Speculation or Portfolio Rebalance during IPOs? Evidence from China

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Abstract

We investigate how retail investors respond to the upcoming IPO events. Using a large sample of retail investors' trading data from a major brokerage firm in China, our findings reveal a nuanced and varied trading behavior among retail investors in the pre-IPO market, encompassing elements of speculation and portfolio rebalancing. Investors exhibit impulsive heavy sells of their stock holdings to generate funds for IPO subscriptions, regardless of the correlation between the sold stocks and the forthcoming IPO stock. However, as the IPO shares are listed or near listing, investors engage in substantial stock repurchases. In contrast to sentiment-driven selling for liquidity creation, these purchases reflect rational behavior indictive of portfolio rebalancing. Empirical evidence indicates a notable preference among investors for buying stocks closely related to or within the same industry as the IPO stock, aligning with a substitution effect. This paper provides a behavioral explanation for the IPO's spillover effect on related companies and offers practical insights for investors on portfolio rebalancing during IPOs. Additionally, it suggests regulatory considerations for moderately simplifying the IPO process.

Key Words: Initial Public Offerings; Retail Investor Trading; Speculation; Portfolio Rebalance; Spillover Effect

JEL Classification Code: G11

1. Introduction

As important corporate events, IPOs (Initial Public Offerings) carry substantial implications for investors, listed companies, and the broader stock market. Previous studies have consistently demonstrated that IPOs can have a negative impact on the stock prices of closely correlated companies. Pioneering work by Braun and Larrain (2009) establishes a lasting adverse effect of IPOs on stocks highly correlated with the IPOs. Further insights from Hsu et al. (2010) indicate that companies within the same industry experience negative stock price reactions following completed IPOs, while withdrawn IPOs yield positive reactions. If the IPO is large enough, it may affect the whole market price level in addition to the impacts on related companies. Shi et al. (2018) provide robust evidence that sizable IPOs depress the market price on not only the listing day but also the offering (subscription) day.

A range of theoretical hypotheses has been advanced to explain why IPOs have negative impacts on related stocks and how long this impact lasts. The main explanation stems from the classic demand-supply theory, which is, in a market with various imperfections and a downward sloping demand curve for stocks, an expected increase of supply of shares through IPOs reduces the market demand for closely substitutable stocks, thereby depressing their equilibrium prices (Scholes, 1972; Mikkelson and Partch, 1985). Alternative perspectives suggest that an IPO might signal intensified competition in the product market for its rival companies, leading to a price decrease of the close substitutes of IPOs (Akhigbe et al., 2003; Hsu et al. 2010). Spiegel and Tookes (2020) further point out that IPOs tend to occur when industry conditions are deteriorating. In either scenario, the negative price impact on related companies is expected to occur upon the release of credible IPO news, rather than after IPO shares are available for trading.

The impact of IPO on peer companies is not conclusively negative. Akhigbe et al. (2003) argue that IPOs convey positive industry-related information, leading to an increase in the market value of their competitors. In a recent study, Li and Zhang (2021) provide evidence, based on Chinese data, that competitor firms benefit from IPO with a 12-day positive cumulative abnormal return (CAR) of 1.21% when their competitors go public. Ritter (1991) also highlights that firms in certain industries opt to go public when investors are over-optimistic about the overall industry's prospects.

Ljungqvist (2004) suggests that IPO researchers should focus more on behavioral approaches to gain a better understanding of the extent of underpricing and related issues. Sentiment investors often engage in speculative trading, anticipating significant underpricing and their trades can be transient, which makes a temporary price impact on related stocks that should reverse relatively quickly (Shi et al., 2018). Alternatively, if investors are more rational and trade IPO stocks for portfolio rebalance purposes, their subscription to IPO shares may involve selling some existing shares that closely resemble the IPO shares. In this case, the decline in those close substitute stocks might persist for a longer term unless it triggers a temporary liquidity shortage (Braun and Larrain, 2009). However, prior studies have relied on stock market data to infer investor reactions to IPOs, as individual investor trading information is typically unavailable. This paper extends this line of research by closely examining investors' pre-IPO trading within a unique window of events in China. It investigates the rationality of their trading activities and the consequential impact on related stocks, with the help of an exclusive dataset obtained from a large brokerage firm.

The characteristics of China's stock market provide an advantageous setting for this research. First, after tree decades of development, China's stock market has evolved into the largest emerging stock market and the world's second largest stock market. By the end of 2021, the A-share market in China boasted 4,684 listed companies with a cumulated market value of 14.37 trillion dollars. Notably, China's stock market differs from those in European and American countries due to strict control over capital flows, leading to its segmentation from other global capital markets. Therefore, IPOs in China's stock market are less affected by international capital flows compared to other stock markets.

Second, China's stock market is dominated by individual investors, therefore, there is a strong speculative atmosphere in China's stock market. According to the statistical yearbook provided by the Shanghai Stock Exchange, China's stock market exhibits the following two characteristics: (1) Investors in China's stock market are still mainly individual investors. By the end of 2017, a total of 195 million investors had opened accounts, of which more than 194 million were individual investors, accounting for 99.7%. (2) The trading volume of China's stock market is mainly provided by individual investors. By the end of 2017, individual investors accounted for only 21.17% of the stock market value, but the transaction volume accounted for 82.01%. Besides, China has one of the highest rates of IPO underpricing in the world, about 191%, on average, for the 2001-2020 period (Yan et al., 2019). Therefore, almost all IPOs are oversubscribed in China. During the years from 2001 to 2020, the oversubscription rate of IPO shares reaches 1845, on average, which means that IPOs in China have captured great attention. The heavy speculation of IPOs should spur investors to behave differently than usual.

Third, in China's stock market, information about IPOs can be viewed as gradually revealed. This characteristic allows us to study not only investor behaviors on and around listing days but also behaviors on and around offering days. The time span between IPO approval and actual listing in China varies from a month to a year, with a median of 2.5 months. Typically, there are several days between the offering day (when subscriptions for IPO shares are submitted) and the lottery day (when investors are notified of share allocations). From 1997 until the end of 2015, subscribers in China were required to pay in full for all the shares they subscribe to, with payments frozen in escrowed accounts at the China Securities Registration and Settlement Company for up to three days when the subscription order was checked and verified between offering day and lottery day. After this frozen period, allocated shares were credited to investors' accounts, and the funds associated with oversubscriptions were returned. For investors without sufficient reserved funds, a common situation among Chinese retail investors, selling existing stocks or raising fund in other ways to create liquidity was necessary, increasing their risk and transaction costs. Reckless selling could also lead to trading losses. What's more, since only a small portion of investors receive new share allocations, large amounts of money were returned to unsuccessful subscribers after the frozen period, heightening their reinvestment risk. This frozen fund policy underwent changes after 2016. In the revised policy, only winners of the subscription were required to pay, and payment occurred only after the allocation of shares is confirmed. This alteration eliminated the freezing of funds between the offering day and lottery day, significantly reducing capital pressure on subscribers. This unique institutional setup allows us to study the IPO effect on investor behaviors around the offering day (subscription day), and data collected before and after 2016 form two samples for comparative analyses. Examining the behaviors investors exhibit in each of these two situations become essential.

There is additional evidence that IPOs in China's stock market may influence investor behaviors. Tian (2011) finds that Chinese IPO underpricing is primarily attributed to government intervention through IPO pricing regulations and the control over IPO share supplies. The China Securities Regulatory Commission (CSRC) placed nine moratoriums on IPOs after 1994[1], each following a sharp or prolonged fall market price decline. After 2014, the CSRC imposed restrictions, limiting the price of new shares from rising or falling by more than 44% on the first day after IPO. While this rule, to some extent, diminishes IPO speculation on the first trading day, it may concurrently disperse the IPO speculation over several days following the listing day. As argued by Shi et al. (2018), these measures aim to mitigate the impacts of IPOs on China's stock market, ultimately benefiting investors.

Using account data from a prominent brokerage in China, we directly investigate how investors respond to IPOs. We find that retail investors' trading pattern in pre-IPO period is inconsistent, with a blend of speculation and portfolio rebalancing. First, investors tend to sell stocks they already own to raise funds for the upcoming IPO subscription. In the sample period from 2012 to 2015, when the frozen fund requirement was in effect, each IPO subscriber's net selling value amounted to 414 RMB in the pre-offering period and 520 RMB on the offering day, respectively. In the subsequent period from 2016 to 2019, when the frozen fund requirement was lifted, each IPO winner's net selling value reaches 149 RMB on the lottery day. Secondly, despite selling substantial quantities of existing stocks to fund upcoming IPOs, these stocks show no significant correlation with the IPO company. This leads us to conclude that investors sell stocks for liquidity purposes rather than based on valuation, suggesting a speculative element. Thirdly, after funds are released post the frozen period, investors who were unsuccessful in securing their desired IPO allocation re-enter the stock market and

[1] The start and end dates of the nine moratoriums are: from July 21, 1994 to December 7, 1994 (for a total of 98 trading days); from January 19, 1995 to June 9, 1995 (for a total of 96 trading days); from July 5, 1995 to January 3, 1996 (for a total of 128 trading days); from July 31, 2001 to November 2, 2001 (for a total of 69 trading days); from August 26, 2004 to January 23, 2005 (for a total of 101 trading days); May 25, 2005 to June 2, 2006 (for a total of 264 trading days); from September 16, 2008 to July 10, 2009 (for a total of 191 trading days); from November 16, 2012 to December 31, 2013 (for a total of 270 trading days); July 5, 2015 to November 30, 2015 (for a total of 99 trading days).

engage in aggressive buying. This phenomenon is more evident before 2016, with each subscriber's net buying value averaging 751 RMB on the unfrozen day, nearly twice the net selling value of investors on the pre-offering or the offering day. Finally, we provide direct evidence that retail investors consider the IPO-related stocks or those in the same industry as substitutes for IPO shares due to constraints in the IPO process, indicative of portfolio rebalancing.

Our paper makes several important contributions to finance literature: first, we extend prior research by providing first-hand empirical evidence regarding theoretical arguments about the IPO spillover effect on related stocks. In contrast to previous studies that draw conclusions based on macro market data or stock market data, our approach offers a more nuanced understanding. Secondly, we focus on behavioral approaches, demonstrate the dynamic trading process of retail investors at different stages during IPOs, and offer explanations for various investors' trading motives. This behavioral perspective adds depth to our understanding of the market dynamics surrounding IPOs. Thirdly, our analyses involve a comprehensive comparison of events. The sample size is substantial, incorporating daily account trading transaction data and investor portfolio holding data, and covers an extended periods. This dataset enhances the reliability and applicability of our findings. Finally, the paper carries theoretical implications for stock price pressures and spillover effects of IPOs. It also has practical implications for investors, suggesting strategies to rebalance their portfolios during IPOs, and regulators, indicating potential avenues for moderately simplifying the IPO process.

The remainder of this paper proceeds as follows. In Section 2, we introduce the institutional background of China's stock market and the accounting data of retail investors used in this paper. In Section 3 we develop the hypotheses and construct the variables used in this paper. Section 4 conducts empirical analyses, and Section 5 provides the robustness test. Section 6 concludes.

2. Institutional Background and Data

2.1 Institutional Background

There are three stock exchanges in mainland of China: the Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange (SZSE), and Beijing Stock Exchange (BSE). The SSE was launched on November 26, 1990, the SZSE on December 1, 1990, and the BSE on September 3, 2021. By the end of 2021, a total of 4,684 companies were listed on these three stock exchanges, with a combined market value reaching 14.37 trillion dollars. Presently, China's stock market stands as the largest emerging stock market and the world's second-largest stock market.

China's stock market displays several distinctive features in its IPO system compared to developed markets like the United States, due to its imperfect legal environment, lack of effective supervision, and the dominance of retail investors. First, China adopts an examination and approval system, in contrast to the registration system in the U. S. Under this system, a company seeking to go public can only obtain the issuance qualification after the approval by the Issuance Appraisal Committee of the CSRC. The system aims to prevent the public issuance of securities of poor quality. However, since the government carries out more administrative intervention and even controls the quantity and rhythm of IPO, it increases the risk of moral hazard and hinders the efficient adjustment of supply and demand. Secondly, information disclosure by listed companies during the IPO process is relatively low in China. A considerable number of listed enterprises are facing changes in performance or even significant declines in performance. Thirdly, the pricing mechanism in China is complex. China's distribution methods include online purchase, offline distribution, and placement to strategic investors. Since institutional investors account for only 10% of all investors, it is difficult for them to play an important role in stabilizing the market.

Although the SSE and the SZSE were officially established only in the early 1990s, the methods of price determination, share issuance, and allocation have undergone numerous changes throughout these years (Cheung et al., 2009; Shen et al., 2013; Shi et al., 2018). In China's IPO market, almost all IPOs were over subscripted. Share is allocated to retail investors using randomized lotteries to cope with the excess demand. From the beginning of 1997 until the end of 2015, investors had to pay in full for all new IPO shares they subscribed to, and the number of new IPO shares each retail investor can subscribe to is based on the average market value of his shareholdings during the past 20 trading days in the SSE and the SZSE on offering day[2] (defined as day [*T*]), and the payment was frozen at the China Securities Registration and Settlement Company for up to two or three days when the subscription order was checked and verified. After the frozen period, the allocated shares were credited to the investors' accounts on lottery day (defined as [*T*+3] or [*T*+4]), and the funds associated with oversubscriptions were returned to investors. Starting from 2016, no frozen funds are required with IPO subscriptions, that is, investors are allowed to subscribe to a certain number of IPO shares based on the average market value of their shareholdings during the past 20 trading days in the SSE and the SZSE without paying for the subscriptions on offering day, subscribers pay when the lottery results are out on lottery day, and they only pay for the shares allocated to them. The interval between an IPO approval and actual listing in

[2] In the SSE, an investor can subscribe 1,000 IPO shares for every RMB 10,000 of tradable stocks listed in the SSE he or she holds. However, things are different in the SZSE. Before June 2018, the threshold for subscription in the SZSE is the same as in the SSE, that is, in order to subscribe IPO shares, an investor must hold at least RMB 10,000 of tradable stocks listed in the SZSE; but for the listed stocks exceeding RMB 10,000, an investor can subscribe 500 IPO shares for every more RMB 5,000 of tradable stocks listed in the SZSE. However, after June 2018, the threshold for subscription in the SZSE is lower, an investor only needs to hold at least RMB 5,000 of tradable stocks listed in the SZSE, and an investor can subscribe 500 IPO shares for every RMB 5,000 of tradable stocks listed in the SSE he or she holds. The calculation of stock value only includes the value of non-restricted A-shares, including the credit securities account of margin trading customers and the securities company's refinancing guarantee securities account. The market value of B-shares, ETFs, funds, bonds or other restricted A-shares are not included, and the multiple securities accounts of the same investor will be combined to calculate the stock value.

China ranges from a month to a year, with a median of 2.5 months.

2.2 Data

We obtain account data of individual investors from a prominent securities broker in mainland China. The dataset comprises three main components: (i) Individual transaction data: this segment includes all trading information for nearly four hundred thousand individual investors. It includes details such as transaction date, stock codes, transaction volume, transaction price, and other relevant information. (ii) Individual portfolio holding data: This component provides information about each investor's portfolio holdings of stocks at the end of each trading day. It includes individual holdings, providing comprehensive details about the investor's holding at the end of each trading day, including stocks and funds. (iii) Individual demographics: This section includes demographic information about investors. encompassing age, gender, education level, length of trading experience, birthplace (proxied by the first six numbers of the ID card, traceable to the exact county of birth), and working place (proxied by the address of the sales department that opened the investors account). The account data spans from January 1, 2012 to September 30, 2019.

Table 1 presents the summary statistics of the investors in our sample, it includes a total of 383,499 retail investors based on brokerage account information. The average investor age is 48.89 years, the average trading experience is 11 years, and their average net worth is 174,791.90 RMB. No significant gender difference is found among investors. Not every investor in our sample has participated in at least one IPO; at the same time, one investor can subscribe to multiple IPOs. In the dataset, the investor-IPO-subscription total is 236,444, and the investor-IPO-lottery wins are 137,655 during the sample period. The average net worth, age, and trading experience of the IPO subscribers are slightly higher than those of the average retail investors in our sample, while the average IPO winners have even higher numbers in these demographic characteristic traits.

[Insert Table 1 Here]

We compare the investor demographic information used in our sample with the one published in the Shanghai Stock Exchange (SSE) Statistical Yearbook. The result is provided in Table 2. The two datasets share similar distribution in all four dimensions including asset, age, education level, and gender. So we can confidently say that the investor sample used in this paper is a good proxy for individual investors in China's stock market.

[Insert Table 2 Here]

We also collect all A-share IPO data from the CSMAR database and the WIND database, including the offering date, lottery date, listing date, issuing size, and frozen funds of each IPO; we also collect the daily stock return, daily stock trading value, daily stock tradable capitalization, and daily stock total capitalization. Table 3 presents the summary statistics of all IPOs during our sample period from 2012 to 2019.

[Insert Table 3 Here]

Braun and Larrain (2009) and Shi et al. (2018) pointed out that an IPO must be large enough before it can have any impact on other stocks. Asquith and Mullins Jr (1986), Krasker (1986), and Corwin (2003) also found a similar phenomenon in SEOs, that is, the larger the size of the SEO is, the larger the impact it has on other asset prices. On the other hand, as the China's capital market increases, the price impact of any single IPO on the complete capital market is less significant. All things considered, we filter out IPOs with issuing proceeds less than 1% of the average daily market trading value in the month before the IPO event[3]. Table 4 presents the summary statistics of the

[3] If there is more than one IPO on the same day, their proceeds are summed. There can be more than one IPO on the listing day, but the corresponding subscription days are likely different, and vice versa. For example, suppose there

selected IPOs from 2012 to 2019 used in this paper.

[Insert Table 4 Here]

3. Hypothesis and Variable Definitions

3.1 Hypothesis Development

During the IPO process, there are four important dates relative to this research: the offering day, the lottery day, the unfrozen day (before 2016), and the listing day. Offering day (OD) is the public online subscription day, defined as day [*T*]. Lottery day (LOD) is the day on which the subscribers of an IPO are informed of the lottery results, usually it is the day [*T*+2]. Unfrozen day (UFD) is the day on which the oversubscription funds are returned to investors[4], typically, it is the day [*T*+3]. Listing day (LD) is the day the new IPO shares get listed. These four Pre-IPO special days are called Event Days.

The key question studied in this paper is whether retail investors subscribe new IPO shares due to speculation or portfolio rebalance. Their trades may follow inconsistent logic around different pre-IPO Event Days. Accordingly, we develop a set of hypotheses that form the basis for the empirical tests in the subsequent sections of this paper.

Our first main hypothesis focus on how keen investors are to subscribe to new IPO shares. China has one of the highest rates of IPO underpricing in the world, about 191%, on average, for the 2001-2020 period (Yan, et al., 2019), therefore, almost all IPOs were over subscripted in China' s IPO market, often by more than a hundred times. Before

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are 3 firms, A, B, and C, the offering day of firms A and B is on the same day [Day_1], and the listing day of firms B and C is on the same day [Day_2]. If we study the investors' reaction to IPOs on the offering day, we sum up the issuing proceeds of firms A and B and call the result $Proceed_1$; if we study the investors' reaction to IPOs on the listing day, we sum up the issuing prodeeds of firms B and C and call the result $Proceed_2$. If $Proceed_1$ is larger than 1% of the average daily market trading value in the month before the IPO event, we select the IPOs of firms A and B into our sample, otherwise we do not include A and B in our sample; If $Proceed_2$ is larger than 1% of the average daily market trading value in the month before the IPO event, we select the IPOs of firms B and C into our sample, otherwise we do not include B and C in our sample.

[4] The unfrozen day only exists in IPOs prior to 2016. After 2016, there are no frozen funds, so there is no unfrozen day.

2016, investors had to pay in full for the new IPO shares they subscribed to despite of the final share allocation they receive. After 2016, investors needed only to pay for the new IPO shares allocated to them. While many Chinese investors have set aside a fund specifically for IPO subscriptions, not all investors have reserved funds to speculate on the IPO. Therefore, a portion of the total subscription money is expected to be raised by selling existing stocks:

Hypothesis 1: Retail investors sell stocks already owned to raise funds for new IPO online subscription on or before the offering/subscription day.

In addition to identifying the trading direction (buy or sell), we are more interested in the relationship between the stocks sold by retail investors and the new IPO stock. Previous studies have shown that IPOs negatively affect the existing stocks which are closely related to the IPOs and even the whole stock market (Akhigbe, et al., 2003; Braun and Larrain, 2009; Hsu, et al., 2010; Shi, et al., 2018). However, the discussion of the IPO price effect on other stocks is more intricate in China. Some researchers believe that investors in China speculate on significant IPO underpricing by selling some existing shares to create liquidity for purchasing IPO shares, which would result in a transitory negative price impact on existing stocks (Shi, et al., 2018); others claim since the number of IPO stocks is far from meeting the needs of investors due to the IPO constraints in China's stock market (Liu, et al., 2019), therefore, investors see the IPO-related stocks as the substitutes of the IPO shares, and drive up their prices (Li and Zhang, 2021). We argue, based on the special circumstances of the Chinese stock market, rational investors should sell the stocks that are not related to the IPOs and keep the ones that are highly related to the IPOs. It is irrational if retail investors sell stocks no matter whether the companies are related to the IPO stock or not.

Hypothesis 2: rational investors sell stocks that are not related to the IPOs and keep the ones that are highly related to the IPOs. It is irrational if retail investors sell stocks no matter whether the companies are related to the IPO stock or not.

Hypotheses 1 and 2 focus on the selling behaviors of retail investors before the online subscription is available to them; in fact, they also buy stocks during IPO issuance periods. According to the IPO subscription system of China's market, investors had to pay in full for the new IPO shares they subscribed to before 2016, which took a lot of funds from investors since the oversubscription rate of IPO shares reaches 1845 times of offering shares on average from 2001 to 2020. This means that once the frozen funds were returned to investors, there would generate considerable liquidity. After 2016, although investors need only to pay for the new IPO shares that were allocated to them, the constraints in China make the inefficient supply of IPOs fails to meet the huge demands of investors. Many previous studies have shown that stocks in investors' investment portfolios are often highly correlated (Choi and Sias, 2009; Jame and Tong, 2014). If investors regard IPO-related stocks as substitutes for IPO shares, then they will buy those stocks that are highly correlated to the IPO in the late IPO process.

Hypothesis 3: Retail investors buy stocks that are highly correlated to the IPOs as substitutes for the IPO stocks in the late pre-IPO period.

3.2 Variable Definitions

For IPOs issued before 2016, we define 8 IPO periods as follows:

(i) Pre-offering period (denoted as PRE_O): one day [*T*-1] or two days [*T*-2, *T*-1] before the offering day.

(ii) Offering day (denoted as OD): the online public subscription day [*T*].

(iii) Frozen period (denoted as FP): the time period between the offering day and the unfrozen day [*T*+1, *T*+2].

(iv) Unfrozen period (UFP): The day the oversubscription funds are returned to investors [UFD] or a 2-day period [UFD, UFD+1].

(v) Pre-listing period (PRE_L): the day before listing [LD-1] or 2 days before listing [LD-2, LD-1].

(vi) Listing day (LD): the day the IPO shares get listed [LD].

(vii) Post-listing day (POST_L): the day after the listing [LD+1] or a 2-day period after the listing [LD+1, LD+2].

(viii) Other trading days (OTHERD): other trading days.

However, the frozen fund requirement was removed in 2016. Therefore, we define 7 IPO event periods after 2016 as follows:

(i) Pre-lottery period (PRE_LO): one day or two days before the lottery day. Usually, the lottery day is [T+2], so the pre-lottery period is [T+1] or [T, T+1].

(ii) Lottery day (LOD): the day on which the public subscription results are out, that is, [T+2].

(iii) Post-lottery period [POST_LO]: the day after the lottery day, [T+3], or 2 days after the lottery day, [T+3, T+4].

(iv) Pre-listing day (PRE_L): the day before listing [LD-1] or 2 days before listing [LD-2, LD-1].

(v) Listing day (LD): the day the IPO shares get listed [LD].

(vi) Post-listing day (POST_L): the day after the listing [LD+1] or a 2-day period after the listing [LD+1, LD+2].

(vii) Other trading days (OTHERD): other trading days.

The complete definitions of important IPO periods are provided in Table 5.

[Insert Table 5 Here]

According to the IPO periods defined in Table 5, we construct 7 dummy variables in the IPO level before 2016 and 6 dummy variables after 2016, just as in Panel B and

C in Table 6. That is, if a trading day t is in some IPO period, the corresponding dummy variable is set to 1, and 0 otherwise.

[Insert Table 6 Here]

For the retail investors trading behaviors, we construct 6 variables. First, the average net buying value (RMB value in thousand) of retail investors on day t, denoted by $NetBuy_t$, is calculated as equation (1):

$$NetBuy_t = \frac{\sum_{s=1}^{S}\left(\sum_{i=1}^{I}\left(Buy_{i,s,t} - Sell_{i,s,t}\right)\right)}{I} \quad (1)$$

where $Sell_{i,s,t}$ denotes the selling value of stock s by investor i on day t, $Buy_{i,s,t}$ denotes the purchasing value of stock s by investor i on day t, I denotes the number of investors who buy or sell stocks on day t, and S denotes the number of stocks bought or sold by all the retail investors on day t.

The second variable is $Imbalance_t$, which measures the trading imbalance of retail investors on day t, it is defined as equation (2):

$$Imbalance_t = \frac{\sum_{s=1}^{S}\left(\sum_{i=1}^{I}\left(Buy_{i,s,t} - Sell_{i,s,t}\right)\right)}{\sum_{s=1}^{S}\left(\sum_{i=1}^{I}\left(Buy_{i,s,t} + Sell_{i,s,t}\right)\right)} \quad (2)$$

the variables and signals in equation (2) are the same as in equation (1).

In order to measure the relationship between the stocks sold/purchased by retail investors and the IPOs, we construct two variables — $IfBuySameInd_t$ and $IfSellSameInd_t$. For the variable $IfBuySameInd_t$, it measures if the IPO shares and the stocks purchased by retail investors on day t are in the same industry. For example, if a trading day t is classified into offering day (OD), it means that at least one IPO can be subscribed on t, we suppose the number of IPOs that can be subscribed on t is N. On the offering day t, and days related to the offering day t, that is, pre-offering period [t-1] or [t-2, t-1] (PRE_O), and frozen period [t+1, t+2] (FP), if a stock, denoted as s, purchased by retail investors is in the same industry with any of the N IPOs, then the variable $IfBuySameInd_{s,t}$ can be defined as 1, and 0 otherwise. We can calculate the variable $IfBuySameInd_t$ as equation (3):

$$IfBuySameInd_t = \sum_{s=1}^{S} \omega_s \cdot IfBuySameInd_{s,t} \tag{3}$$

where S is the number of stocks purchased by retail investors on day t, and ω_s is the value weight of stock s, which is calculated according to the trading value of each stock purchased by retail investors on day t. On other Event Days, that is, unfrozen day (UFP), lottery day (LOD), and listing day (LD), and the periods related to these Event Days, the calculation of $IfBuySameInd_t$ is similar.

What needs to be emphasized is the calculation of $IfBuySameInd_t$ on other trading days (OTHERD). The $IfBuySameInd_t$ on other trading days measures if the stocks purchased by retail investors on day t are in the same industry with the IPOs which are taken into account in the prior Event Day. For example, if a trading day is 5 days after a listing day (LD), denoted as LD+5, and it is not classified as any Event Day, then it can be seen as one of the other trading days (OTHERD). If a stock, denoted as s, purchased by retail investors on day LD+5 is in the same industry with any one of the IPOs listed on LD, then the variable $IfBuySameInd_{s,t}$ can be defined as 1, and 0 otherwise. The variable $IfBuySameInd_t$ can then be calculated as equation (3).

As for the variable $IfSellSameInd_t$, it measures if the IPO shares and the stocks sold by retail investors on day t are in the same industry. The calculation of $IfSellSameInd_t$ is similar to that of the variable $IfBuySameInd_t$, except for using the stocks sold by retail investors rather than the stocks purchased by retail investors, as shown in equation (4).

$$IfSellSameInd_t = \sum_{s=1}^{S} \omega_s \cdot IfSellSameInd_{s,t}, \tag{4}$$

Following Braun and Larrain (2009), another two variables we construct to measure the relationship between the stocks sold/purchased by retail investors and the IPOs are $BuyCorr_t$ and $SellCorr_t$. For the variable $BuyCorr_t$, it measures the correlation between the IPO shares and the stocks purchased by retail investors on day t. The proximity of two stocks can be proxied by the correlation of their returns. However, there are no stock returns for a firm before IPO. To solve this problem, we calculate the correlation between the daily returns of a stock purchased by retail investors and the daily returns of the industry which the IPO firms is in. For example, if a trading day t is classified as offering day (OD), it means that at least one IPO can be subscribed on t, we suppose the number of IPOs that can be subscribed on t is N. On the offering day t, and days related to the offering day t, that is, pre-offering period [t-1] or [t-2, t-1] (PRE_O), and frozen period [t+1, t+2] (FP), if a stock, denoted as s, is purchased by retail investors, we separately calculate the correlations between the daily returns of stock s and the daily industry returns which the N IPOs are in from one year before t to t, denoted as $BuyCorr_{s,n,t}$ ($n = 1 \ldots N$), just as equation (5):

$$BuyCorr_{s,n,t} = \begin{cases} \frac{Cov(ret_{s,t-250,t}, ret_{n,t-250,t})}{\sqrt{D(ret_{s,t-250,t})} \cdot \sqrt{D(ret_{n,t-250,t})}}, & s \neq n \\ 1, & s = n \end{cases} \tag{5}$$

where $ret_{s,t-250,t}$ is the daily returns of stock s purchased by retail investors from one year (there are about 250 trading days in a year) before day t to day t, and $ret_{n,t-250,t}$ is the returns of the industry which the IPO n is in from one year before day t to day t. It is worth noting that when the stock purchased by the investors is an IPO stock (the situation that will occur on the listing day and after), that is, when s is equal to n, we directly assign value of $BuyCorr_t$ to 1; otherwise, we calculate the value of $BuyCorr_t$ as equation (5).

Then we select the biggest correlation for stock s and take the value-weighted average of all the S stocks purchased by retail investors on day t. Specially, the calculation of $BuyCorr_t$ is shown in equation (6):

$$BuyCorr_t = \sum_{s=1}^{S} \omega_s \cdot \left(Max_{n=1}^{N}\{Corr_{s,n,t}\}\right) \tag{6}$$

where ω_s is the value weight of stock s, which is calculated according to the trading value of each stock purchased by retail investors on day t; S is the number of stocks purchased by retail investors on day t; $Max_{n=1}^{N}\{Corr_{s,n,t}\}$ is the biggest correlation for stock s with the returns of the N industries which the N IPOs are in. On other Event Days, that is, unfrozen day (UFP), lottery day (LOD), and listing day (LD), and the periods related to these Event Days, the calculation of $BuyCorr_t$ is similar.

Similarly to the calculations of $IfBuySameInd_t$ and $IfSellSameInd_t$ on other trading days (OTHERD), it is needed to emphasize the calculation of $BuyCorr_t$ on other trading days. The $BuyCorr_t$ on other trading days measures the correlation between the stocks purchased by retail investors and the IPOs was taken into account on the prior Event Day. For example, if a trading day is 5 days after a listing day (LD), denoted as *LD*+5, and it is not classified as any Event Day, then it can be seen as one of the other trading days. If a stock, denoted as s, is purchased by retail investors on day *LD*+5, we separately calculate the correlations between the daily returns of stock s and the daily industry returns which the N IPOs listed on day *LD* are in from one year before *LD* to *LD*. Then we calculate the $BuyCorr_t$ as equations (5) and (6).

As for the variable $SellCorr_t$, it measures the correlation between the IPO shares and the stocks sold by retail investors on day t. The calculation of $SellCorr_t$ is similar to that of the variable $BuyCorr_t$, except for using the stocks sold by retail investors rather than the stocks purchased by retail investors. These are the variables associated with the retail investor behaviors, we present these variables in the Panel A of Table 6.

Besides, we also control the market excess return. The market return is proxied by the HS300 index return, and the risk-free return is proxied by the 1-year bank deposit rate. The market excess return on day t is denoted as $ExcRet_t$.

All the variables we define in this paper are presented in Table 6.

4. Empirical Analysis

As outlined in Section 3, we measure the IPO process and the behaviors of retail investors in several different ways. In this section, we present regression results on retail investors' reactions around IPOs, including pre-IPO and post-IPO reactions.

4.1 Trading Directions

The first hypothesis states that retail investors will sell stocks they already own to raise money for an upcoming IPO subscription. In order to test this hypothesis, we first calculate, for each subscriber, the percentage of his net sells (sell-buy) amount of money to his subscription total. Before 2016, according to the policy of the China Securities Regulatory Commission (CRSC), investors had to pay in full for the new IPO shares they subscribed to, and the payment is frozen at the China Securities Registration and Settlement Company. Therefore, we calculate the ratio as net sells over the frozen funds. After 2016, the frozen fund requirement was removed and an investor only needs to pay for his allocated shares. Therefore, the ratio is defined as the net sells over the allocation value. The results are presented in Table 7.

[Insert Table 7 Here]

From Table 7 we can see that during the period between 2012 and 2015, 74.85% of subscribers sell stocks (net sell) in the three-day window before an IPO's subscription/offering day. On average, the ratio of net sells to frozen funds of all IPO subscribers is 91.52%, indicating that almost all the money needed for the escrow account comes from investors' selling of other stocks. This intriguing evidence suggests that Chinese investors are so eager to participate in an IPO and they have to sell their holdings in order to prepare the fund needed.

After 2016 when the frozen fund requirement was removed, 55.28% of IPO winners sell stocks (net sell) in the three-day window before an IPO's lottery day. On average, the ratio of net sells to lottery value of all IPO winners is 15.17%, which is much lower compared with the ratio of the net sells to frozen funds of all IPO subscribers before 2016, indicating that the impact of the IPOs on other stocks is reduced, as the removal of the frozen fund requirement reduces the amount of money locked from investors.

The results in Table 7 suggest that investors do sell existing stocks to raise funds for upcoming IPOs, especially before 2016. To further investigate the selling behaviors of retail investors, we conduct regression analysis as equation (7):

$$Imbalance_t = \alpha + \beta_1 \cdot Imbalance_{t-1} + \beta_2 \cdot ExcRet_t + \mathbf{B}^{\mathbf{T}} \cdot \mathbf{Period} + Year + \varepsilon_t \quad (7)$$

where $Imbalance_t$ denotes the trading imbalance of retail investors on day t; $ExcRet_t$ denotes the market excess return on day t. **Period** denotes the column vector composed of the Event Period variables defined in Panel B or C in Table 6. Since there was the frozen fund requirement before 2016, but not after 2016, the variables represented by **Period** are different before 2016 and after 2016. That is, before 2016, **Period** denotes the column vector of $[PRE\_O_t, OD_t, FP_t, UFP_t, PRE\_L_t, LD_t, POST\_L_t]^T$; after 2016, **Period** denotes the column vector $[PRE\_LO_t, LOD_t, POST\_LO_t, PRE\_L_t, LD_t, POST\_L_t]^T$; year dummies are created for each calendar year in the sample to control for the time-specific effect.

The regression results of equation (7) are presented in Table 8, Panel A presents the results of IPOs issued from 2012 to 2015, and Panel B presents the results of IPOs issued after 2016. For each IPO, we separate the data into three sub-samples based on investors' participation: 1. All the IPO non-subscribers (who do not subscribe to IPO shares); 2. the IPO subscribers (who subscribe to at least one hundred IPO shares); and 3. the IPO winners (who receive allocated IPO shares). The IPO winners group is the subset of the IPO subscribers group. We run regression model as in equation (7) for the three subsamples, respectively. Columns (1) and (2) present the results of non-subscribers, columns (3) and (4) present the results of IPO subscribers, and columns (5) and (6) present the results of IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (7) of different groups of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

[Insert Table 8 Here]

The results in Table 8 reveal quite dramatic different patterns among the three groups of investors. We focus on the signs of coefficients of those special IPO day dummy variables. When the coefficients are negative, it's interpreted as investors sell more than they buy; and when the coefficients are positive, it indicates more investors buy than sell. In Panel A (before 2016 with frozen fund requirement), for non-subscribers (columns (1) ~ (2)), most of the special day dummy variable coefficients are not significant, showing their trading is not correlated with any IPO events. These investors follow their own plans and rhythms irrelevant to the IPOs as the coefficient of $Imbalance_{t-1}$ is significant. However, the IPO subscribers and the IPO winners have notable reactions to the IPOs. For all subscribers (Columns (3) ~ (4)), the coefficients of PRE_O_t and OD_t are all significantly negative at the 1% level, indicating that the IPO subscribers place significantly more sell orders than buy orders on or before the IPO subscription day, plausible for the purpose of raising funds for the upcoming IPOs. Specifically, there is a 4.13% decrease in a trading imbalance in the pre-offering period and a 5.69% decrease in trading imbalance on the offering day, respectively.

Due to the frozen fund requirement, a large number of funds are frozen before the unfrozen day, which is hundreds of times of the proceeds raised by the IPO. Therefore, once the frozen funds are returned to investors, there will generate huge liquidity. The results in Table 8 are also consistent with this conjecture. In columns (3) and (4) of Panel A in Table 8, the coefficient of the variable UFP_t is significantly positive at 1% level, which means the IPO subscribers show significant net buying behaviors on the unfrozen day. Specifically, there is a 8.44% increase in trading imbalance on the unfrozen day.

As for the IPO winners, things are similar to that of the IPO subscribers. The only difference is that we find that the IPO winners have significant net selling behaviors on and after the listing day, as the coefficients of LD_t and $POST\_L_t$ in columns (5) and (6) of Panel A in Table 8 are all significantly negative at 5% or 10% level. Specifically, there is a 4.75% decrease in trading imbalance on the listing day and a 3.19% decrease in trading imbalance on the post-listing day, respectively. This result may be due to IPO winners selling IPO shares for the benefit deriving from the IPO underpricing.

However, things are different for IPOs issued after 2016. In 2016, the frozen fund requirement was removed. From this point on, investors do not need to pay any funds for the IPO shares they subscribe on the subscription day, they only need to pay for the IPO shares allocated to them on the lottery day. Since the lottery value of retail investors is far less than the frozen fund, the financial pressure of the retail investors in the face of IPOs will be greatly reduced. Therefore, investors will have less incentive to sell existing stocks due to IPOs. The results in Panel B of Table 8 are consistent with our conjecture. Similar to prior to 2016, columns (1) and (2) in Panel B of Table 8 indicate that IPOs do not cause significant changes in trading behaviors of IPO non-subscribers since they have their own investment plans. As for the IPO subscribers, columns (3) and (4) in Panel B of Table 8 indicate that the due to the relief of financial pressure, the trading behaviors of the IPO subscribers during the IPO period also do not show significant differences from usual.

The only type of investors whose trading behaviors during IPOs show significantly differently than usual are the IPO winners. Since the coefficient of the variable LOD_t is significantly negative both in columns (5) and (6) of Panel B in Table 8, the results indicate that although the financial pressure for retail investors to participate in IPOs will ease after 2016, IPO winners will still sell their existing stocks on the lottery day to raise funds. Specifically, there is a 2.13% decrease in trading imbalance for IPO winners on the lottery day, and this decrease is smaller than that on and before the subscription day before 2016. Besides, we also find that the IPO winners have significant net selling behaviors on the listing day, as the coefficient of LD_t in columns (5) and (6) of Panel B of Table 8 is significantly negative at 5% level. Similar to the behaviors of IPO winners on listing days prior to 2016, this result may be due to IPO winners selling IPO shares for the benefit deriving from the IPO underpricing. In the robust test, we replace the variable $Imbalance_t$ with $NetBuy_t$ to directly investigate how investors' net selling value changes at different periods of IPOs, the results are basically consistent with those in Table 8.

4.2 Types of Stocks Traded

The results in Table 8 illustrate that investors do have unusual trading behaviors during the IPOs, but they do not tell us what investors buy and what investors sell during the different periods of IPOs. In this subsection, we mainly investigate these questions.

4.2.1 Types of Stocks Sold

The results in subsection 4.1 tell us that retail investors will sell existing stocks to raise money for the upcoming IPOs, but the results tell us nothing about the relationships between the stocks the retail investors sell and the IPOs. Hypothesis 2 focuses on the relationships between the stocks sold by investors and the IPOs, that is, if they are highly related or in the same industry. Previous studies have shown that the IPOs have significant impacts on their industries (Ritter (1991); Akhigbe, Borde et al. (2003)). To illustrate what significant impact the IPOs have on the related stocks, in Table 9, we compare the proceeds or the unfrozen funds of IPOs with the average daily industry trading value in the different periods of IPOs.

[Insert Table 9 Here]

In Table 9 we can see that during the period from 2012 to 2015, 508 IPOs were offered, and these IPOs were concentrated on 184 offering days, 184 Unfrozen days, and 176 listing days. The average ratio of the IPO proceeds to the daily industry trading values reaches to 39% in all three IPO periods. As for the unfrozen funds, we can see that the unfrozen funds returned to the investors amount to 25 times of the average daily industry trading value. It clearly shows how important impacts IPOs have on the capital market, as well as the related stocks. Things are a little different after 2016. As the frozen fund requirement has been removed since 2016, investors do not need to pay for the IPO shares they subscribe on the subscription day, instead they only need to pay for the IPO shares allocated to them on the lottery day. So we only compare the IPO proceeds with the average daily industry trading value. Compared to that of the year before 2016, the ratios of the IPO proceeds to the average industry trading value on the lottery day and the listing day drop to 15.50% and 16.21%, respectively, which show the impacts of the IPOs become less on the overall capital market and the related stocks. One possible explanation is that as the China's stock market becomes larger after 2016, the sizes of the IPOs are getting smaller in both relative and absolute terms.

In any case, the results in Table 9 show that IPOs have significant impacts on the related stocks and even the whole stock market. Changes in the stock market are closely related to investor behaviors. However, the results in Table 9 cannot show investors' trading behaviors for the IPO-related stocks. In this subsection, we further use regression analysis to explore investors' trading behaviors for related stocks in face of IPOs, as equation (8).

$$SellCorr_t = \alpha + \beta_1 \cdot SellCorr_{t-1} + \beta_2 \cdot ExcRet_t + \mathbf{B}^{\mathbf{T}} \cdot \mathbf{Period} + Year + \varepsilon_t \quad (8)$$

where $SellCorr_t$ denotes the correlations between the IPOs and the stocks sold by retail investors on day t; $ExcRet_t$ denotes the market excess return on day t. **Period** denotes the column vector composed of the Event Period variables defined in Panel B or C in Table 6. Since there was the frozen fund requirement before 2016, but not after 2016, the variables represented by **Period** are different before 2016 and after 2016. That is, before 2016, **Period** denotes the column vector of $[PRE\_O_t, OD_t, FP_t, UFP_t, PRE\_L_t, LD_t, POST\_L_t]^T$; after 2016, **Period** denotes the column vector $[PRE\_LO_t, LOD_t, POST\_LO_t, PRE\_L_t, LD_t, POST\_L_t]^T$; year dummies are created for each calendar year in the sample to control for the time-specific effect.

The regression results of equation (8) are presented in Table 9, Panel A presents the results of IPOs issued from 2012 to 2015, and Panel B presents the results of IPOs issued after 2016. For each IPO, the retail investors can be divided into three kinds, that is, the IPO non-subscribers (who do not subscribe to IPO shares), the IPO subscribers (who subscribe at least one hundred IPO shares), and the IPO winners (who are ultimately allocated IPO shares), therefore, we run the regression (8) for the three kinds of investors, respectively. Columns (1) and (2) present the results of the IPO non-subscribers, columns (3) and (4) present the results of IPO subscribers, and columns (5) and (6) present the results of IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (8) of different kinks of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

[Insert Table 10 Here]

For the IPOs issued before 2016, the results in Table 9 indicate that the IPO subscribers and IPO winners will sell existing stocks in their portfolios to raise money for the upcoming IPOs. However, the results in Table 10 indicate that when the IPO subscribers and the IPO winners sell the existing stocks to raise funds for the upcoming IPOs on and before the subscription day, they treat the stocks in their portfolios indiscriminately, that is, they show no significant tendency to sell the IPO-related or the IPO-unrelated stocks, as the coefficients of the variables PRE_O_t and OD_t are all insignificant in Panel A of Table 10. Things are similar for the IPOs issued after 2016. The results in Table 9 indicate that the IPO winners will sell existing stocks to raise money for the new IPO shares allocated to them when they are informed of the lottery results; however, the results in Table 10 indicate that when the IPO winners sell the existing stocks to raise money for the IPO shares allocated to them, they also never consider the relationship between the stocks sold and the IPOs, as the coefficients of the variables LOD_t are both insignificant in columns (5) and (6) of Panel B of Table 10. In conclusion, when retail investors sell existing stocks to raise funds for IPOs, they do not take into account the relationship between the stocks sold by them and the IPOs. Therefore, at this stage, investors' speculative motives prevail.

Surprisingly, it seems that the retail investors become rational in the latter of the IPO stage. Because of the IPO constraints in China's stock market (Liu, Stambaugh et al. (2019)), the number of IPO stocks is far from meeting the needs of investors, therefore, investors see the IPO-related stocks as the substitutes of the IPO shares (Li and Zhang (2021)). So if the retail investors are rational, they will not sell the IPO-related stocks. The results in Table 10 confirm our conjecture. The coefficients of the variables LD_t and $POST\_L_t$ in columns (1) and (2) are significantly negative at 5% and 10% levels, respectively, this result means that the stocks sold by the IPO non-subscribers on and after the listing day are less related to the IPOs both before and after 2016, which means they keep the stocks that related to the IPOs. These characteristics are more pronounced in IPO subscribers, as the coefficients of the variables PRE_L_t, LD_t and $POST\_L_t$ are significantly negative at 5%, 5%, and 10% levels, respectively. These results mean that not only are the stocks that the IPO subscribers sell on the listing day and after less related to the IPOs, but the stocks they sell before the listing day are less related to the IPOs.

It is worth noting that the stocks sold by the IPO winners on and after the listing day are related to the IPO, as the coefficients of the variables of LD_t and $POST\_L_t$ are significantly positive at 10% level in columns (5) and (6) of Table 10 both before and after 2016. This result is also preliminarily shown in Table 9. We suspect that the IPO winners will sell the IPO shares allocated to them on and after the listing day according to the results of Table 9, but the causal relationship here is not very clear. The results in Table 10 are clearer. The stocks sold by the other two types of retail investors on the listing day and after are all significantly negatively correlated with the IPO stocks, but the stocks sold by the IPO winners are significantly positively correlated with the IPOs, which indicate that the IPO winners sell the IPO shares allocated to them.

All in all, in the whole process of the IPOs, retail investors show the characteristics of being irrational first and then rational. Specifically, in the early stage of the IPOs, that is, when investors sell existing stocks to raise funds for the IPOs, the retail investors are irrational, as the stocks sold by them in this stage are not significantly negatively related to the IPOs; however, in the latter stage of the IPOs, that is, when the IPO shares are officially listed, the retail investors are rational, as the stocks sold by them are significantly negatively related to the IPOs. In the robustness test, we directly study whether the stocks sold by retail investors during the IPOs and the IPO shares are in the same industry rather than studying the correlations between the stocks sold by retail investors during the IPOs and the IPO shares, and the results are consistent with the results in Table 10.

The shortage is that in this subsection we only investigate the relationship between the stocks sold by retail investors during the process of IPOs and the IPOs, in the next subsection, we will continue to study the relationship between the stocks bought by retail investors during the process of IPOs and the IPOs.

4.2.2 Types of Stocks Purchased

The results in subsection 4.2.1 tell us the relationships between the IPOs and the stocks sold by retail investors in different periods of the IPOs. Hypothesis 3 focuses on the relationships between the IPOs and the stocks purchased by retail investors in different periods of the IPOs, that is, if they are highly related or in the same industry. Previous studies have shown that because of the constraints in the process of the IPOs, the number of IPO shares is far from meeting the demand of the investors (Liu, Stambaugh et al. (2019)), therefore, retail investors will see IPO-related stocks as substitutes for the IPO stocks (Li and Zhang, 2021). In this subsection, we measure how IPOs affect retail investors' buying behaviors using equation (9).

$$BuyCorr_t = \alpha + \beta_1 \cdot BuyCorr_{t-1} + \beta_2 \cdot ExcRet_t + \mathbf{B^T} \cdot \mathbf{Period} + Year + \varepsilon_t \quad (9)$$

where $BuyCorr_t$ denotes the correlations between the IPOs and the stocks purchased by retail investors on day t; $ExcRet_t$ denotes the market excess return on day t. **Period** denotes the column vector composed of the Event Period variables defined in Panel B or C in Table 6. Since there was the frozen fund requirement before 2016, but not after 2016, the variables represented by **Period** are different before 2016 and after 2016. That is, before 2016, **Period** denotes the column vector of $[PRE\_O_t, OD_t, FP_t, UFP_t, PRE\_L_t, LD_t, POST\_L_t]^T$; after 2016, **Period** denotes the column vector $[PRE\_LO_t, LOD_t, POST\_LO_t, PRE\_L_t, LD_t, POST\_L_t]^T$; year dummies are created for each calendar year in the sample to control for the time-specific effect.

The regression results of equation (9) are presented in Table 11, Panel A presents the results of IPOs issued from 2012 to 2015, and Panel B presents the results of IPOs issued after 2016. For each IPO, the retail investors can be divided into three kinds, that is, the IPO non-subscribers (who subscribe to no IPO shares), the IPO subscribers (who subscribe to at least one hundred IPO shares), and the IPO winners (who are ultimately allocated IPO shares), therefore, we run the regression (9) for the three kinds of investors, respectively. Columns (1) and (2) present the results of IPO non-subscribers, columns (3) and (4) present the results of IPO subscribers, and columns (5) and (6) present the results of IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (9) of different kinks of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

[Insert Table 11 Here]

The results in Table 11 clearly indicate that trades are diverged among investors of different interests and positions in pre-IPO. In Panel A of Table 11, that is, IPOs issued before 2016 when the frozen fund requirement was not removed, columns (1) and (2) show that in the early stage of the IPOs, the IPO non-subscribers do not pay much attention to the IPOs, as well as the stocks which are related to the IPOs, as the coefficients of the variables PRE_O_t, OD_t, FP_t, UFP_t and PRE_L_t in columns (1) and (2) in Panel A of Table 11 are all insignificant; however, the stocks bought by the IPO non-subscribers on and after the listing days are significantly correlated with the IPOs, as the coefficients of the variables LD_t and $POST\_L_t$ in columns (1) and (2) in Panel A of Table 11 are significantly positive at 10% level, this results indicates the IPOs increase retail investors' attention to IPO-related stocks, that is, the retail investors see the IPO-related stocks as substitutes of the IPO shares.

Things are similar for the IPO subscribers and the IPO winners, in other words, IPO subscribers and IPO winners also increase their attention to IPO-related stocks in face of IPOs, the only difference is that the IPO subscribers and the IPO winners will pay attention to IPO-related stocks earlier than the IPO non-subscribers. Columns (3) to (6) in Panel A of Table 11 indicate that the IPO subscribers and IPO winners will pile into IPO-related stocks in the unfrozen period, as the coefficients of the UFP_t are all significantly positive. Due to the frozen fund requirement, a large amount of funds will be returned to investors on the unfrozen day. Therefore, driven by the huge liquidity and attention to IPO-related stocks, the IPO subscribers and the IPO winners will buy large amounts of IPO-related stocks during the unfrozen periods.

As for the IPOs issued after 2016, investors' buying behaviors during the IPOs are similar to that of the IPOs issued before 2016. In short, the IPO non-subscribers do not focus on the IPO-related stocks until the listing day, and buy them on the listing day and after in large quantities, as the coefficients of the LD_t and $POST\_L_t$ are significantly positive in the columns (1) and (2) in Panel B of Table 11. As for the IPO subscribers and the IPO winners, because of the frozen fund requirement has been removed since

2016, they will buy large amounts of stocks that are highly related to the IPOs when they are informed of the lottery results, that is, on the lottery day. This result can be seen from the columns (3) to (6) that the coefficients of the variable LOD_t are all significantly positive at 10% level.

To sum up, because of the constraints of the process of the IPOs in China's stock market, the number of the IPO shares is far from meeting the needs of the investors, therefore, investors in China will see the IPO-related stocks as the substitutes of the IPO shares. For investors' buying behaviors during the IPOs, the results in Table 11 indicate that during the IPO periods, investors will pay more attention to the IPO-related stocks and buy up them. While different types of investors start paying attention to IPOs and IPO-related stocks at different points, they have the same attitude toward the IPO-related stocks, that is, buying in bulk. In the robustness test, we directly study whether the stocks bought by retail investors during the IPOs and the IPO shares are in the same industry rather than studying the correlation between the stocks bought by retail investors during the IPOs and the IPO shares, and the results are consistent with the results in Table 11.

5. Robust Test

In this section, we conduct robust tests for the results in Section 4. In Section 4, we analyze the trading directions of retail investors, and the correlations between the IPOs and the stocks sold or bought by retail investors during the IPO process, respectively. To conduct the robust tests, we use other methods to measure retail investors' trading directions, and the correlations between the IPOs and the stocks sold or bought by retail investors during the IPO process.

5.1 Robust Test of The Trading Directions

In equation (7), we use the $Imbalance_t$ as the dependent variable, which measure the trading imbalance of the retail investors during the IPO periods. In this subsection, we use the $NetBuy_t$ as the dependent variable instead of the $Imbalance_t$, which can directly show the net buying or selling behaviors of investors during the IPOs. This method is as shown in equation (10).

$$NetBuy_t = \alpha + \beta_1 \cdot NetBuy_{t-1} + \beta_2 \cdot ExcRet_t + \mathbf{B}^{\mathbf{T}} \cdot \mathbf{Period} + Year + \varepsilon_t \quad (10)$$

where $NetBuy_t$ denotes the average net buying value of retail investors on day t; $ExcRet_t$ denotes the market excess return on day t. **Period** denotes the column vector composed of the Event Period variables defined in Panel B or C in Table 6. Since there was the frozen fund requirement before 2016, but not after 2016, the variables represented by **Period** are different before 2016 and after 2016. That is, before 2016, **Period** denotes the column vector of $[PRE\_O_t, OD_t, FP_t, UFP_t, PRE\_L_t, LD_t, POST\_L_t]^T$; after 2016, **Period** denotes the column vector $[PRE\_LO_t, LOD_t, POST\_LO_t, PRE\_L_t, LD_t, POST\_L_t]^T$; year dummies are created for each calendar year in the sample to control for the time-specific effect. The regression results of equation (10) are presented in Table 12.

[Insert Table 12 Here]

The results in Table 12 clearly show the net sells of different kinds of investors in the face of IPOs. In Panel A of Table 12, that is, IPOs issued before 2016 when the frozen fund requirement is not removed, columns (1) and (2) show that IPO non-subscribers do not pay much attention to IPO events, as the coefficients of the period variables are all insignificant. However, the IPO subscribers and the IPO winners have notable reactions to the IPOs. Columns (3) and (4) indicate that the IPO subscribers show significant net selling behaviors on and before the IPO subscription days in order to raise funds for the upcoming IPOs, as the coefficients of the PRE_O_t and the OD_t are all significantly negative at the 1% level. On average, each IPO subscriber's net selling value reaches 414 RMB in the pre-offering period and 520 RMB on the offering day, respectively. Due to the frozen fund requirement, a large number of funds are frozen before the unfrozen day, which are hundreds of times of the proceeds raised by the IPO. Therefore, once the frozen funds are returned to investors, there will generate huge liquidity. In columns (3) and (4) of Panel A in Table 12, the coefficients of the variable UFP_t are significantly positive at 1% level, which means the IPO subscribers show significant net buying behaviors on the unfrozen day. On average, each subscriber's net buying value amounts to 751 RMB on the unfrozen day. As for the IPO winners, things are similar to that of the IPO subscribers. The only difference is that we find that the IPO winners have significant net selling behaviors on and after the listing day, as the coefficients of LD_t and $POST\_L_t$ in columns (5) and (6) of Panel A in Table 12 are significantly negative at 5% or 10% level. On average, each IPO winner's net selling value reaches 165 RMB on the listing day and 148 RMB on the post-listing day, respectively. Compared with that on the pre-offering and the offering day, the IPO winners' net selling values on listing day and after are relatively small. This result is because of the IPO winners selling IPO shares for the benefit deriving from the IPO underpricing.

However, things are different for IPOs issued after 2016. In 2016, the frozen fund requirement was removed. From this point on, investors do not need to pay any funds for the IPO shares they subscribe on the subscription day, they only need to pay for the IPO shares allocated to them on the lottery day. Since the lottery value of retail investors is far less than the frozen fund, the financial pressure of the retail investors in the face of IPOs will be greatly reduced. Therefore, investors will have less incentive to sell existing stocks due to IPOs. Similar to prior to 2016, columns (1) and (2) in Panel B of Table 12 indicate that IPOs do not cause significant changes in net sellings of IPO non-subscribers since they have their own investment plans. As for the IPO subscribers, columns (3) and (4) in Panel B of Table 12 indicate that the due to the relief of financial pressure, the net sellings of the IPO subscribers during the IPO period also do not show significant differences from usual.

The only type of investors whose trading behaviors during IPOs show significantly differently than before 2016 are the IPO winners. Since the coefficient of the variable LOD_t is significantly negative both in columns (5) and (6) of Panel B in Table 12, the results indicate that although the financial pressure for retail investors to participate in IPOs will ease after 2016, IPO winners will still sell their existing stocks on the lottery day to raise funds. On average, each IPO winner's net selling value reaches 149 RMB on the lottery day, and the number is smaller than that on and before the subscription day before 2016. Besides, we also find that the IPO winners have significant net selling behaviors on the listing day, as the coefficients of LD_t in columns (5) and (6) of Panel B of Table 12 are significantly negative at 5% level. Similar to the behaviors of IPO winners on listing days prior to 2016, this result may be due to IPO winners selling IPO shares for the benefit deriving from the IPO underpricing.

Overall, the results in Table 12 are basically consistent with those in Table 8, that is, retail investors will sell existing stocks to raise funds for the upcoming IPOs, and will buy stocks again when their liquidity is sufficient.

5.2 Robust Test of the Types of Stocks Sold

In equation (8) we analyze the relationship between the IPOs and the stocks sold by retail investors in face of the IPOs. In this subsection, we use the $IfSellSameInd_t$ as the dependent variable instead of the $SellCorr_t$, which can directly indicate if the IPOs and the stocks sold by retail investors are in the same industry. This method is as equation (11).

$$IfSellSameInd_t = \alpha + \beta_1 \cdot IfSellSameInd_{t-1} + \beta_2 \cdot ExcRet_t + \mathbf{B}^{\mathbf{T}} \cdot \mathbf{Period} + Year + \varepsilon_t \quad (11)$$

where $IfSellSameInd_t$ denotes if the IPOs and the stocks sold by retail investors on day t are in the same industry. **Period** denotes the column vector composed of the Event Period variables defined in Panel B or C in Table 6. Since there was the frozen fund requirement before 2016, but not after 2016, the variables represented by **Period** are different before 2016 and after 2016. That is, before 2016, **Period** denotes the column vector of $[PRE\_O_t, OD_t, FP_t, UFP_t, PRE\_L_t, LD_t, POST\_L_t]^{\mathrm{T}}$; after 2016, **Period** denotes the column vector $[PRE\_LO_t, LOD_t, POST\_LO_t, PRE\_L_t, LD_t, POST\_L_t]^{\mathrm{T}}$; year dummies are created for each calendar year in the sample to control for the time-specific effect. The regression results of equation (11) are presented in Table 13.

[Insert Table 13 Here]

For the IPOs issued before 2016, the results in Table 13 indicate that when the IPO subscribers and IPO winners sell the existing stocks to raise funds for the upcoming IPOs in the early stage of the IPOs, they treat the stocks in their portfolios indiscriminately, that is, they show no significant tendency to sell the stocks that are in or not in the same industry as the IPOs, as the coefficients of the variables PRE_O_t and OD_t are all insignificant in Panel A of Table 13. Things are similar for the IPOs issued after 2016. The results in Table 13 indicate that when the IPO winners sell the existing stocks to raise funds for the IPO shares allocated to them, they also never consider if the stocks sold by them are in the same industry as the IPOs, as the coefficients of the variable LOD_t are both insignificant in columns (5) and (6) of Panel B of Table 13. In conclusion, when retail investors sell existing stocks to raise funds for IPOs, they do not take into account whether the stocks sold by them are in the same industry as the IPOs.

However, in the latter of the process of the IPOs, things are different. In Table 13, we can see that the coefficients of the variables LD_t and $POST\_L_t$ in columns (1) and (2) are significantly negative, respectively, which means that the stocks sold by the IPO non-subscribers are not in the same industry as the IPOs both before and after 2016. These characteristics are more pronounced in IPO subscribers as shown in columns (3) and (4) of both Panel A and Panel B in Table 13.

It is worth noting that the stocks sold by the IPO winners on and after the listing day are in the same industry as the IPOs, as the coefficients of the variables of LD_t and $POST\_L_t$ are significantly positive in columns (5) and (6) of Table 12 both before and after 2016. This result is consistent with our conjecture that on the listing days and the post-listing days, the IPO winners sell the IPO shares that allocated to them on the lottery day.

All in all, the results in Table 13 are basically consistent with those in Table 10. That is, in the early stage of the IPOs, investors behave irrationally, specifically, the stocks sold by retail investors are not significantly out of the same industry as the IPOs; however, in the latter of the IPO process, investors behave rationally, specifically, the stocks sold by retail investors are significantly out of the same industry as the IPOs.

5.3 Robust Test of the Types of Stocks Purchased

In equation (9) we analyze the relationship between the IPOs and the stocks purchased by retail investors in face of the IPOs. In this subsection, we use the $IfBuySameInd_t$ as the dependent variable instead of the $BuyCorr_t$, which can directly indicate if the IPOs and the stocks bought by retail investors are in the same industry. This method is as equation (12).

$$IfBuySameInd_t = \alpha + \beta_1 \cdot IfBuySameInd_{t-1} + \beta_2 \cdot ExcRet_t + \mathbf{B}^{\mathbf{T}} \cdot \mathbf{Period} + Year + \varepsilon_t \tag{12}$$

where $IfBuySameInd_t$ denotes if the IPOs and the stocks bought by retail investors on day t are in the same industry. **Period** denotes the column vector composed of the Event Period variables defined in Panel B or C in Table 6. Since there was the frozen fund requirement before 2016, but not after 2016, the variables represented by **Period** are different before 2016 and after 2016. That is, before 2016, **Period** denotes the column vector of $[PRE\_O_t, OD_t, FP_t, UFP_t, PRE\_L_t, LD_t, POST\_L_t]^T$; after 2016, **Period** denotes the column vector $[PRE\_LO_t, LOD_t, POST\_LO_t, PRE\_L_t, LD_t, POST\_L_t]^T$; year dummies are created for each calendar year in the sample to control for the time-specific effect. The regression results of equation (12) are presented in Table 14.

[Insert Table 14 Here]

The results in Table 14 clearly indicate whether the stocks investors buy during the IPOs are in the same industry as the IPOs. In Panel A of Table 14, that is, IPOs issued before 2016 when the frozen fund requirement was not removed, columns (1) and (2) show that in the early stage of the IPOs, the IPO non-subscribers investors do not pay much attention to the IPOs, as well as the stocks that are in the same industry as the IPOs, as the coefficients of the variables PRE_O_t, OD_t, FP_t, UFP_t and PRE_L_t in columns (1) and (2) in Panel A of Table 14 are all insignificant; however, the stocks bought by the retail investors on and after the listing days are in the same industry as the IPOs, as the coefficients of the variables LD_t and $POST\_L_t$ in columns (1) and (2) in Panel A of Table 14 are significantly positive at 10% level. This result indicate that the IPOs increase retail investors' attention to the stocks that are in the same industry as the IPOs.

Things are similar for the IPO subscribers and IPO winners, in other words, IPO subscribers and IPO winners also increase their attention to the stocks that are in the same industry as the IPOs, the only difference is that the IPO subscribers and the IPO winners will pay attention to the stocks that are in the same industry as the IPOs earlier than the IPO non-subscribers. Columns (3) to (6) in Panel A of Table 14 indicate that the IPO subscribers and IPO winners will pile into the stocks in the same industry as the IPOs in the unfrozen period, as the coefficients of the UFP_t are all significantly positive at 5% level. This is because the funds returned to investors on the unfrozen day bring huge liquidity to investors, so they will pay more attention to the stocks in the same industry as the IPOs at this stage.

As for the IPOs issued after 2016, investors' buying behaviors during the IPOs are similar to that of the IPOs issued before 2016. In short, the IPO non-subscribers do not focus on the stocks in the same industry as the IPOs and buy them until the listing day, as the coefficients of the variables LD_t and $POST\_L_t$ are significantly positive in columns (1) and (2) in Panel B of Table 14. As for the IPO subscribers and IPO winners, because of the frozen fund requirement has been removed since 2016, they will buy large amounts of stocks that are in the same industries as the IPOs when they are informed of the lottery results, that is, on the lottery day. This result can be seen from the columns (3) to (6) that the coefficients of the variable LOD_t are all significantly positive at 10% level.

To sum up, because of the constraints of the process of the IPOs in China's stock market, the number of the IPO shares is far from meeting the demands of the investors, therefore, investors in China will see the stocks that are in the same industry as the IPOs as the substitutes of the IPO shares. For investors' buying behaviors during the IPOs, the results in Table 14 indicate that during the IPO periods, investors will pay more attention to the stocks in the same industry as the IPOs, and buy up them. On the whole, the results in Table 14 are basically consistent with those in Table 11.

6. Conclusion

Previous studies have demonstrated the substantial impact of initial public offerings (IPOs) on other listed stocks and the broader stock market. Specific to China's stock market, the number of the IPO shares are far from meeting the demands of investors due to the constraints in the process of the IPOs in China, therefore, investors treat the IPO-related stocks or the stocks that are in the same industry as the IPOs as substitutes of the IPOs, and drive up their prices. However, most researchers have studied this phenomenon from the perspective of stock price movements and market transactions, and few researchers have studied this phenomenon from the perspective of investors' trading behaviors. In this paper, we directly investigate the trading characteristics of the investors in face of the IPOs using IPO samples and retail investors' transaction data from China. We find that when faced with IPOs, retail investor behaviors are mix of portfolio rebalance and speculation. First, investors will sell the existing stocks in order to raise funds for the upcoming IPOs. For the period when the frozen fund requirement is not removed, on average, each IPO subscriber's net selling value reaches 414 RMB in the pre-offering period and 520 RMB on the offering day, respectively; for the period when the frozen fund requirement is removed, on average, each IPO winner's net selling value reaches 149 RMB on the lottery day. These net selling funds account for a significant proportion of the investors' subscription value.

Secondly, although investors will sell large numbers of existing stocks to raise funds for the upcoming IPOs, they do not further consider the relationship between the stocks sold by them and the IPOs when they sell the existing stocks. In other words, investors sell stocks for no other purpose than to raise funds. Previous research has shown that since the number of IPO shares in China cannot meet the demands of investors, and investors will treat the IPO-related stocks or stocks that are in the same industry as the IPOs as substitutes for IPO shares (Liu, et al. (2019); Li and Zhang (2021)). However, in the results of Sections 4 and 5, we find that when investors sell existing stocks to raise funds for IPOs, they do not treat IPO-related stocks or stocks that are in the same industry as IPOs differently from other stocks. In other words, investors showed a certain degree of blindness and speculation at this stage.

Thirdly, when liquidity is plentiful, investors will buy large amounts of shares again, and this phenomenon is even more pronounced before the removal of the frozen fund requirement. The results in Sections 4 and 5 indicate that each subscriber's net buying value amounts to 751 RMB on the unfrozen day, which is almost twice the net selling value of investors on the pre-offering or the offering day.

Finally, we give direct evidence that the retail investors treat the IPO-related stocks or the stocks that are in the same industry as the IPOs as substitutes for the IPO shares because of the constraints in the process of the IPOs. The results in Sections 4 and 5 indicate that the retail investors will buy large numbers of IPO-related stocks or stocks in the same industry as the IPOs during the IPO process, the only difference is that different groups of retail investors buy these stocks at different time points. For IPO non-subscribers, their attention to IPOs is relatively late, usually in the latter stage of the IPOs, so IPO non-subscribers will buy large numbers of IPO-related stocks or stocks in the same industry as the IPOs on a listing day and after. For the IPO subscribers and IPO winners, they are more concerned about IPOs than the IPO non-subscribers, so they start to buy large numbers of IPO-related stocks or stocks in the same industry as the IPOs on the unfrozen day or the lottery day. All in all, because the number of IPO shares cannot meet the demands of investors, investors will regard the IPO-related stocks or stocks in the same industry as the IPOs as substitutes for IPOs, and buy them in large quantities.

This paper examines investors' trading behaviors during IPOs from a dynamic perspective, which also provides some policy recommendations. First, the results of the paper show that the cancellation of the frozen fund requirement not only relieves investors' financial pressure in face of IPOs, but also reduces the abnormal trading volume in the market, which is helpful to the stability of the market. Second, our findings also suggest that the CSRC should moderately simplify the IPO process in order to improve the severe shortage of new IPO shares in China's stock market. More generally, our findings also have theoretical implications for stock price pressures and practical implications for investors and regulators.

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Table 1

Summary Statistics of Investors

This table presents the summary statistics of the investors in our sample. Wealth is the average of an investor's total account value including stocks and cash, and it is RMB in thousand. Experience is the average years of trading of each investor in our sample. Gender is a dummy variable equal to 1 for males and 0 for females. Education is a dummy variable equal to 1 if an investor has a college or above level education, and 0 otherwise. The Age, Wealth, Experience, Education is calculated at the end of each month, and the Gender is calculated at the end of the sample used in this paper, that is, the end of September 2019. Panel A presents the summary statistics of all investors, Panel B presents the summary statistics of investors who have subscribed at least one IPO, and Panel C presents the summary statistics of investors who have successfully subscribed for at least one IPO.

Variables	Mean	Std.	Min	25%	Median	75%	Max	N
Panel A: Summary Statistics of All Retail Investors								
Wealth	174.79	2465.54	0.00	14.23	43.12	121.16	474967.90	383,499
Age	48.89	12.42	20.00	40.00	48.00	57.00	100.00	383,499
Experience	10.59	5.99	1.00	5.00	10.00	13.00	27.00	383,499
Gender	0.56	0.50	0.00	0.00	1.00	1.00	1.00	383,499
Education	0.51	0.50	0.00	0.00	1.00	1.00	1.00	383,499
Panel B: Summary Statistics of IPO Subscribers								
Wealth	235.07	2156.27	0.01	33.15	76.45	183.37	474967.90	236,444
Age	50.06	12.20	20.00	41.00	49.00	57.00	99.00	236,444
Experience	11.03	6.22	1.00	5.00	11.00	14.00	27.00	236,444
Gender	0.56	0.50	0.00	0.00	1.00	1.00	1.00	236,444
Education	0.51	0.50	0.00	0.00	1.00	1.00	1.00	236,444
Panel C: Summary Statistics of IPO Winners								
Wealth	346.77	2870.54	0.48	57.85	125.53	275.31	474967.90	137,655
Age	51.86	12.21	20.00	43.00	51.00	59.00	99.00	137,655
Experience	11.93	6.27	1.00	6.00	11.00	18.00	27.00	137,655
Gender	0.55	0.50	0.00	0.00	1.00	1.00	1.00	137,655
Education	0.5	0.5	0.00	0.00	1.00	1.00	1.00	137,655

Table 2

The Distribution of Investors

This table presents the distribution of investors. Panel A displays the distribution of assets in investors' accounts from 2012 to 2019. Columns (1) and (2) show the number and proportion of investors with different asset sizes in the dataset; columns (3) and (4) show the number and proportion of investors with different asset sizes published in the Shanghai Stock Exchange Statistical Yearbook.
Panel B displays the distribution of investors' age from 2012 to 2015[5]. Columns (1) and (2) show the number and proportion of investors in different age ranges in the dataset; columns (3) and (4) show the number and proportion of investors in different age ranges in the Shanghai Stock Exchange Statistical Yearbook from.
Panel C displays the distribution of investors' education level from 2012 to 2015[6]. Columns (1) and (2) show the number and proportion of investors with different educational backgrounds in the sample data; columns (3) and (4) show the number and proportion of investors with different educational backgrounds in the SSE.
Panel D displays the distribution of investors' gender from 2012 to 2015[7]. Columns (1) and (2) show the number and proportion of different genders in the sample data; columns (3) and (4) show the number and proportion of different genders in the SSE.

	Investors in our sample		Investors in SSE	
	Number of Investors	The proportion of Investors (%)	Number of Investors (Million)	The proportion of Investors (%)
	(1)	(2)	(3)	(4)
Panel A: Asset Distribution of Investors				
less than 100 thousands	246091	64.17%	22.7991	65.58%
100 thousands to 1 million	127169	33.16%	10.7878	29.04%
1 million to 3 millions	7746	2.02%	1.3937	3.67%
3 millions to 10 millions	2033	0.53%	0.4394	1.15%
more than 10 millions	460	0.12%	0.1337	0.35%
Panel B: Age Distribution of Investors				
below 30 years old	90467	22.20%	36.9801	36.53%
30 years old to 40 years old	117524	28.84%	32.0513	31.81%
40 years old to 50 years old	119195	29.25%	19.3341	19.18%
50 years old to 60 years old	51142	12.55%	7.9780	7.93%
above 60 years old	29178	7.16%	4.5398	4.56%
Panel C: Education Level Distribution of Investors				
below technical secondary school	120250	31.23%	25.6673	26.43%
technical secondary school	79417	20.62%	24.9887	25.57%
junior college	94083	24.43%	25.9051	26.28%
bachelor degree	82528	21.43%	18.0891	18.00%
master degree and above	8803	2.29%	3.6804	3.73%
Panel D: Gender Distriubtion of Investors				
male	225557	55.36%	55.9454	55.37%
female	181899	44.64%	44.9293	44.63%

[5] Since the SSE no longer published the data on the age distribution of individual investors after 2016, in order to be consistent with the date caliber of the SSE, we calculate the annual average of the number and proportion of investors in each age group from 2012 to 2015 in the sample dataset.
[6] Since the SSE no longer published the data on the education level distribution of individual investors after 2016, in order to be consistent with the date caliber of the SSE, we calculate the annual average of the number and proportion of investors in each education level group from 2012 to 2015 in the sample dataset.
[7] Since the SSE no longer published the data on the gender distribution of individual investors after 2016, in order to be consistent with the date caliber of the SSE, we calculate the annual average of the number and proportion of different genders in the sample dataset.

Table 3

Summary Statistics of IPOs from 2012 to 2019

This table presents the summary statistics of all China's A-share IPOs from 2012 to 2019. The number of listed firms, tradable market capitalization and total market capitalization are calculated at the end of each year. Market trading volume is the annual average of the daily trading value of China's A-share market. The frozen fund ratio is defined as the ratio of the online frozen fund divided by the online issuing proceeds. The issuing proceeds, market trading value, tradable market capitalization and total market capitalization are RMB in billion. The underpricing of each IPO is calculated as Yan, et al. (2019).

Year	No. of IPOs	No. of Listed Firms	Avg. Issuing Proceeds (billion)	Avg. Frozen Funds Ratio Online	Mkt. Trading Volume (billion)	Tradable Mkt. Cap. (billion)	Total Mkt. Cap. (billion)	Avg. Underpricing	No. of Neg. Underpricing
2012	153	2406	0.6857	107.12	128.56	17976.12	22902.53	26%	40
2013	0	2406			194.97	19852.81	23857.39		
2014	122	2528	0.5388	142.54	301.11	31450.71	37283.94	178%	0
2015	222	2750	0.7221	268.90	1040.97	41905.07	53461.03	403%	0
2016	227	2977	0.6590	3314.76	518.50	39002.89	50671.79	423%	0
2017	438	3415	0.5277	4138.19	458.20	44622.06	56519.03	267%	0
2018	105	3520	1.3125	3036.82	369.14	35192.36	43383.58	202%	0
2019	203	3723	1.2387	2691.28	520.27	48235.23	59296.60	170%	1

Table 4

Summary Statistics of Selected IPOs from 2012 to 2019

This table presents the summary statistics of selected China's A-share IPOs from 2012 to 2019. The frozen funds ratio is defined as the ratio of the fund frozen online divided by the issuing proceeds online of an IPO. The issuing proceeds is RMB in billion. The underpricing of each IPO is calculated as Yan, Xiong et al. (2019).

Year	No. of IPOs	Avg. Issuing Proceeds (billion)	Avg. Frozen Funds Ratio Online	Avg. Underpricing	No. of Neg. Underpricing
2012	133	0.7313	99.66	22.86%	38
2013					
2014	87	0.5359	130.22	148.82%	0
2015	80	1.1762	217.62	310.19%	0
2016	36	1.6016	3036.38	434.05%	0
2017	44	0.8819	3611.23	316.75%	0
2018	32	2.7926	1933.93	169.91%	0
2019	71	1.5287	2307.10	150.26%	1

Table 5
Event Periods

This table presents the definition of important IPO periods from 2012 to 2019.

Period	Definitions
Panel A: From 2012 Through 2015	
PRE_O	Pre-offering period: The day before the public offering [*T*-1] or 2 days before the public offering [*T*-2, *T*-1]. *T* denotes the offering day or the subscription day.
OD	Offering day: the online public subscription day [*T*].
FP	Frozen period: The day after the offering day to the day before the unfrozen day [*T*+1,*T*+2].
UFP	Unfrozen period: The day the oversubscription fund is returned to investors [UFD] or a 2-day period [UFD, UFD+1].
PRE_L	Pre-listing day: The day before listing [LD-1] or 2 days before listing [LD-2, LD-1].
LD	Listing day: The day the IPO shares get listed.
POST_L	Post-listing day: The day after the listing [LD+1] or 2 days after the listing [LD+1, LD+2].
OTHERD	Other trading days: OTHERD1 and OTHERD2 correspond to 1- or 2-day definitions for PRE_O, UFP, PRE_L, and POST_L, respectively.
Panel B: After 2016	
PRE_LO	Pre-lottery period: the day before the lottery day or 2 days before the lottery day. Usually the lottery day is *T*+2, so this period is [*T*+1] or [*T*, *T*+1].
LOD	Lottery day: the day on which the public subscription results are out, that is, [*T*+2]
POST_LO	Post-lottery period: the day after the lottery day [*T*+3] or 2 days after the lottery day [*T*+3, *T*+4].
PRE_L	Pre-listing day: The day before listing [LD-1] or 2 days before listing [LD-2, LD-1].
LD	Listing day: The day the IPO shares get listed.
POST_L	Post-listing day: The day after the listing [LD+1] or 2 days after the listing [LD+1, LD+2].
OTHERD	Other trading days: OTHERD1 and OTHERD2 correspond to 1- or 2-day definition for PRE_O, UFP, PRE_L, and POST_L, respectively.

Table 6
Variables and Definitions

This table presents the definitions of the variables used in this paper. Panel A presents the variables related to retail investors' trading behaviors; Panels B and C present the variables related to the IPO periods, and Panel D presents the control variable.

Variables	Definitions
Panel A: Investor-Level Variables	
$NetBuy_t$	The average net buying amount of retail investors on day *t.* The calculation is shown in formula (1).
$Imbalance_t$	The trading imbalance of retail investors on day *t*. The calculation is shown in formula (2).
$IfBuySameInd_t$	This variable measures if the IPO shares and the stocks purchased by retail investors on day *t* are in the same industry. The calculation can be seen in formula (3).
$IfSellSameInd_t$	This variable measures if the IPO shares and the stocks sold by retail investors on day *t* are in the same industry. The calculation can be seen in formula (4).
$BuyCorr_t$	This variable measures the correlation between the IPO shares and the stocks purchased by retail investors on day *t*. The calculation can be seen in formulas (5) and (6).
$SellCorr_t$	This variable measures the correlation between the IPO shares and the stocks sold by retail investors on day *t*. The calculation can be seen in formulas (5) and (6).
Panel B: IPO-Level Variables From 2012 Through 2015	
PRE_O_t	Dummy variable equal to one if day *t* is during the pre-offering period of at least one IPO in our sample, and zero otherwise.
OD_t	Dummy variable equal to one if day *t* is the offering day of at least one IPO in our ample, and zero otherwise.
FP_t	Dummy variable equal to one if day *t* is during the frozen period of at least one IPO in our sample, and zero otherwise.
UFP_t	Dummy variable equal to one if day *t* is during the unfrozen period of at least one IPO in our sample, and zero otherwise.
PRE_L_t	Dummy variable equal to one if day *t* is during the pre-listing period of at least one IPO in our sample, and zero otherwise.
LD_t	Dummy variable equal to one if day *t* is the listing day of at least one IPO in our sample, and zero otherwise.
$POST\_L_t$	Dummy variable equal to one if day *t* is during the post-listing period of at least one IPO in our sample, and zero otherwise.
Panel C: IPO-Level Variables After 2016	
PRE_LO_t	Dummy variable equal to one if day *t* is during the pre-lottery period of at least one IPO in our sample, and zero otherwise.
LOD_t	Dummy variable equal to one if day *t* is the lottery day of at least one IPO in our sample, and zero otherwise.
$POST\_LO_t$	Dummy variable equal to one if day *t* is during the post-lottery period of at least one IPO in our sample, and zero otherwise.
PRE_L_t	Dummy variable equal to one if day *t* is during the pre-listing period of at

	least one IPO in our sample, and zero otherwise.
LD_t	Dummy variable equal to one if day *t* is the listing day of at least one IPO in our sample, and zero otherwise.
$POST\_L_t$	Dummy variable equal to one if day *t* is during the post-listing period of at least one IPO in our sample, and zero otherwise.
Panel D: Control Variables	
$ExcRet_t$	The market excess return on day *t*. The market return is proxied by the HS300 index return, and the risk-free return rate is the 1-year bank deposit rate.

Table 7
Summary Statistics of the Ratio of Net Sells to Frozen Funds/Allocation Value

This table presents the summary statistics of the ratio of net sells to frozen funds or lottery value of each retail investor. Before 2016, investors had to pay in full for the IPO shares they subscribed to, so we calculate the ratio of the net sells to the frozen funds of each investor, and the results are presented in Panel A. After 2016, the frozen fund requirement was removed, and investors do not need to pay for the IPO shares they subscribe to on the subscription day, they only need to pay for the IPO shares allocated to them on the lottery day, therefore, we calculate the ratio of the net sells to the lottery value of each investor, and the results are presented in Panel B.

Panel A: IPOs from 2012 to 2015									
Net Sells/Frozen Fund During Different Periods for All IPO Subscribers (%)									
Period	**Mean**	**Std**	**Min**	**25%**	**Median**	**75%**	**Max**	**N**	The portion of subscribers whose net sell is positive (%)
T	66.83	853.63	-104387.17	-27.47	16.51	104.78	138,970.09	114,356	70.53
[T-1, T]	85.83	942.42	-105201.01	-26.02	26.12	125.21	138,970.09	114,356	73.52
[T-2, T]	91.52	1362.63	-129431.99	-29.16	30.00	138.51	132,814.05	114,356	74.85
Net Sells/Frozen Fund During Different Periods for IPO Subscribers Whose Net Sells Are Positive (%)									
Period	**Mean**	**Std**	**Min**	**25%**	**Median**	**75%**	**Max**	**N**	
T	212.31	817.91	0.27	27.94	89.73	182.81	138970.09	80,655	
[T-1, T]	247.04	899.82	0.03	33.23	99.94	217.09	138970.09	84,074	
[T-2, T]	270.61	984.07	0.27	37.33	102.92	237.49	132,814.05	85,595	
Panel B: IPOs Issuing After 2016									
Net Sells/allocation Value During Different Periods for All IPO Winners (%)									
Period	**Mean**	**Std**	**Min**	**25%**	**Median**	**75%**	**Max**	**N**	The portion of subscribers whose net sell is positive (%)
T+2	11.28	124.21	-9,397.25	-20.16	5.42	41.24	9,161.35	85,239	52.14
[T+1, T+2]	13.53	139.42	-10,417.23	-22.43	6.74	48.59	10,161.35	85,239	53.71
[T, T+2]	15.17	142.08	-11,675.62	-24.18	7.61	57.23	10,161.35	85,239	55.28
Net Sells/Allocation Value During Different Periods for IPO Winners Whose Net Sells Are Positive (%)									
Period	**Mean**	**Std**	**Min**	**25%**	**Median**	**75%**	**Max**	**N**	
T+2	22.58	78.95	0.08	4.12	10.54	19.21	9,161.35	44,443	
[T+1, T+2]	24.63	84.16	0.12	6.43	11.28	20.46	10,161.35	45,782	
[T, T+2]	25.17	90.24	0.25	7.16	11.96	21.33	10,161.35	47,120	

Table 8

The Trading Imbalance of Different Retail Investors During Different Periods of IPOs

This table presents the regression results of equation (7). Panel A presents the results of IPOs issued before 2016, and Panel B presents the results of IPOs issued after 2016. For each IPO, there are three different kinds of investors, that is, IPO non-subscribers who subscribe to no IPO shares, the IPO subscribers who subscribe to at least one hundred IPO shares, and the IPO winners who are ultimately allocated IPO shares. Therefore, this table presents the regression results for these three kinds of investors, respectively. Columns (1) and (2) present the results for IPO non-subscribers, columns (3) and (4) present the results for IPO subscribers, and columns (5) and (6) present the results of IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (7) of different groups of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

	Dependent Variable: ***Imbalance$_t$***					
Variables	IPO Non-subscribers		IPO Subscribers		IPO Winners	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IPOs Issued From 2012 to 2015						
Intercept	-0.0009	-0.0011	-0.0064	-0.0001	-0.0120	-0.0110
	(-0.870)	(-0.970)	(-0.894)	(-0.006)	(-1.090)	(-0.976)
Imbalance$_{t-1}$	0.0621**	0.0601**	0.0311	0.0013	0.0478	0.0390
	(2.223)	(2.152)	(0.744)	(0.030)	(1.114)	(0.889)
ExcRet$_t$	-0.0101***	-0.0101***	-0.0113***	-0.0108***	-0.0068*	-0.0063*
	(-6.798)	(-6.791)	(-4.142)	(-3.881)	(-1.953)	(-1.793)
PRE_O$_t$	-0.0036	-0.0030	-0.0413***	-0.0515***	-0.0532***	-0.0526***
	(-1.135)	(-1.095)	(-4.131)	(-5.220)	(-4.608)	(-4.181)
OD$_t$	-0.0067*	-0.0063*	-0.0569***	-0.0581***	-0.0516***	-0.0509***
	(-1.835)	(-1.631)	(-5.478)	(-5.608)	(-3.934)	(-3.895)
FP$_t$	-0.0032	-0.0028	-0.0065	-0.0094	-0.0147	-0.0161
	(-1.070)	(-0.956)	(-0.651)	(-0.934)	(-1.160)	(-1.270)
UFP$_t$	0.0046	0.0040	0.0844***	0.0767***	0.0843***	0.0756***
	(1.506)	(1.490)	(8.541)	(7.440)	(6.796)	(5.805)
PRE_L$_t$	-0.0034	-0.0032	-0.0131	-0.0040	-0.0210	-0.0192
	(-1.252)	(-1.183)	(-1.424)	(-0.0424)	(-1.643)	(-1.596)
LD$_t$	-0.0068	-0.0050*	-0.0083	-0.0149*	-0.0475**	-0.0506**
	(-1.418)	(-1.776)	(-0.0875)	(-1.580)	(-2.328)	(-2.198)
POST_L$_t$	0.0011	0.0009	0.0130	0.0032	-0.0319**	-0.0298*
	(0.406)	(0.365)	(1.401)	(0.345)	(-2.065)	(-1.898)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	969	969	969	969	969	969
Adj. R^2	0.261	0.261	0.283	0.267	0.222	0.206
Panel B: IPOs Issued After 2016						
Intercept	0.0055*	0.0044*	0.0019	0.0045	-0.0133	-0.0121
	(1.913)	(1.918)	(0.649)	(1.335)	(-1.305)	(-1.165)
Imbalance$_{t-1}$	-0.0512**	-0.0497**	-0.0408	-0.0435	-0.0677**	-0.0680**
	(-2.052)	(-1.986)	(-1.516)	(-1.615)	(-2.080)	(-2.199)
ExcRet$_t$	-0.0218***	-0.0217***	-0.0182***	-0.0181***	-0.0213***	-0.0213***
	(-6.972)	(-6.900)	(-5.487)	(-5.446)	(-5.314)	(-5.282)
PRE_LO$_t$	-0.0023	-0.0024	-0.0015	-0.0017	-0.0064	-0.0072
	(-1.048)	(-1.088)	(-0.670)	(-0.762)	(-0.964)	(-1.091)
LOD$_t$	-0.0008	-0.0007	-0.0030	-0.0032	-0.0213***	-0.0260***
	(-0.337)	(-0.295)	(-1.327)	(-1.438)	(-3.164)	(-2.889)
POST_LO$_t$	-0.0009	-0.0007	0.0001	0.0002	-0.0046	-0.0039

	(-0.419)	(-0.332)	(0.024)	(0.111)	(-0.691)	(-0.584)
PRE_L_t	-0.0004	-0.0003	-0.0008	-0.0011	-0.0027	-0.0053
	(-0.182)	(-0.136)	(-0.386)	(-0.443)	(-0.437)	(-0.737)
LD_t	-0.0035	-0.0034	-0.0036*	-0.0033	-0.0067**	-0.0062**
	(-1.617)	(-1.508)	(-1.687)	(-1.530)	(-2.072)	(-1.996)
$POST\_L_t$	0.0025	0.0006	0.0008	0.0027	-0.0074	-0.0024
	(1.208)	(0.256)	(0.377)	(1.620)	(-1.193)	(-0.332)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	927	927	927	927	927	927
Adj. R^2	0.431	0.430	0.340	0.341	0.375	0.374

Table 9
The Impacts of IPOs on the Industries

This table presents the summary statistics of the proceeds or the unfrozen funds of IPOs to the average daily industry trading value in different periods of IPOs. Panel A presents the results for IPOs issued before 2016. As there was the frozen fund requirement before 2016, we compare the proceeds and the unfrozen funds of the IPOs with the average daily industry trading value of different periods, respectively. Panel B presents the results for IPOs issued after 2016. As the frozen fund requirement had been removed since 2016, we only compare the proceeds of the IPOs with the average daily industry trading value of different periods.

Panel A: From 2012 to 2015									
Periods	**Mean**	**std**	**Min**	**25%**	**Median**	**75%**	**Max**	**No. Days**	**No. IPOs**
IPO Proceeds/Average Industry Trading Value (%)									
Offering Day	39.32	128.43	0.19	2.12	6.46	21.41	1,664.41	184	503
Unfrozen Day	39.12	126.77	0.18	2.07	6.25	20.99	1,563.62	184	503
Listing Day	39.46	126.75	0.15	1.94	6.04	22.11	1,536.71	176	503
Unfrozen Fund/Average Industry Trading Value (%)									
Unfrozen Day	2,563.32	6,411.01	64.58	317.91	695.68	2,013.98	73,789.97	184	503
Panel B: After 2016									
IPO Proceeds/Average Industry Trading Value (%)									
Lottery Day	15.50	48.23	0.16	1.42	3.72	11.09	1044.13	538	902
Listing Day	16.21	53.19	0.17	1.54	3.88	11.99	1203.34	517	902

Table 10
Correlations Between IPOs and Stocks Sold by Investors over Different Periods

This table presents the regression results of equation (8). Panel A presents the results of IPOs issued before 2016, and Panel B presents the results of IPOs issued after 2016. For each IPO, there are three different kinds of investors, that is, the IPO non-subscribers who do not subscribe to IPO shares, the IPO subscribers who subscribe at least one hundred IPO shares, and the IPO winners who are ultimately allocated IPO shares. Therefore, this table presents the regression results for these three kinds of investors, respectively. Columns (1) and (2) present the results for IPO non-subscribers, columns (3) and (4) presents the results for IPO subscribers, and columns (5) and (6) present the results for IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (8) of different kinks of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

Variable	Dependent Variable: ***SellCorr$_t$***					
	IPO non-subscribers		IPO Subscribers		IPO Winners	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. During the Period from 2012 to 2015						
Intercept	0.1205***	0.1243***	0.1325***	0.1316***	0.1153***	0.1173***
	(8.430)	(8.329)	(8.014)	(7.629)	(7.213)	(7.072)
SellCorr$_{t-1}$	0.1363***	0.1292***	0.1166***	0.1040***	0.1602***	0.1500***
	(4.239)	(4.002)	(3.337)	(3.006)	(3.511)	(3.184)
ExcRet$_t$	0.2934	0.2819	0.2794	0.2729	0.4106***	0.4180***
	(1.523)	(1.475)	(1.411)	(1.406)	(2.271)	(2.298)
PRE_O$_t$	-0.0092	-0.0004	-0.0090	0.0024	-0.0052	-0.0003
	(-1.048)	(-0.062)	(-1.269)	(0.337)	(-0.800)	(-0.044)
OD$_t$	0.0093	0.0087	0.0105	0.0097	0.0101	0.0099
	(1.294)	(1.275)	(1.339)	(1.328)	(1.231)	(1.295)
FP$_t$	-0.0098	-0.0107	-0.0101	-0.0092	-0.0103	-0.0094
	(-1.419)	(-1.494)	(-1.424)	(-1.302)	(-1.580)	(-1.449)
UFP$_t$	0.0009	-0.0029	0.0010	-0.0043	0.0021	-0.0043
	(0.128)	(-0.549)	(0.148)	(-0.595)	(0.324)	(-0.657)
PRE_L$_t$	0.0079	0.0098	-0.0161**	-0.0172**	0.0081	0.0117
	(1.289)	(1.474)	(-2.126)	(-2.205)	(1.340)	(1.396)
LD$_t$	-0.0287***	-0.0302***	-0.0225***	-0.0206***	0.0191*	0.0175*
	(-4.362)	(-4.413)	(-2.807)	(-2.536)	(1.933)	(1.769)
POST_L$_t$	-0.0139**	-0.0108*	-0.0141***	-0.0137**	0.0114*	0.0111
	(-2.053)	(-1.853)	(-2.089)	(-2.099)	(1.591)	(1.560)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	969	969	969	969	969	969
Adj. R^2	0.223	0.218	0.361	0.355	0.328	0.322
Panel B. During the Period from 2016 to 2019						
Intercept	0.0575***	0.0537***	0.0556***	0.0590***	0.0554***	0.0558***
	(6.342)	(6.412)	(6.245)	(6.213)	(6.788)	(6.668)
SellCorr$_{t-1}$	0.1923***	0.1899***	0.1910***	0.1887***	0.1903***	0.1874***
	(5.790)	(5.361)	(5.781)	(5.327)	(5.429)	(5.686)
ExcRet$_t$	0.4789***	0.5126***	0.4500***	0.4532***	0.5137***	0.5187***
	(4.571)	(5.045)	(4.281)	(4.313)	(5.012)	(5.065)
PRE_LO$_t$	-0.0017	-0.0021	-0.0020	-0.0019	-0.0018	-0.0023
	(-0.653)	(-0.727)	(-0.723)	(-0.704)	(-0.677)	(-0.850)
LOD$_t$	0.0028	0.0031	0.0014	0.0014	0.0032	0.0027
	(0.988)	(1.109)	(0.497)	(0.512)	(1.172)	(0.989)
POST_LO$_t$	-0.0009	-0.0012	-0.0017	-0.0017	-0.0070	-0.0076
	(-0.505)	(-0.536)	(-0.643)	(-0.634)	(-2.661)	(2.517)
PRE_L$_t$	-0.0002	0.0012	-0.0061**	-0.0057**	0.0006	0.0015

	(-0.086)	(0.419)	(-2.051)	(-1.991)	(0.223)	(0.507)
LD_t	-0.0061**	-0.0057**	-0.0047**	-0.0046**	0.0046*	0.0044*
	(-2.484)	(-2.30)	(-2.051)	(-2.019)	(1.840)	(1.786)
$POST\_L_t$	-0.0059*	-0.0054*	-0.0063**	-0.0062*	0.0078*	0.0082*
	(-1.703)	(-1.694)	(-1.973)	(-1.809)	(1.891)	(1.833)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	927	927	927	927	927	927
Adj. R^2	0.204	0.198	0.218	0.223	0.215	0.209

Table 11
Correlations Between IPOs and Stocks Purchased by Investors over Different Periods

This table presents the regression results of equation (9). Panel A presents the results of IPOs issued before 2016, and Panel B presents the results of IPOs issued after 2016. For each IPO, there are three different groups of investors, that is, the IPO non-subscribers who subscribe to no IPO shares, the IPO subscribers who subscribe to at least one hundred IPO shares, and the IPO winners who are ultimately allocated IPO shares. Therefore, this table presents the regression results for these three kinds of investors, respectively. Columns (1) and (2) present the results for IPO non-subscribers, columns (3) and (4) present the results for IPO subscribers, and columns (5) and (6) present the results for IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (9) of different groups of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

Variable	Dependent Variable: $BuyCorr_t$					
	All Retail Investors		Retail IPO Subscribers		Retail IPO Winners	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. During the Period from 2012 to 2015						
Intercept	0.0253^{***}	0.0269^{***}	0.0263^{***}	0.0261^{***}	0.0274^{***}	0.0281^{***}
	(4.398)	(4.573)	(4.545)	(4.459)	(4.594)	(4.664)
$BuyCorr_{t-1}$	0.1880^{***}	0.1794^{***}	0.1728^{***}	0.1255^{***}	0.1227^{***}	0.1214^{***}
	(5.723)	(5.684)	(5.603)	(5.265)	(5.343)	(5.068)
$ExcRet_t$	-0.1718^{**}	-0.1739^{***}	-0.1615^{**}	-0.1531^{**}	-0.1171^{*}	-0.1045
	(-2.535)	(-2.586)	(-2.420)	(-2.291)	(-1.736)	(-1.546)
PRE_O_t	-0.0024	0.0008	-0.0025	0.0017	-0.0028	-0.0005
	(-1.031)	(0.186)	(-1.057)	(0.738)	(-1.168)	(-0.220)
OD_t	0.0021	0.0011	0.0017	0.0002	0.0029	0.0018
	(0.702)	(0.431)	(0.678)	(0.073)	(1.148)	(0.713)
FP_t	-0.0009	0.0003	-0.0026	-0.0023	-0.0030	-0.0026
	(-0.395)	(0.142)	(-1.082)	(-0.954)	(-1.242)	(-1.070)
UFP_t	0.0042	0.0036	0.0065^{***}	0.0062^{***}	0.0046^{**}	0.0048^{**}
	(1.594)	(1.533)	(2.778)	(2.640)	(1.982)	(2.087)
PRE_L_t	0.0009	-0.0002	0.0014	-0.0003	-0.0005	-0.0020
	(0.423)	(-0.101)	(0.644)	(-0.142)	(-0.241)	(-0.880)
LD_t	0.0054^{*}	0.0067^{*}	-0.0048^{**}	-0.0039^{*}	-0.0022	-0.0016
	(1.795)	(0.192)	(-2.127)	(-1.732)	(-0.943)	(-0.706)
$POST\_L_t$	0.0042^{*}	0.0038^{*}	0.0032	0.0028	0.0028	0.0017
	(1.879)	(1.725)	(1.438)	(1.266)	(1.247)	(0.750)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	969	969	969	969	969	969
Adj. R^2	0.182	0.175	0.239	0.238	0.240	0.242
Panel B. During the Period from 2016 to 2019						
Intercept	0.0536^{***}	0.0527^{***}	0.0470^{***}	0.0501^{***}	0.0385^{***}	0.0395^{***}
	(5.978)	(5.871)	(5.677)	(5.685)	(5.724)	(5.420)
$BuyCorr_{t-1}$	0.2318^{***}	0.2304^{***}	0.2082^{***}	0.2061^{***}	0.2259^{***}	0.2252^{***}
	(6.827)	(6.748)	(6.332)	(6.865)	(6.571)	(6.655)
$ExcRet_t$	-0.0381	-0.0418	-0.0582	-0.0560	-0.0865	-0.0875
	(-0.458)	(-0.511)	(-0.603)	(-0.581)	(-1.051)	(-1.042)
PRE_LO_t	-0.0021	-0.0019	-0.0013	-0.0012	-0.0014	-0.0016
	(-0.971)	(-0.807)	(-0.532)	(-0.482)	(-0.664)	(-0.737)
LOD_t	0.0009	-0.0007	0.0038^{*}	0.0035^{*}	0.0038^{*}	0.0037^{*}
	(0.427)	(-0.310)	(1.732)	(1.673)	(1.683)	(1.691)
$POST\_LO_t$	0.0004	-0.0002	-0.0023	-0.0024	0.0003	0.0003

	(0.166)	(-0.082)	(-0.914)	(-0.954)	(0.118)	(0.161)
PRE_L_t	-0.0024	-0.0031	-0.0012	-0.0033	-0.0003	0.0005
	(-0.892)	(-1.141)	(-0.517)	(-1.207)	(-0.163)	(0.232)
LD_t	0.0055^{**}	0.0054^{*}	-0.0017	-0.0016	-0.0012	-0.0012
	(2.048)	(1.912)	(-0.719)	(-0.694)	(-0.607)	(-0.620)
$POST\_L_t$	0.0050^{*}	0.0045^{*}	0.0041^{*}	0.0045^{*}	0.0003	0.0017
	(1.811)	(1.803)	(1.736)	(1.935)	(0.173)	(0.714)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	927	927	927	927	927	927
Adj. R^2	0.161	0.157	0.135	0.133	0.153	0.152

Table 12
The Net Sells of Different Retail Investors During Different Periods of IPOs

This table presents the regression results of equation (10). Panel A presents the results of IPOs issued before 2016, and Panel B presents the results of IPOs issued after 2016. For each IPO, there are three different groups of investors, that is, the IPO non-subscribers who subscribe no IPO shares, the IPO subscribers who subscribe at least one hundred IPO shares, and the IPO winners who are ultimately allocated IPO shares. Therefore, this table presents the regression results for these three kinds of investors, respectively. Columns (1) and (2) present the results of the IPO non-subscribers, columns (3) and (4) present the results of IPO subscribers, and columns (5) and (6) present the results of IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (10) of different kinks of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

Variables	**Dependent Variable: *NetBuy$_t$***					
	All Retail Investors		Retail IPO Subscribers		Retail IPO Winners	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IPOs Issued From 2012 to 2015						
Intercept	0.0698	0.0704	-0.0342	0.0115	-0.0803	-0.0060
	(1.263)	(1.273)	(-0.532)	(0.147)	(-1.237)	(-0.075)
NetBuy$_{t-1}$	0.1428***	0.1404***	0.0380	0.0099	0.1004**	0.1030**
	(5.142)	(5.066)	(0.904)	(0.228)	(2.273)	(2.329)
ExcRet$_t$	-0.1127***	-0.1129***	-0.1054***	-0.1016***	-0.0503**	-0.0476*
	(-6.341)	(-6.354)	(-4.279)	(-4.112)	(-2.014)	(-1.909)
PRE_O$_t$	-0.0688	-0.1053	-0.4145***	-0.5032***	-0.3671***	-0.5171***
	(-0.798)	(-1.327)	(-4.619)	(-5.713)	(-4.012)	(-5.784)
OD$_t$	-0.0905*	-0.0995*	-0.5200***	-0.5302***	-0.4383***	-0.4361***
	(-1.632)	(-1.651)	(-5.568)	(-5.728)	(-4.639)	(-4.674)
FP$_t$	-0.0963	-0.0881	0.1199	0.1460	0.2265	0.2400
	(-1.110)	(-1.025)	(1.329)	(1.628)	(2.499)	(2.675)
UFP$_t$	0.1322	0.1483	0.7512***	0.6934***	0.6442***	0.5940***
	(1.356)	(1.553)	(8.449)	(7.548)	(7.139)	(6.378)
PRE_L$_t$	-0.0965	-0.0898	-0.1160	-0.0622	-0.1142	-0.1016
	(-1.202)	(-1.130)	(-1.404)	(-0.736)	(-1.364)	(-1.191)
LD$_t$	-0.1311	-0.1347	-0.1404	-0.1360	-0.1648**	-0.1626*
	(-1.593)	(-1.579)	(-1.636)	(-1.640)	(-2.333)	(-1.913)
POST_L$_t$	0.0376	0.0303	0.0830	0.0895	-0.1487*	-0.1120
	(0.471)	(0.418)	(0.999)	(1.100)	(-1.752)	(-1.362)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	969	969	969	969	969	969
Adj. R^2	0.274	0.275	0.300	0.295	0.288	0.288
Panel B: IPOs Issued After 2016						
Intercept	0.0799	0.1006	0.0515	0.1364	0.0318	0.0153
	(1.058)	(1.139)	(0.587)	(1.306)	(0.327)	(0.132)
NetBuy$_{t-1}$	0.0464*	0.0454*	0.0976**	0.0990**	0.1260***	0.1267***
	(1.843)	(1.797)	(2.305)	(2.374)	(3.945)	(3.966)
ExcRet$_t$	-0.5618***	-0.5608***	-0.3531***	-0.3513***	-0.2303***	-0.2295***
	(-5.306)	(-5.248)	(-3.617)	(-3.562)	(-3.002)	(-3.970)
PRE_LO$_t$	-0.0636	-0.0668	0.0424	0.0414	-0.0488	-0.0561
	(-1.093)	(-1.142)	(0.635)	(0.619)	(-0.657)	(-0.753)
LOD$_t$	-0.0351	-0.0344	-0.0930	-0.0947	-0.1492***	-0.1483***
	(-0.587)	(-0.572)	(-1.362)	(-1.377)	(-2.973)	(-2.945)
POST_LO$_t$	-0.0232	-0.0183	-0.0162	-0.0115	-0.0284	-0.0208
	(-0.395)	(-0.311)	(-0.242)	(-0.172)	(-0.381)	(-0.279)
PRE_L$_t$	-0.0092	-0.0010	-0.0104	-0.0410	-0.0527	-0.0633

	(-0.166)	(-0.001)	(-0.166)	(-0.560)	(-0.754)	(-0.780)
LD_t	-0.0762	-0.0710	-0.0676	-0.0620	-0.1276**	-0.1302**
	(-1.387)	(-1.287)	(-1.072)	(-0.987)	(-2.124)	(-1.998)
$POST\_L_t$	0.0551	0.0078	0.0067	0.0751	-0.0819	-0.0751
	(1.004)	(0.125)	(0.107)	(1.037)	(-1.175)	(-1.160)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	927	927	927	927	927	927
Adj. R^2	0.417	0.416	0.174	0.248	0.075	0.074

Table 13
The Industries of the Stocks Sold by Investors

This table presents the regression results of equation (11). Panel A presents the results of IPOs issued before 2016, and Panel B presents the results of IPOs issued after 2016. For each IPO, there are three different groups of investors, that is, the IPO non-subscribers who subscribe no IPO shares, the IPO subscribers who subscribe at least one hundred IPO shares, and the IPO winners who are ultimately allocated IPO shares. Therefore, this table presents the regression results for these three groups of investors, respectively. Columns (1) and (2) present the results for IPO non-subscribers, columns (3) and (4) presents the results for IPO subscribers, and columns (5) and (6) present the results for IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (11) of different groups of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

Variable	Dependent Variable: ***IfSellSameInd$_t$***					
	All Retail Investors		Retail IPO Subscribers		Retail IPO Winners	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. During the period from 2012 to 2015						
Intercept	0.0415***	0.0432***	0.0365***	0.0411***	0.0353***	0.0362***
	(4.330)	(4.239)	(4.104)	(3.992)	(3.351)	(3.702)
IfSellSameInd$_{t-1}$	0.1248***	0.1276***	0.1293***	0.1220***	0.1312***	0.1345***
	(3.919)	(4.111)	(3.794)	(3.891)	(3.545)	(3.648)
ExcRet$_t$	0.1927	0.1875	0.1936	0.1899	0.2031	0.2104
	(1.472)	(1.477)	(1.452)	(1.446)	(1.527)	(1.604)
PRE_O$_t$	-0.0102	-0.0064	-0.0087	0.0032	0.0063	0.0016
	(-1.148)	(-0.083)	(-1.196)	(0.425)	(0.791)	(0.082)
OD$_t$	0.0089	0.0093	-0.0009	-0.0084	0.0011	0.0009
	(1.301)	(1.329)	(-0.475)	(-1.436)	(0.437)	(0.376)
FP$_t$	-0.0128	-0.0113	-0.0139	-0.0152	-0.0093	-0.0102
	(-1.399)	(-1.428)	(-1.548)	(-1.604)	(-1.040)	(-1.049)
UFP$_t$	0.0081	-0.0032	0.0024	-0.0032	0.0036	-0.0039
	(0.201)	(-0.473)	(0.305)	(-0.404)	(0.443)	(-0.598)
PRE_L$_t$	0.0128	0.0101	0.0119	0.0097	0.0089	0.0094
	(1.395)	(1.407)	(1.563)	(1.482)	(1.442)	(1.455)
LD$_t$	-0.0302***	-0.0285***	-0.0337***	-0.0329***	0.0283**	0.0262*
	(-4.471)	(-4.458)	(-5.012)	(-4.783)	(2.182)	(1.843)
POST_L$_t$	-0.0149**	-0.0168**	-0.0297***	-0.0225**	0.0192*	0.0152
	(-2.538)	(-2.574)	(-3.638)	(-2.392)	(1.839)	(1.525)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	969	969	969	969	969	969
Adj. R^2	0.263	0.262	0.306	0.303	0.294	0.290
Panel B. During the period from 2016 to 2019						
Intercept	0.0286***	0.0301***	0.0363***	0.0308***	0.0248***	0.0285***
	(3.937)	(4.223)	(4.129)	(3.174)	(3.375)	(3.767)
IfSellSameInd$_{t-1}$	0.1765***	0.1697***	0.1802***	0.1668***	0.1709***	0.1774***
	(4.769)	(4.310)	(4.839)	(4.236)	(4.542)	(4.664)
ExcRet$_t$	0.3846***	0.4011***	0.3902***	0.4056***	0.3698***	0.3894***
	(3.821)	(4.102)	(3.881)	(4.012)	(3.795)	(4.011)
PRE_LO$_t$	0.0011	0.0009	-0.0033	-0.0028	-0.0015	-0.0017
	(0.292)	(0.207)	(-0.795)	(-0.695)	(-0.484)	(-0.573)
LOD$_t$	0.0022	0.0021	-0.0009	-0.0012	-0.0010	-0.0008
	(0.588)	(0.579)	(-0.363)	(-0.402)	(-0.328)	(-0.296)
POST_LO$_t$	-0.0011	-0.0009	-0.0058*	-0.0057*	-0.0069**	-0.0068**
	(-0.402)	(-0.393)	(-1.773)	(-1.795)	(-2.332)	(2.138)
PRE_L$_t$	-0.0008	0.0003	-0.0010	-0.0013	0.0008	-0.0002

	(-0.236)	(0.096)	(-0.352)	(-0.367)	(0.279)	(-0.106)
LD_t	-0.0056**	-0.0054**	-0.0087***	-0.0085***	0.0070*	0.0074*
	(-2.040)	(-2.005)	(-2.812)	(-2.803)	(1.871)	(1.607)
$POST\_L_t$	-0.0050	-0.0062*	-0.0065*	-0.0063*	0.0061	0.0058
	(-1.501)	(-1.756)	(-1.885)	(-1.827)	(1.532)	(1.574)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	927	927	927	927	927	927
Adj. R^2	0.187	0.182	0.176	0.173	0.223	0.219

Table 14
The Industries of the Stocks Purchased by Investors

This table presents the regression results of equation (12). Panel A presents the results of IPOs issued before 2016, and Panel B presents the results of IPOs issued after 2016. For each IPO, there are three different groups of investors, that is, the IPO non-subscribers who subscribe no IPO shares, the IPO subscribers who subscribe at least one hundred IPO shares, and the IPO winners who are ultimately allocated IPO shares. Therefore, this table presents the regression results for these three kinds of investors, respectively. Columns (1) and (2) present the results for IPO non-subscribers, columns (3) and (4) presents the results for IPO subscribers, and columns (5) and (6) present the results for IPO winners. As there are two alternative definitions for the IPO periods of PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L (see Table 5), two regression results are presented for equation (12) of different groups of investors. Columns (1), (3), and (5) define the PRE_O, PRE_LO, UFP, POST_LO, PRE_L, and POST_L periods as one-day dummies, while columns (2), (4), and (6) define them as two-day dummies.

Variable	Dependent Variable: $IfBuySameInd_t$					
	All Retail Investors		Retail IPO Subscribers		Retail IPO Winners	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. During the period from 2012 to 2015						
Intercept	0.0208***	0.0202***	0.0213***	0.0211***	0.0198***	0.0201***
	(3.863)	(3.757)	(3.693)	(3.682)	(3.579)	(3.586)
$IfBuySameInd_{t-1}$	0.1799***	0.1788***	0.1517***	0.1494***	0.1199***	0.1214***
	(5.696)	(5.631)	(4.775)	(4.268)	(4.667)	(4.712)
$ExcRet_t$	-0.1346**	-0.1401**	-0.1602**	-0.1528**	-0.1069	-0.1102*
	(-2.252)	(-2.304)	(-2.386)	(-2.282)	(-1.624)	(-1.655)
PRE_O_t	-0.0019	0.0005	-0.0026	-0.0005	-0.0018	0.0005
	(-1.010)	(0.137)	(-1.057)	(-0.573)	(-1.086)	(0.190)
OD_t	0.0012	0.0011	0.0005	-0.0002	0.0033	0.0021
	(0.417)	(0.403)	(0.219)	(-0.083)	(1.205)	(0.802)
FP_t	-0.0010	-0.0003	-0.0016	0.0008	-0.0029	0.0026
	(-0.407)	(-0.152)	(-0.998)	(0.894)	(-1.139)	(1.359)
UFP_t	0.0041	0.0036	0.0072***	0.0069***	0.0058**	0.0055**
	(1.483)	(1.395)	(2.938)	(2.850)	(2.012)	(1.977)
PRE_L_t	0.0007	-0.0002	0.0024	0.0021	0.0016	0.0014
	(0.435)	(-0.208)	(1.232)	(1.220)	(1.003)	(0.982)
LD_t	0.0044*	0.0043*	0.0028	0.0017	-0.0021	-0.0012
	(1.709)	(1.698)	(1.132)	(0.975)	(-0.897)	(-0.696)
$POST\_L_t$	0.0045*	0.0042*	0.0012	0.0008	-0.0008	-0.0005
	(1.778)	(1.724)	(0.381)	(0.305)	(-0.162)	(-0.150)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	969	969	969	969	969	969
Adj. R^2	0.157	0.156	0.198	0.196	0.175	0.173
Panel B. During the period from 2016 to 2019						
Intercept	0.0203***	0.0218***	0.0197***	0.0201***	0.0187***	0.0196***
	(2.877)	(2.898)	(2.609)	(2.635)	(2.597)	(2.613)
$IfBuySameInd_{t-1}$	0.1328***	0.1315***	0.1097***	0.1094***	0.1509***	0.1485***
	(3.728)	(3.714)	(3.182)	(3.171)	(3.528)	(3.492)
$ExcRet_t$	-0.0402	-0.0422	-0.0589	-0.0580	-0.0737	-0.0799
	(-0.479)	(-0.513)	(-0.614)	(-0.605)	(-0.915)	(-1.024)
PRE_LO_t	-0.0032	-0.0028	-0.0012	-0.0011	-0.0010	0.0009
	(-1.453)	(-1.407)	(-0.523)	(-0.479)	(-0.346)	(0.374)
LOD_t	0.0016	0.0009	0.0035**	0.0029*	0.0027*	0.0028*
	(0.628)	(0.237)	(2.033)	(1.702)	(1.686)	(1.703)
$POST\_LO_t$	-0.0005	0.0007	0.0018	0.0019	0.0020	0.0022
	(0.171)	(0.193)	(0.703)	(0.872)	(0.719)	(0.885)
PRE_L_t	0.0019	-0.0018	-0.0014	-0.0024	0.0005	0.0007

	(0.702)	(-0.829)	(-0.536)	(-1.322)	(0.114)	(0.186)
LD_t	0.0025^{*}	0.0021^{*}	0.0015	0.0016	-0.0009	-0.0003
	(1.721)	(1.662)	(0.891)	(0.904)	(-0.386)	(-0.114)
$POST\_L_t$	0.0029^{*}	0.0019	0.0031^{*}	0.0025	-0.0012	-0.0015
	(1.712)	(1.411)	(1.727)	(1.592)	(-0.637)	(-0.714)
Year	Control	Control	Control	Control	Control	Control
No. of obs.	927	927	927	927	927	927
Adj. R^2	0.125	0.123	0.171	0.169	0.155	0.153