.2.2 Professional Information Providers and Their Impacts on Trading and Pricing After the 2000s

The most common professional information providers are analysts, specialized professionals who collect and process information about stocks and then release their analyses through periodic reports, forecasts, and recommendations. The analyst industry gradually develops after the 2000s, and analysts are officially required to register after 2010. According to official statistics, the number of analysts increases from 1,958 in the year 2011 to 3,588 in the year 2021, with an annual growth rate of 6%.[9] Even though the analysts have their own incentives and may carry various biases, their professional services improve the information quality for the investment community in general.

For instance, Andrade, Bian, and Burch (2013) study how analyst coverage shapes information generation during the 2007 stock market bubble. Over the six-month bubble forming period, they document a large increase in daily turnover from 230% to 950%, and a large inflow of novice traders by 7.8 million, which represents a 21% increase in the *total* number of retail A-share accounts during just six months. The authors construct composite bubble measures (a combination of bubble measures, such as cumulative returns, PE ratios, and announcement returns) at the firm level, and find that the bubbles are significantly smaller in magnitude for firms with more analyst coverage. That is, with one standard deviation increases in analyst coverage, the bubble magnitude proxy, cumulative returns, decreases by 0.34 standard deviation (or 0.34*95.2%

[9] Please see https://www.sac.net.cn/yjcbw/zqhyfzbg/2022/.

= 32.4%). Conversely, stocks with lower analyst coverage have larger bubbles during the sample period. The authors provide supportive evidence that analysts reduce the bubble magnitude by coordinating investor beliefs and thus reduce disagreements among investors, which consequently decreases the magnitudes of extreme mispricing in the form of bubbles.

Jia, Wang, and Xiong (2017) provide an interesting and different perspective by examining the interactions between investors and analysts in the mainland A share market and Hong Kong H share market. Similar to the A-B premium, where A shares have higher prices than B shares for the same stock, there is also an A-H premium, where A shares also have higher prices than H shares for the same stock. In the A-H setting, domestic analysts presumably have tighter social ties with domestic investors, and potential services provided by domestic analysts are more catered to domestic investors. Similar reasoning can be applied to foreign analysts and foreign investors. The closer relation between domestic investors and analysts predicts that domestic investors, relative to foreign investors, would react more towards information provided by domestic analysts, and vice versa. Indeed, the authors provide significant empirical results supporting these predictions. Generally consistent with the analyst literature, the authors find that analysts' services bring prices closer to fundamentals and analysts attenuate the A-H premiums. The authors caution that in some cases, investor differential responses to different analysts can also exacerbate the A-H premiums, especially for firms with more analyst recommendations: as more analyst recommendations may lead to higher foreign and domestic investors' disagreement on stock prices, therefore wider A-H premium and market segmentation. [10]

[10] Other studies of investors' reactions on analyst recommendations include Kong, Lin, Liu, and Tan (2021).

3.2.3 Information Disclosure Regulations and Their Impacts on Trading and Pricing After the 2000s

Over the past decades, regulators around the globe pay tremendous attention to information quality and information disclosure practices. The Chinese regulators also join the endeavors of improving information quality, and experiment with multiple innovations designed for the Chinese market.

One innovation in information disclosure is enacted in 2010, when the two exchanges (Shanghai and Shenzhen) launch investor interactive platforms (IIP) to facilitate communications between firms and investors. That is, the investing community can raise questions on these IIPs and the corporate managements need to answer them. This design is quickly accepted by many investors and 99% of all listed firms, and is particularly beneficial to retail investors who face more costs when attempting to integrate public firm information into their trading decisions. Over 2010 to 2017, 2.5 million questions are posted on IIPs, and a vast majority receives formal answer(s) from company managements. Lee and Zhong (2022) use BERT algorithm (an AI approach for natural language processing) to analyze these 2.5 million questions. Their findings are two-fold. First, the questions submitted by investors clearly show that investors have difficulty in processing publicly available information, which justify the innovative creation of IIPs. Second, IIPs significantly help investors to understand and process the publicly available information, and consequently, investors increase their trading on these firms and the returns on trading these stocks are positive. The authors interpret these findings as evidence that IIPs reduce the information acquisition and processing costs and improve price efficiencies and firm liquidity in general. [11]

[11] More studies on IIP include Ding, Lv and Chen (2018), Blankespoor (2022), etc.

Duan, Li, Rogo, and Zhang (2024) investigate a different information disclosure channel, namely the mandatory disclosure based on comment letters. These letters are issued by listing exchanges, which contain concerns from the exchange and are required to be answered by these firms. Over the sample period of 2013 to 2018, the authors find that in general the receipts of comment letters are interpreted as negative signals by the investors, which lead to significant price drops. The reason is simple, these comment letters normally raise questions about the firm's operations, liabilities etc., which can potentially lead to problems, rather than successes, for the future. So the action of the exchanges by making the inquiries public provides information and warning to the investment community. Interestingly, the later answering of these comment letters does not generate improvements in previous price drops, indicating that the issuance of letters is a major negative signal that cannot be easily reversed.

The campaign of opening up the Chinese stock market to foreign capital also provides an interesting setup for examining how information disclosure regulations affect trading and pricing. Yoon (2021) examines how the HKC program, which allows foreign investors to directly invest in the Chinese mainland market through Hong Kong. Presumably, companies in the HKC pilot program are likely to have more foreign institutional investors who impose additional information disclosure demands on these firms. This study focuses on how firms strategically react to information disclosure shocks. Yoon (2021) finds that, as a result of the pilot program, affected firms strategically respond by increasing the number of private disclosures, including private corporate access events and private dial-ins. This practice of private disclosure is more prevalent among firms with strong track record of public disclosure, and expecting more financing. More private disclosures lead to significant increases in foreign institutional holding and trading.

Subsequently, these firms enjoy fast price discovery and low transaction costs, which are improvements for all investors on these firms.[12]

3.2.4 Latest Developments in Information Disclosure in China

Turning to the information disclosure initiated by firms, analysts, and investors, there are many recent developments in this area. Early studies, such as Feng and Seasholes (2004) show that investors prefer to trade stocks with headquarters close to their locations when they trade. This finding supports the notion that distance probably serves as a proxy for information acquisition cost, investors with further distances to the firms are likely less informed than investors closer to the firms, and investors trade according to their relative information (dis)advantages.

Recent articles mostly focus on information acquisition through physical company visits. Chen, Ma, Martin, and Michaely (2022) use the high speed rail (HSR) as an interesting exogenous shock to the cost of information acquisition. This study presents three interesting findings. First, better HSR access leads to more visits from analysts, with an annual increase of 4.9%. Second, the quality of the generated information also becomes significantly higher in the sense that analysts' forecast precision improves by 2.1%. Third, analysts pass these positive effects to the investment community and improve price efficiency in general. Compared to control firms, investors react more significantly, by 1.7%, to the forecast revisions and an increase of 1.9% in recommendation changes for firms post-HSR access. Intuitively, the authors propose that HSR access facilitates onsite visits, which help analysts to collect valuable soft and contextual information.

Cheng, Du, Wang and Wang (2016) and Han, Kong, Liu (2018) report similar findings to Chen et al. (2022). In addition, Chen, Qu, Shen, Wang, and Xu (2022) provide further evidence

[12] Other research in HKC program includes Bian, Chan, Han, and Shi (2023), Gao, Pittman, Wang, and Wang (2023), etc.

that mutual fund managers prefer to visit close-by firms, and these company visits significantly and positively affect funds' trading activities in these firms. Using post-investment returns, the authors also find that visits, which probably generate valuable information, improve future fund performances in these stocks. Dong, Fisman, Wang, and Xu (2021) also study company visits, and provide an interesting perspective that air pollution level during these company visits can negatively affect analysts' recommendations after the visits, which introduces a pollution bias in their information production.

Investors, especially retail investors, normally don't participate in physical company visits. Instead, they are more used to online searches for the firms' information. Xu, Xuan, and Zheng (2021) examine the impact of Google's unexpected withdrawal from China in 2010. According to their study, the loss of this important information channel leads to many negative impacts for firms with more Google searches. For instance, their crash risk increases by 19%, sensitivity towards negative online posts increase by 35.8%, and liquidity significantly decrease by 17.7%. Wang, Yu, and Zhang (2023) examine the same event from a different perspective. With the change in information access without Google, firms strategically change their disclosure to domestic investors, particularly when they become more optimistic when disclosing information related to foreign transactions (which is more difficult to search on local search engines, such as Baidu). These strategic information disclosure choices by firms allow more profitable insider trading, or less profitable uninformed trading. The optimistic bias becomes particularly stronger when the information itself is negative. Fortunately, the authors find that the bias is mitigated with the presence of foreign analysts and foreign investors.

After the discussion of information efficiency and disclosure development in China over the past 20 years, one might wonder whether how information is directly linked to trading and return predictability, as mentioned in Section 2. The answers are partially provided in Jones et al. (2024) and Lundblad et al. (2023). The first study links trading by retail and institutional investors to information on firm fundamentals and finds that smaller retail investors fail to process public information and make larger mistakes on information-intensive days, while large retail investors and institutions seem to be able to process firm-level information related to fundamentals. The second study examines whether trading of institutional investors, local or foreign, are driven by information at the market and firm levels, with the prior that foreign investors might have information disadvantage relative to local investors. Their findings provide strong evidence that both local and foreign institutional investors are informed about firm-level fundamentals and foreign investors are not at information disadvantage, possibly because they hire high-quality local talents.

In this section, we summarize studies on the information environment in the Chinese capital market and how it affects various investors' processing of information, and their trading behaviors. The information environment clearly improves over the past 20 years, through efforts by regulators, professional analysts, firms, and investors. We generally find that sophisticated investors, mostly institutional and large retail investors benefit from and contribute to the improvements on information environment, while small retail investors still have difficulties in processing information.

4. Why Investors Trade: The Behavioral Channel

As mentioned in the introduction, retail investors account for 80% of daily trading in recent years. Why do they trade? Other than trading on information, many believe that the retail investors trading might be driven by their financial illiteracy, and various behavioral properties (some call them behavioral biases). For instance, previous studies on the U.S. stock market find individual investors are overconfident (Barber and Odean, 2001), have disposition effect (Odean, 1998), are net buyers of attention-grabbing stocks (Barber and Odean, 2008), have extrapolation bias (Cassella and Gulen, 2018), have salience bias (Bordalo, Gennaioli, and Shleifer, 2013), prefer lottery-type stocks, and have the propensity to gamble (Kumar, 2009).

Most of the studies on Chinese retail investors are devoted to documenting behavioral biases, old and new ones, and how they affect retail investors trade. This is understandable, because the large population of Chinese retail investors provide excellent testing grounds for behavioral experiments. But before we get into these studies, we would like to examine the context more closely and ask why Chinese retail investors might be different from the retail investors in other markets. One potential reason, tracing back to the discussion in the introduction, is probably the status of the Chinese economy. As a developing market, China enjoys rapid growth, but also enduring large uncertainties and the relatively opaque information structure. Meanwhile, it is also possible that Chinese retail investors in general have low financial literacy and are more susceptible towards behavioral misconducts.

Song (2020) directly examines the issue of financial illiteracy by using a field experiment on compound interest in China in 2009. Compound interest is a simple yet important concept for long term investments, for instance, pension plans. Song (2020) randomly assigns 1,000 rural households in China into three groups: control, calculation and education groups. For the control group, the author explains the pension plan and directly surveys them on background information. For the calculation group, the author calculates the pension benefits for the family and shows them the information. For the education group, the author teaches them to compute compound interest correctly. The author collaborates with the local government and collects administrative data on their households' actual pension contributions. The author finds that 56% of households don't know how to compound, and 73% of households who claim knowing compound interest underestimate the compound interest. This is clear evidence of low financial literacy. A similar study conducted in the U.S. in 2004, Lusardi and Mitchell (2014), actually find 67.1% of U.S. correspondents can correctly answer the compound interest question. The education treatment in Song (2020) increases annual contribution to pension plan by 49-53 RMB, 40% higher than the 133 RMB in the control group. The author also conducts a welfare computation and finds that the lifetime utility can be improved by 10% if the investors understand or partially understand the compound interest rates. This study provides first-hand direct evidence on the low financial literacy of households in China.

Another study, Titman, Wei, and Zhao (2022) study how corporate manipulates retail investors in stock splits, which indirectly illustrate the low financial literacy issue in China. Normally, stock splits happen when the firm has positive shocks, and previous rational models show that stock splits can be costly when the firm has no positive information, because stock splits attract attention and intensify scrutiny, punishing manipulative actions. However, in a market full of less-sophisticated and less-educated retail investors, firms can introduce splits without positive information, and prices can be inflated for a short period, which facilitates sales from insiders. This study provides evidence that a set of suspicious corporations is aware of the low financial literacy of retail investors, especially the small ones, and takes advantage of it by stock splits. Through this manipulation, the corporate insiders sell large blocks of shares and obtain loans using the higher-priced stocks as collateral. Unfortunately, the empirical results show that smaller retail investors are attracted to these stock splits, and their buying significantly increases, while more sophisticated investors are not attracted and become net sellers. [13]

4.1 Status, Complexity, Attention, Salience, and Extrapolation

In this section, we investigate established behavioral properties, which are already studied in earlier papers using data from other developed markets. Many Chinese studies extend previous established behavioral studies using Chinese data and have new findings. For instance, Hong, Jiang, Wang, and Zhao (2014) examine trading related to keeping-up-with-the-Joneses preference. The authors use data from brokerage accounts, stock message boards, and local stock turnover, over year 1998 to 2012, and find that retail investors, especially from affluent areas, trade to track their neighbor's wealth. This trade motive partially explains why many retail investors trade excessively, which might be the reason for retail investors dominance in Chinese stock market trading. Alternatively, Chan, Liao, Martin, and Wang (2023) examine peer pressure in crowdfunding, and find the opposite result: peer pressure leads to 7-8% lower donations, and many individuals choose not to be influenced by peer pressure and choose not to be informed about peers' donations.

Attention is another reason why many retail investors trade. Jiang, Liu, Peng, and Wang (2022) study the relation between investor attention and asset pricing anomalies in China. The stock-level attention measure is computed using number of posts on an investor forum (Eastmoney.com). Their hypothesis is straightforward: high attention normally leads to over-reaction, and higher anomaly returns. The authors find that anomaly returns are indeed higher following higher attention days. They also find that the large traders specifically trade aggressively on these higher attention days, suggesting that these traders might better understand the return

[13] Similar studies on retail manipulation around stock splits include Li, Yu, Lu, and Xu (2014), Hu, Liu, and Xu (2021), Hu, Lin, and Liu (2022), etc.

dynamics on high attention days and reap in higher trading profits on these days. Alternatively, Chen, An, Wang, and Yu (2023) examine a novel perspective for attention-induced trading: the attention spillover from one stock to stocks listed next to them in a screen display. They find that stocks with neighboring high return stocks also experience higher returns over short term, which reverses over the long term. This finding suggests that retail investors tend to trade more after positive returns, and likely trade neighboring stocks to high return stocks.

The other side of high attention is limited attention or inattention. Liao, Wang, Xiang, Yan, and Yang (2021) use the setting of online peer-to-peer lending platforms, which set time pressure on retail investors' choices and decisions. With limited time, retail investors pay more attention to payoffs, but less attention to risks in their choices. Fortunately, the consequences of fast thinking and the induced misjudgment can be reversed if more time is provided.

Related to limited attention, complexity is also studied in previous behavioral papers. Gao, Hu, Kelly, Peng, and Zhu (2024) investigate this phenomenon in China. From the perspective of investor sophistication, the authors study a complex product, the B funds, which contains embedded leverage (similar to mortgage backed securities in the U.S.). They find that return differences between investors with low and high sophistications is significantly larger using the B funds, than average products. That is, the more sophisticated investors better understand the more complexed products and have performance advantages on complexed products than less sophisticated investors.

Salient information is also directly linked to investor attention. Frydman and Wang (2020) experiment with screen display and change information salience towards investors in an experiment setting for Chinese investors, and examine how the information salience affect their trading activities. The experiment is conducted on a Chinese trading platform, and the authors vary the prominence of the display of a stock's capital gain (by providing more data points and more colors). The authors find that variations in screen display significantly increase the investor disposition effect by 17%, which not only shows the existence of behavioral properties related to salience, but also provides information on how platforms can change trading behaviors and investment decisions of investors. Hong, Lu, and Pan (2024) have similar findings for mutual fund distribution on fintech platforms. [14]

Recent literature pays increasing attention to investor extrapolation. Does this pattern also exist in China? Liao, Peng, and Zhu (2022) take the extrapolation to a bubble set up. They propose a theoretical framework where the interaction between extrapolative beliefs and disposition effects lead the investors to quickly buy stocks with good returns and quickly sell them if the good returns continue. These quick buys and sells trading dynamics help to explain the volume spikes during the bubble formation period. [15]

4.2 Gambling, Superstition, and Air Pollution

In this section, we focus on behavioral properties with China-specific characteristics. For instance, both gambling during the New Year and superstition can be traced back to ethnical and cultural traditions in China, while air pollution is related to a distinctive feature of a developing China over the past decade.

Traditionally, Chinese farmers take the month of lunar Chinese New Year off for entertainments and celebrations. One of these activities, unfortunately, is gambling. Doran, Jiang, and Peterson (2012) examine the gambling and lottery preferences of investors during the month of January and the month of Chinese New Year (January or February). They find the out-of-money

[14] More studies on salience include Qiu, Wu, and Zhang (2021), Sun, Wang, and Zhu (2023), etc.
[15] An interesting herding behavioral of institution investors is studied in Xu, Yu, and Yin (2013).

calls have higher demands during these months, and retail sentiment is more bullish for stocks with lottery features, both implying the impacts of gambling preferences. There are interesting differences between Chinese retail investors and retail investors from other countries. Specifically, the gambling preferences show up in January for the non-Chinese retail population, but only in the Chinese New Year month for the Chinese retail population.

In terms of superstition, Hirshleifer, Jian and Zhang (2018) examine how numerological superstition, some numbers are considered lucky while others are not, affects the IPO market. Their study shows that firms have preferences for lucky listing code, and investors react positively to the lucky listing numbers. The direct impact is more trading, higher IPO prices, but lower post-IPO returns. Fisman, Huang, Ning, Pan, Qiu and Wang (2023) examine how zodiac year affects risk taking at firm level. That is, everybody's birth year corresponds to a zodiac year, and the person in the zodiac year is supposed to be more cautious than usual. They find supportive evidence that firms with executives in their zodiac years reduce risk-taking significantly, both in investments and other firm decisions. Finally, Bazley, Cronqvist, and Mormann (2021) examine how colors affect trading decisions. The color red conveys danger in western countries, but indicates prosperity in China. The authors document negative trading reactions to information displayed in red for countries other than China, but the impact is muted in China.

Two studies investigate the relation between levels of air pollution in China and investor's trading accordingly. Huang, Xu, and Yu (2020) directly document negative relations between air pollution level and investor trading and later performances, and positive relation between air pollution level and behavioral biases, such as attention-driving trading and disposition effect. Putting together, the authors suggest that air pollution imposes negative impacts on stock market investors. Li, Massa, Zhang, and Zhang (2021) have similar findings, but with bigger datasets and more causal identifications.

4.3 Pooling Multiple Biases and Link Them to Trading

Previous sections provide many individual pieces of evidence on behavioral traits, and some of them have similar implications for trading dynamics and return performances. Therefore, it is much needed to understand how many biases coexist in a large population of China retail investors, and how these biases make their ways to real trading. That is exactly what Liu, Peng, Xiong, and Xiong (2022) achieve in their study. This influential study has two integrated parts. The authors first conduct a national survey in 2018 with more than 10,000 correspondents, which covers an exhaustive list of behavioral biases. Then, they compare their survey results on biases with real trading records from Shenzhen Stock Exchange. Unlike previous studies, Liu et al. (2022) has the best of the survey and real trading data, which help to understand connection between the subjective survey data on bias and objective trading data in an integral framework. From the survey, the most prominent biases are gambling and perceived information advantage (or overconfidence), and these two biases explain trading by 21% and 24%, respectively. These biases-induced trading leads to annualized trading fees of 0.6-0.7%, and accounts for a large part of excessive trading. This study not only provides comprehensive empirical findings for Chinese investors, but also serves as a new benchmark for studies on behavioral traits and trading in general.

Jones et al. (2024) also examine behavioral properties in retail trading dynamics. Based on the finding in Liu et al. (2022), they specifically focus on gambling and overconfidence. They find that the smaller retail investors display significant gambling and overconfidence biases, which probably attributes to their negative predictive power for future returns. However, larger retail investors don't display obvious behavioral biases and trade against the smaller investors when they display behavioral biases, suggesting that the large retail investors are more sophisticated and suffer less from behavioral biases than the small retail investors do.

We focus on behavioral studies on Chinese retail investors in this section. Given the low financial literacy, these retail investors are susceptible towards behavioral influences, some of which have been studied in the U.S. and other stock markets, such as attention, salience, extrapolation, gambling, and these Chinese studies offer additional evidence. Meanwhile, some of the topics are not studied in other markets, such as superstition and air pollution, and the Chinese evidence provides new and interesting insights into the literature. We end the session by Liu et al. (2022) study, which involves a comprehensive comparison of these behavioral biases and directly links them to investors' trading.

5. Regulations and Their Impact on Trading

Other than information and behavioral traits, regulations on capital market obviously affect trading dynamics and return predictability. As mentioned in the introduction, Chinese regulators frequently adjust regulations, maintain dual goals of growth and stability, while western policymakers generally refrain from substantial policy interventions except during crisis periods. In this section, we start with direct trading rules such as stamp taxes and price limits. Then we move on to influential regulation changes, which receive much academic attention, the warrant bubbles, and the IPO regulations. Finally, we discuss the government's direct involvement during financial crises.

5.1 Trading Rules: Tobin Tax, Daily Price Limit, and Circuit Breaker

Tobin tax is the security transaction tax, or the stamp tax on each trade. Deng, Liu, and Wei (2018) study how the tax changes affect trading and return volatility. Over the period of 1997 to 2008, there are 7 changes in Tobin tax for A shares listed in mainland exchanges, and 3 changes for H shares listed in Hong Kong exchange. These dual-listed stocks with identical fundamentals, strict capital control between mainland and Hong Kong and different timelines of tax changes make the identification in this study clean and effective. As discussed earlier for the case of A-H premium, retail investors are quite active in the A-share market, while more sophisticated foreign institutional investors dominate trading in the H-share market. The authors find that when stamp tax is raised, trading decreases in both markets. More intriguingly, the authors find in the A-share market volatility decreases with lower trading, while in the H-share market, volatility increases with lower trading. This drastic contrast shows that informativeness of trading in the A-share market probably is much lower than the informativeness of H-share trading. That is, retail trading, which accounts for most A-share trading volume are not informative, and higher Tobin tax deters this type of noise trading, while more informative trading in H-share market is reduced when Tobin tax raises costs for transaction and increases uncertainty.

A parallel study by Cai, He, Jiang and Xiong (2021) examine stamp tax increases in 2007. Instead of comparing trading in A- and H-shares market, they compare trading in the stock market, which is subject to the tax change, and trading in the derivatives market, which is not subject to the tax change. As reported in Deng et al. (2018) and Cai et al. (2021), a higher stamp tax significantly reduces retail trading in the stock market. These squeezed out retail flows migrate to the derivatives market, namely, the warrant market. The large inflow of retail investors, potentially those with low financial literacy and speculative motives, quickly generate trading frenzies and a large bubble in the warrant market.

Another trading rule which attracts substantial attention is the daily price limit. To stabilize the market, the exchanges impose daily price limits of 10% for regularly stocks, and 5% for special treatment stocks (or troubled "ST" stocks). When stock prices move beyond the daily limits, trading halts are imposed. Chen, Gao, He, Jiang, and Xiong (2019) examine whether daily price limits really achieve the goal of stabilization. Contrary to the expectation and the intention of rule makers, they find that large retail investors actually take advantage of this rule and potentially engage in price manipulation, which leads to destructive trading and unnecessary uncertainties. In particular, large investors buy large quantities of stocks on the day of limit-hitting, likely pumping the price to the 10% price limit, and trading is halted for that day. Then the next day, these investors quickly dump their inventory, while small investors under bullish illusions buy in. The direct result of this hump-and-dump scheme is excessive volatility and low returns for affected stocks. [16]

Another market stabilization mechanism that attracts significant attention is the market-wide circuit breaker (MWCB) policy. To curb excessive volatility, Chinese regulators start to implement MWCB from 1st January 2016, which halts trading in all securities for 15 minutes (or until the market closes) if the CSI 300 Index changes by 5% (or 7%). However, it is triggered on the first trading day 2016 and again in the same week. The repeated trading halts arouse a massive sell-off as panicked investors rush to sell before hitting the thresholds. The mechanism is then quickly abolished by regulators to stabilize the market. Chen, Petukhov, Wang, and Xing (2024) propose a theoretical model to explain this phenomenon, suggesting that a circuit breaker tends to lower the stock price in general, and especially when prices approach the threshold, it would increase volatility substantially and thus trigger the circuit breaker. Empirically, Wang, Xu, and Zhang (2019) find that MWCB actually has no "cooling effect" in decelerating falling prices and reducing market volatility, and Wang, Kim, and Suardi (2022) show investors' herding increases the likelihood of MWCB being triggered.

5.2 The Warrant Bubble

[16] More studies on price limit include Lin, Qiu and Zheng (2023). Other interesting trading rules in China include the T+1 trading rule (Bian, Su and Wang, 2022)).

Warrants are options to exchange strike prices and underlying stocks. The call warrants allow owners to pay strike prices to obtain shares, and the sell warrants allow owners to sell shares at the strike prices. As an initial trial of an option market, the Chinese government allows a set of publicly listed firms to issue 12 put warrants and 37 call warrants on the two stock exchanges during 2005-2008. As mentioned in Cai et al. (2021), these warrants attract substantial attention of retail investors, which leads to trading frenzy and price bubbles in the warrant market. Because of the frenzied speculation in these warrants, the Chinese government discontinues the warrant market in 2008, since when options on individual stocks are not allowed to be traded on any exchange. Given this interesting set up, many studies are conducted on the warrant bubble in China.

Xiong and Yu (2011) use the warrant bubble episode to examine multiple bubble theories, and find both short-sale constraint and divergence in opinions are main drivers for the warrant bubble. Liu, Zhang, and Zhao (2015) document strong spillover of the speculative trading in warrant market transfer to the stock market for the underlying firms, in the sense that trading volumes explode and volatility spikes for these stocks. Gong, Pan, and Shi (2017) focus on one particular warrant, the Baosteel warrant, and find the bubble already forms at the opening auction, and lasts over the duration of the warrant. Pearson, Yang, and Zhang (2021) propose that extrapolation and speculative trading are the reasons for the warrant bubble, which is similar to the finding of Liao, Peng, and Zhu (2022).

How do different investors trade and interact at the warrant bubble episode? Li, Subrahmanyam, and Yang (2021) provide a more comprehensive view. They find that unskilled /losses, while skilled investors, potential institutional investors or large retail investors, trade on the other side and make profits during this bubble episode. In an efficient market, prices return back to fundamentals after a while, but the imposed price limits in the Chinese warrant market become obstacles in multiple cases, defer the price discovery process and fail to stop the trading frenzy.

Warrants are one form of derivatives. Introduction of derivatives normally allows leverage trading, which facilitates risk management practice, but might also induce speculative trading. For instance, the introduction of stock index futures in 2010 leads to the rapid growth of quantitative investing strategies in the stock market. We refer readers to Hu and Wang (2022) for the market evolution on index futures and options, and the studies they review to obtain insight on various roles of derivatives. Another related leveraged instrument is margin trading. Bian, Da, He, Lou, Shue, and Zhou (2023) use account-level data to study margin trading during the 2015 bubble-crash episode. They find that margin trading is mostly driven by retail investors' overconfidence and lottery preference, and later tightening leverage constraints lead to selling and lower prices. Subrahmanyam, Tang, Wang, and Yang (2024) use intraday transactions data at a future brokerage and find that leverage is negatively related to performance across all investors. They further find unskilled investors' leverage amplifies losses from lottery preferences and the disposition effect, while leverage stimulates liquidity provision by skilled investors.

5.3 Regulations on IPOs

Over the past few decades, the regulators lean towards more direct financing from the stock market, and they experiment with multiple designs to encourage high quality IPOs, which would attract more direct finance. The IPO regulation is adjusted several times, from the quota system before 1999, to the approval system after the introduction of Securities Law, to the registration system which is initiated on Shanghai Stock Exchange's STAR market in year 2019 and expanded to all markets in 2023. Qian, Ritter and Shao (2024) focus on the Chinese style of IPOs, which is drastically different from the U.S. style. They find that stricter regulations, such as the P/E cap pricing restrictions, suppress share prices but induce high IPO returns. That is, with low share prices, going public becomes a costly choice for firms for financing. Meanwhile, the high returns over the IPO periods make these IPOs lottery tickets for investors, which promotes lottery preferences and gambling among all investors. [17]

Since strict regulations do not serve the purpose of IPOs efficiently (Shao and Wu, 2009; Zhang, Chen and Wei, 2020), the registration-system reform is undergoing and achieves certain progress, reflected by a lower IPO return in Lai, Lan and Qin (2022), better information environment in Wu, Rao and Yue (2022), and higher professionalism of intermediaries in Luo, Dong and Li (2023), for instances. Specifically, the registration system does not require listing firms to be profitable, and the offer price is not limited to a set P/E ratio. Qian et al. (2024) empirically compare IPOs under the registration system and those still under the approval system, and find the latest reform has achieved some of its intended goals and its long-term success and sustainability still remain to be seen.

5.4 Government Involvements During Crisis

Beyond regulation, the government may directly participate in the market through open-market operations with the goal of stabilization, especially during periods of crises. For instance, state-affiliated entities, often referred to as the "national team", act on behalf of the government to invest in markets to raise confidence and stabilize prices. Li, Jin, Zhang (2019) provide evidence that during the 2015 market crash, national team ownership effectively mitigates tail risk, provides liquidity, and bolsters market confidence. Their study shows that a one standard deviation increase in national team ownership is associated with a 10% decrease in the standard deviation of left tail risk. Dang, Li, Wang (2024) decompose the intervention impact of the national team into two

[17] Other studies of IPO lottery include Gao, Shi, and Zhao (2021).

components: a direct trading effect and a disclosure effect, showing that both lead to reduced volatility. However, the disclosure effect undermines stock price informativeness, suggesting that investors have a stronger incentive to acquire information regarding government intervention rather than fundamental information, which actually supports the implications from the "government-centric equilibrium" modeled by Brunnermeier et al. (2022).

6. Conclusion

The composition of the Chinese stock market (the second-largest stock market) is quite different from that of developed markets, with a dominance of retail investors, relatively weak institutions, and active government participation. Therefore, it is important to understand the trading dynamics of these investors and how their trading is related to price discovery and price efficiency. In this review, we discuss the composition of the Chinese stock market investors, namely, retail investors, institutional investors, and foreign investors; investigate their trading dynamics and return predictive powers; and examine their trading motives, mostly associated with information, behavioral traits, and/or regulation changes.

We make three observations after reviewing nearly 100 papers. First, China has the largest retail population in the world, and retail investors with different account balances display distinctive patterns. Smaller retail investors have lower financial literacy and are susceptible to behavioral biases; they trade in the wrong directions of future price movements; and they fail to process public information. In contrast, large retail investors and institutional investors are mostly sophisticated and trade on relevant information, and can correctly predict future price movements. Second, the information environment in China is gradually improving with the efforts of professionals, such as analysts and fund managers, and regulatory innovations, such as interactive investor communication platforms. Third, the regulators design the rules and policies to serve the dual goals of growth and stability. Many of the regulations are effective and suit the current status of the market, but some others may generate unintended consequences.

There are three potential directions for future research. First, with the large population of retail investors likely migration from direct and individual stock investments to diversified portfolios (such as pension funds) in the near future, institutional investors are expected to be more important in the Chinese capital market. Therefore, studies on their trading behaviors and their impacts on systematic risks are greatly needed. Second, with the advances in fintech, such as machine learning and AI, it is interesting to examine how they facilitate information discovery and reduce the behavioral biases of retail investors. Finally, it is worth studying how regulators, in China and other emerging markets, design effective and efficient policies to promote market efficiency and guard against potential risks and vulnerabilities.

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Appendix. Studies Categorization

We categorize all papers cited in this review into three types: (a) Chinese investors demonstrate different trading behaviors than their counterparts in other markets; (b) Chinese data is used to examine certain theories that can't be tested in other markets; (c) Chinese market, with similarities to other emerging market, actually provides a useful channel to understand other emerging markets.

Section	Studies	Category
1	Jones, Shi, Zhang, and Zhang (2024), Brunnermeier, Sockin, and Xiong (2022), Carpenter, Lu, and Whitelaw (2021), Bekaert, Ke, Wang, and Zhang (2023), Allen, Qian, and Gu (2017), Carpenter and Whitelaw (2017), Hachem (2018), Song and Xiong (2018), Allen, Qian, and Qian (2019), Hu, Pan, and Wang (2021), Hu and Wang (2022)	b&c
2.1	Jones, Shi, Zhang, and Zhang (2024), An, Lou, and Shi (2022), Choi, Jin, and Yan (2013), Pan, Tang, and Xu (2016), Ng and Wu (2007), Chen, Yuan, and He (2013), Li, Geng, Subrahmanyam, and Yu (2017)	b&c
2.2	Chui, Subrahmanyam, and Titman (2022)	a
	Lundblad, Shi, Zhang, and Zhang (2023), Chen, Du, Li, Ouyang (2013)	b&c
3.1	Guo, Jia, and Sun (2023), Ammer, Rogers, Wang, and Yu (2023), Han and Hong (2014), He, Wang, Zhu (2023)	b&c
3.2.1	Chan, Menkveld, and Yang (2008), Chan, Menkveld, and Yang (2007)	a
	Gul, Kim, and Qiu (2010), Yan, Xu, Shi, and Wang (2012)	b&c
3.2.2	Andrade, Bian, and Burch (2012), Kong, Lin, Liu, Tan (2021)	b&c
	Jia, Wang, and Xiong (2017)	a
3.2.3	Lee and Zhong (2022), Ding, Lv, and Chen (2018), Blankespoor (2022), Duan, Li, Rogo, and Zhang (2024), Yoon (2021), Bian, Chan, Han, and Shi (2023), Gao, Pittman, Wang, and Wang (2023)	a
3.2.4	Feng and Seasholes (2004), Chen, Ma, Martin, and Michaely (2022), Cheng, Du, Wang, and Wang (2016), Han, Kong, Liu (2018), Chen, Qu, Shen, Wang, and Xu (2022), Dong, Fisman, Wang, and Xu (2021)	a
	Xu, Xuan, and Zheng (2021), Wang, Yu, and Zhang (2023)	b&c
4	Song (2020), Titman, Wei, and Zhao (2022), Li, Yu, Lu, Xu (2014), Hu, Liu, and Xu (2021), Hu, Lin, and Liu (2022)	b&c
4.1	Hong, Jiang, Wang, and Zhao (2014), Jiang, Liu, Peng, and Wang (2022), Chen, An, Wang and Yu (2023), Frydman and Wang (2020), Hong, Lu, and Pan (2024), Liao, Peng, and Zhu (2022), Qiu, Wu and Zhang (2021), Sun, Wang and Zhu (2023), Xu, Yu and Yin (2013)	b
	Chan, Liao, Martin, and Wang (2023), Liao, Wang, Xiang, Yan, and Yang (2021), Gao, Hu, Kelly, Peng, and Zhu (2024)	a

4.2	Doran, Jiang, and Peterson (2012), Hirshleifer, Jian, and Zhang (2018), Fisman, Huang, Ning, Pan, Qiu, and Wang (2023), Bazley, Cronqvist, and Mormann (2021), Huang, Xu, and Yu (2020), Li, Massa, Zhang, and Zhang (2021)	a&c
4.3	Liu, Peng, Xiong, and Xiong (2022)	b
5.1	Deng, Liu, and Wei (2018), Cai, He, Jiang, and Xiong (2021), Chen, Petukhov, Wang, and Xing (2024), Wang, Xu, and Zhang (2019), Wang, Kim, and Suardi (2022)	b
	Chen, Gao, He, Jiang, and Xiong (2019), Lin, Qiu, and Zheng (2023), Bian, Su, and Wang (2022)	a
5.2	Xiong and Yu (2011), Liu, Zhang, and Zhao (2015), Gong, Pan, and Shi (2017), Pearson, Yang, and Zhang (2021), Li, Subrahmanyam, and Yang (2021)	a
	Bian, Da, He, Lou, Shue, and Zhou (2023), Subrahmanyam, Tang, Wang, and Yang (2024)	b&c
5.3	Qian, Ritter, and Shao (2024), Gao, Shi, and Zhao (2021), Shao and Wu (2009), Zhang, Chen, and Wei (2020), Lai, Lan, and Qin (2022), Wu, Rao, and Yue (2022), Luo, Dong, and Li (2023)	b&c
5.4	Li, Jin, Zhang (2019), Dang, Li, and Wang (2023)	a&c