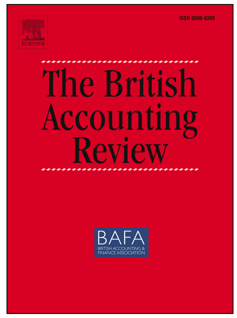
Journal Pre-proof



What Drives Individual Investors in the Bear Market?

Rong Xu, Yaodong Liu, Nan Hu, Jie (Michael) Guo

PII: S0890-8389(22)00042-7

DOI: https://doi.org/10.1016/j.bar.2022.101113

Reference: YBARE 101113

To appear in: *The British Accounting Review*

Received Date: 17 June 2021

Revised Date: 13 May 2022

Accepted Date: 15 June 2022

Please cite this article as: Xu, R., Liu, Y., Hu, N., Guo, J.(M.), What Drives Individual Investors in the Bear Market?, *The British Accounting Review*, https://doi.org/10.1016/j.bar.2022.101113.

What Drives Individual Investors in the Bear Market?

Rong Xu [a], Yaodong Liu [b, *], Nan Hu [c], Jie (Michael) Guo [d]

[a] *School of Finance & China Financial Policy Research Centre, Renmin University of China, Beijing, Email:* xurongfsi@gmail.com *(First Author)*

[b, *] *Business School, University of Aberdeen, Edward Wright Building, Aberdeen, AB24 3QY, UK, Email:* yaodong.liu@abdn.ac.uk *(Corresponding Author)*

[c] *Adam Smith Business School, Glasgow University, Glasgow, University Ave, G12 8QQ, UK, Email:* nan.hu@glasgow.ac.uk

[d] *Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, UK, Email:* jie.guo@durham.ac.uk

What Drives Individual Investors in the Bear Market?

Abstract

This study uses a unique dataset from a large anonymous brokerage firm to examine the net investment of individual investors during a bear market. The study's empirical evidence reveals that individual investors provide liquidity by acting as net buyers. Particularly, male and younger investors tend to have a higher buying intensity than the others during the market downturn. Besides, better performances when the market crashed encourage investors to be overconfident, thus exhibiting self-attribution bias since we do not find similar results in the bull-market subsample. Results from the stock-level analysis imply that investors tend to buy stocks with worse short-term past performance, higher liquidity, and larger market capitalization. Our findings on the individual investor trading behaviour cannot be explained by either a superior stock-picking ability or a higher tendency to gamble during the market downswing.

Keywords: Individual investors; Financial crisis; Chinese stock markets; Self-attribution bias

1. Introduction

Stock markets are inherently volatile. Historical and recent lessons show that long periods of rallies are often followed by significant downturns in the stock market. Following the bursting of the dot-com bubble in 2001 and the housing bubble in 2008, global stock markets experienced sharp declines. More recently, the stock market upswing that followed the quantitative easing after the outbreak of the Covid-19 was also joined by selloffs in anticipation of tapering and interest rate hikes.[1] As one of the key players in the stock market, how do individuals react to stock market turmoil? In December 2008, a *Wall Street Journal* (Browning, 2008) article titled *"Stock Investors Lose Faith, Pull Out Record Amounts"* stated that individual investors had withdrawn $72 billion in the stock market crash that occurred back in October 2008. Similarly, Deutsche Bank Research and Deloitte and Touche report that the trading activities of retail investors and the growth rate of online accounts are dramatically declined due to the turmoil in 2001. Previous studies reveal that individual investors have a higher tendency to herd when facing market pressure; in particular, they are more likely to crowd on the sell-side during a financial crisis (Chang, Cheng, & Khorana, 2000; Hsieh, 2013). However, recent findings in developed stock markets suggest that, in general, individual investors provide liquidity and do not take a lower risk when the market crashes (Barrot, Kaniel, & Sraer, 2016; Dorn & Weber, 2013; Hoffmann, Post, & Pennings, 2013).[2] This paper aims to examine the factors that influence the trading behaviour of individual investors in the Chinese stock market, with a focus on the financial crisis that began in November 2007.

Theoretically, it is not possible that all investors are sellers since there must be at least one buyer for every seller, consequently investors as a group cannot all be sellers. As a risk-averse or risk-neutral individual, an investor should avoid buying or leaving the market upon

[1] In the wake of the epidemic in 2020, many governments adopted low interest rates and handed out subsidies to stimulate the economy. In this context, numerous stocks experienced a massive surge, especially technology stocks, which reached all-time highs during this period. However, the expectation of tapering and its implementation led to the S&P 500 dropping 13% from 2022 to early May. Likewise, the Shanghai Stock Exchange Composite (SSEC) Index lost more than 15% of its market capitalization from 2022 to the end of April on concerns about the pandemic and economic growth.

[2] In addition to empirical findings, a report from the the Autorité des marchés financiers (AMF) found that individual investors, particularly those with little trading experience, were extremely active and buying stocks during the early stage of the financial crisis caused by the outbreak of the Covid-19.

perceiving imminent market risk. Investors must have an incentive to absorb liquidity demands during a financial crisis (Hoopes, Langetieg, Nagel, & Stuart, 2016). For instance, mean-reversion believers may use the depreciation of share prices as an opportunity to enter the market (Hoffmann et al., 2013). Besides, a bear market provides a superb opportunity for investors to repurchase stocks at the bottom since they are more likely to have a positive experience when the share price drops after being sold. Some investors provide liquidity during a bear market simply because they are poorly informed or have higher risk tolerances. Notwithstanding this, contemporary research investigating the behaviour of individual investors during the financial crisis remains reticent on several questions: i) Who is more inclined to buy stocks in the face of a market in turmoil? Specifically, do personal characteristics, such as gender, age, trading experience affect the net purchase behaviour during the crisis period? ii) Why do individual investors engage in buying when the market crashes? Is it because they believe too much in their own abilities, or because they have extraordinary stock-picking skills, or are they simply gambling?

Motivated by recent findings of individual investors' trading behaviour in the stock markets, we investigate the determinants of net buying by Chinese investors during a bear market. Compared to the US stock market, the Chinese stock market has a unique investor structure. According to the China Securities Depository and Clearing Corporation, the proportion of individual investor accounts in the Chinese stock market exceeded 99.7% of the total accounts, reaching 159 million by the end of 2019. In addition, substantial prior studies have found that Chinese individual investors trade extremely frequently and account for a large market share (Feng & Seasholes, 2003; Allen, Qian, Shan, & Zhu, 2020).

Apart from the structure of investors, the Chinese A-share stock market also has two distinct differences in terms of trading mechanism compared to the US market. First, both SSE and SZSE have a 'T+1' trading regime, which means that stocks bought on the day can only be sold on the next trading day. Second, the Chinese stock market imposes price limits; excluding the first trading day of resumption after suspension and the first trading day of IPO stocks, the price change of A-share stocks cannot exceed 10% in a single day, while the single-day price change of 'ST' stocks cannot exceed 5%.[3] In a sense, this trading mechanism can mitigate speculative trading and provide more stability to the market (Allen et al., 2020). Given the unique trading mechanism of the Chinese stock market and the enormous influence of individual investors, it is particularly worth examining the underlying factors that influenced the buying behaviour of these investors during the crash.

Four research questions are addressed in this study. Firstly, do the personal characteristics of individual investors, such as age, gender, and experience, affect their buying intensity during a crash? Secondly, we examine the relationship between past trading performance and net investment. Thirdly, we conduct a stock level analysis to study whether stocks with specific characteristics potentially have higher buying intensities. Lastly, we investigate whether a superb stock-picking ability or gambling behaviour contributes to high net buying during the financial crisis.

To answer these research questions, we collect the trading data of individual investors from a large anonymous Chinese brokerage firm. This unique dataset has made it possible to retrieve daily stock holdings, transaction records, cash balances, and personal information relating to Chinese investors between 1st January 2007 and 31st July 2009. We focus primarily on the bear market period from the beginning of November 2007 to the end of October 2008. The Chinese stock market experienced its darkest time between late 2007 and late 2008, somewhat earlier than the global financial turmoil in mid-2008. The SSEC Index dropped from 6,124 to 1,664 between mid-October 2007 and October 2008. To ensure its validity, only active investors' data is used.[4] Also, we only include A-share stocks traded or held by individual investors and listed on the Shanghai and Shenzhen Stock Exchanges (SSE and SZSE).[5] In total, the whole dataset

---

[3] When a listed company incurs losses for two consecutive years, it will experience the co-called 'special treatment' process. Subsequently, the 'ST' company will be at risk of mandatory delisting if it suffers a loss again in the third year.

[4] Investors who have at least one transaction record or hold one stock are considered to be active investors.

[5] A-share stocks are stocks quoted in CNY and traded on the SSE and SZSE. This contrasts with B-share stocks, which are quoted in foreign currencies and can be purchased by foreign investors who do not qualify to invest in A-share stocks due to Chinese government restrictions.

used contains transaction records of 1,549,468 individual investors from across the country, including 1,233,684 investors who actively engaged in trading during the crash period.

Our study constructs an individual-level measurement to identify the net investment of each investor. Empirical evidence demonstrates that, on average, individual investors act as net buyers, especially during the crash period. Outcomes obtained from a panel regression model suggest that male and younger investors exhibit higher buying intensities than female and elderly investors. A relatively higher inclination for buying during a market downswing by males, or younger generations, can be explained by their lower sensitivity towards an increase in market risk.

This paper also explores the impact of past market returns and portfolio performances on future net investment. Empirical results show that the buying intensity of individual investors increases following a rise of the market return, while past portfolio performances are not directly linked to net investment. Furthermore, we uncover that, in the crisis period, investors with positive portfolio returns in the previous month have a significantly higher inclination to invest during the following month. However, this is not the case during the upswing period. Such results suggest that individual investors show a self-attribution bias and that the crisis period amplifies the overconfidence of individuals with good past performance and encourages them to invest more aggressively.

Additionally, this paper finds that, at the aggregate level, individual investors tend to have a higher buying intensity on stocks with worse short-term returns, larger market capitalization, and better liquidity. We also attempt to explain the intensive buying behaviour by using a superior stock-picking ability and a propensity to gamble. Nevertheless, the evidence shows that buy-side stocks significantly underperform sell-side stocks in the short and relatively long term. Finally, we find that net buyers neither hold a higher proportion of lottery-type stocks in their portfolio nor actively seek to buy lottery-type stocks.

The contributions of this study are as follows. Firstly, it focuses on the buying behaviour of individual investors in a bear market. Previous studies, such as Barrot et al. (2016) as well as Hoopes et al. (2016), take individual investors as a group and analyse issues, such as their liquidity provision during financial crises. Hoffmann et al. (2013) use data from only a very small sample, 1,376 investor accounts, to study the risk-taking of individual investors during a stock market crash. The data used in this paper contains over one million investor accounts, and using individual-level analysis, we demonstrate that buying intensity varies across investors with different personal characteristics. Also, in contrast to previous studies, we use investors' buying behaviour during the bull market as a comparison when investigating the impact of past returns on net investment during stock market crashes. Accordingly, as a crucial complement for the overconfidence theory and the experimental findings of Duxbury (2012), our study highlights that compared to the market upswing, the market turmoil is more likely to amplify the overconfidence of well-performed investors: investors who had done well, only show overconfidence during the market downturn, exhibiting a self-attribution bias and thus increasing their investment.

Our research also contributes to the literature on the exponentially expanding Chinese stock market in two respects. First, in studying the Chinese stock market crash, previous studies mainly focus on market effectiveness, the contagion effects of other financial market crises, and predicting market turmoil (Jiang et al., 2010; Zhao, Li, & Xiong, 2014; Shen, Li, Wang, & Su, 2015; Lleo & Ziemba, 2018). In contrast, our paper benefits from individual investors' trading records and socio-demographics during the crash and pays attention to the trading behaviour of these investors during this period. Second, we also add to a series of recent works that examine the behavioural bias of Chinese individual investors. Liu, Peng, Xiong, and Xiong (2021) find that gambling preferences can explain the excessive trading of Chinese retail investors. Liao, Peng, and Zhu (2021) argue that retail investors' co-existing nonstandard beliefs and nonstandard preferences lead to excessive trading during the stock market bubble. Our paper, instead, finds that the financial crisis has prompted a surge in buying among well-performing investors and that this behaviour is more likely to be the result of self-attribution bias rather than gambling.

The remainder of this paper is arranged as follows: Section 2 reports hypothesis development. Section 3 provides the methodology and describes the data. Section 4 offers empirical analyses.

Section 5 gives alternative explanations and robustness of the results, and Section 6 concludes the paper.

2. Hypothesis development

The possible impacts of investors' personal characteristics on trading behaviour have been widely analysed (Croson & Gneezy, 2009; Bucciol & Miniaci, 2011; Dohmen et al., 2011). For instance, several studies show that male investors are more likely to be overconfident, which leads to more active trading (Benos, 1998; Barber & Odean, 2001; Hirshleifer & Luo, 2001). Apart from different investment styles, risk perception may also influence trading intensity, especially in a volatile market (Hoffmann et al., 2013). In particular, psychological studies suggest that gender plays an essential role in trading intensity as females tend to trade less than males because they are more sensitive to perceived risk (Diener, Sandvik, & Larsen, 1985; Larsen & Diener, 1987).

The aging process also has an impact on trading and risk-taking behaviour. Although the trading performance of elders may decline with their cognitive abilities, researchers generally agree that elderly investors are more likely to follow investment advice and more sensitive to risk (Korniotis & Kumar, 2011; Chai, Horneff, Maurer, & Mitchell, 2011; Benjamin, Brown, & Shapiro, 2013). The literature on the relationship between trading experience and investor behaviour is mixed. Some researchers find that individuals with more investment experience are better at decision-making and market timing (Arrow, 1962; Seru, Shumway, & Stoffman, 2010; Feng & Seasholes, 2005; Dhar & Zhu, 2006). However, other studies show that some investors overestimate their investment experience by making irrational decisions (Kaustia & Knüpfer, 2008; Chiang, Hirshleifer, Qian, & Sherman, 2011).

Yet only a handful of studies have focused on behaviour in turbulent times. Greenwood and Nagel (2009) suggest that inexperienced investors tend to be more optimistic during a market downturn. Hoopes et al. (2016) employ the population tax return data from the US market during the market downswing to investigate individual selling behaviour. The evidence from their study shows that only individual investors with several specific characteristics, such as being in the highest income and elder groups, tend to sell stocks during the downturn.

Investors live in a world where financial crises continue to happen, their investment style has a biological basis, and it can be affected by hedging demand, behavioural bias, and investors' life experiences (Boin, 2004; Cronqvist, Siegel, & Yu, 2015). In line with this argument, therefore, we expect that:

H1: Investors with specific characteristics tend to buy more aggressively during the financial crisis period.

Meanwhile, investors' past performance in the stock market may also have an impact on their future buying behaviour. Malmendier and Nagel (2011) suggest that investors' experiences of economic fluctuation could shape their willingness to take additional risks. Andersen, Hanspal, and Nielsen (2019) reveal that personal experience of losses during a financial crisis induces investors to shy away from risk-taking. Similarly, Glaser and Weber (2009) show that the past performance of the market index, or individual portfolios, has a significantly positive effect on the trading intensity in the following month. Campbell, Ramadorai, and Ranish (2014) find relatively better past trading performance contributes to more aggressive investment. Huang (2019) argues that individual investors with previous profitable experience in their stocks are more likely to buy stocks in the same industries.

Meanwhile, investors using extrapolation are often susceptible to recent stock performance when making decisions (Da, Huang, & Jin, 2021). Duxbury (2012) employs experiments and finds that individuals tend to make a re-invest decision following a sunk benefit than a sunk cost only in the face of poor investment opportunities. Investors with a positive performance, especially when most other investors suffer losses during market downturns, are highly likely to over-extrapolate the influence of their stock-picking ability and exhibit a self-attribution bias. Accordingly, this may lead successful investors to become overconfident and thus invest more. Hence, in this study, we hypothesize that:

H2: Investors with better past performances tend to have a higher buying inclination during the market downswing.

During a market crash, stocks with specific characteristics potentially have higher buying intensities. Yu and Hsieh (2010) find that stocks with extreme intraday returns are more likely to attract individual investors. Investors may act as net buyers of stocks that have lost considerable amounts of market value if they believe in the mean reversion, while they might show a higher buying intensity for stocks that performed relatively better in a bear market if they use a momentum trading strategy. Barber and Odean (2008) also note that stocks with specific characteristics, such as high trading volume and high past returns, have a higher potential to draw investors' attention; hence they may have a higher net buying than other stocks. We expect that:

H3: The buying tendency differs across stocks when the market crashes.

Apart from past portfolio performance and personal characteristics, one possible reason investors buy is that they have better stock-picking abilities. Barrot et al. (2016) argue that if investors reverse their trades sufficiently promptly after providing liquidity, they can be compensated by liquidity providing during the financial crisis period before the benefits dissipate. If so, then stocks with a higher buy-side tendency should outperform those sold during the crisis. From another perspective, a bear market also provides excellent opportunities to buy stocks at the bottom. Thus, individuals may also be gambling by investing heavily during this period. Accordingly, we develop a contradictory hypothesis:

H4a: Intensive buying can be explained by a superior stock-picking ability or the tendency to gamble.

H4b: Intensive buying cannot be explained by a superior stock-picking ability or the tendency to gamble.

3. Data and Methodology

3.1 Data source

Individual trading data in our study is collected from one of the top-tier brokerage firms in China. The whole sample period of this dataset is from the beginning of January 2007 to the end of July 2009. Between 6th June 2005 and mid-October 2007, China's stock market experienced a bull market lasting more than two years, and the SSEC Index increased from 998 points to 6,124 points. This was followed by a year-long bear market in China between mid-October 2007 and 28th October 2008, when the SSEC Index dropped 72.8% from 6,124 points to 1,664 points. Since then, the A-share stock market has gradually emerged from a bear market, with the SSEC Index more than doubling from the bottom to 3,412 points by the end of July 2009. Figure 1 shows the performance of market indices during our sample period. Consequently, our database can be split into three parts, (i) a bull market period from 1st January 2007 to mid-October 2007, when the SSEC Index hit its historically highest peak; (ii) a crash period from November 2007 to the end of October 2008, and (iii) a recovery period from November 2008 to the end of July 2009. This database is ideal for the research because it enables us to explore how investors trade in different market states. This division of the 2007-2009 sample into three parts is consistent with previous studies investigating the financial crisis of Chinese stock markets (Jiang et al., 2010; Wang, Xie, Lin, & Stanley, 2017).

The composition of our dataset is closely aligned with some of the previous and recent datasets used for individual investors in China and the US (Feng & Seasholes, 2005; Barber & Odean, 2000, 2001; Chan, Wang, & Yang, 2019; Frydman & Wang, 2020). For each trading account, the dataset provides information as follows, (i) customers' profiles, (ii) their cash balances on each trading day, (iii) their stock holdings, and (iv) their transaction files. All customer profiles include a unique identification number for each account, the date when the account was opened, birthdate, and gender identification.[6] The balance files have daily cash balances of every investor after each trading day; the stock holding files contain information regarding stocks and the number of shares held, while the transaction files show their trading histories, such as (i) transaction dates, (ii) stocks traded, (iii) the number of shares purchased or sold, (iv) the price of stock traded, (v) the total number of shares after each transaction, and (vi) the transaction type – buying or selling. Information about the account balance, stock holdings, and trading records is updated daily.

The whole dataset contains the account information of more than two million individual investors. To abide by our research purposes, only the accounts with complete information that

[6] Different from the security accounts system of the US stock market, individual investors can only have one trading account in each stock exchange (Zhao, Lee, & Yu, 2020). The brokerage firm has also assigned a unique number to each investor. Each identification number, therefore, corresponds to a unique and distinct investor.

actively traded A-share stocks are kept for further study. The other accounts, such as those only have B-share stocks or those that only hold security investment funds or index funds, are deleted. We require the age of investors to be over eighteen when accounts are opened. Accounts with abnormal values, such as negative stock holdings or cash balances, are deleted. Also, individual investors are required to be active during the sample period. To ensure data consistency, investors who cancelled their accounts during our sample period are excluded. Besides the above primary dataset, stock market data is collected from the China Stock Market and Accounting Research (CSMAR).[7] Finally, a cross-check is conducted with the stock data in the RESSET Financial Research Database (RESSET/DB), another professional financial data vendor in China.

3.2 Methodology

To examine the net investment of individual investors during the crisis period, we use net individual trading (NIT thereafter) as a proxy for the net purchase behaviour. Kaniel, Saar, and Titman (2008) use the stock-level NIT to investigate the impact of investors trading on stock returns. This study takes advantage of a more comprehensive dataset, including the share prices of each transaction, to construct an individual-level NIT.[8] For each investor, we construct the NIT and update it every month. Hence, each month, the NIT is computed as the transaction value bought, minus the transaction value sold and divided by the total transaction value for that investor:

$$NIT_{i,t} = \frac{\sum_{j=1}^{n}(Buy\_Value_{i,j,t} - Sell\_Value_{i,j,t})}{\sum_{j=1}^{n}(Buy\_Value_{i,j,t} + Sell\_Value_{i,j,t})} \quad (1)$$

Where $NIT_{i,t}$ is the net individual trading of investor i at month t. $Buy\_\mathrm{Value}_{i,j,t}$ is the real transaction value (in RMB) of stock j purchased by investor i at month t, while $Sell\_Value_{i,j,t}$ is the transaction value of stock j sold by investor i at month t. This measurement takes the net investment of each investor into consideration.

[7] The data of daily share price, index returns, trading volume, market value, risk-free rate, and Fama-French three factors are collected from the CSMAR database.

[8] The trading records in our data report the share price of buying and selling transactions. Consequently, we are able to identify the net investment of an investor.

The portfolio turnover is controlled when investigating the relationship between net individual trading and investors' characteristics. In particular, it is the average value of the sell turnover and the buy turnover. The monthly sell turnover is calculated as the number of shares sold during month t multiplied by the price at the beginning of the month and divided by the market value of the portfolio held by that investor.[9] The monthly buy turnover is measured as the number of shares bought multiplied by the beginning-of-next-month price per share scaled by the portfolio's total market value at the beginning of the following month.[10]

To investigate the correlation between past portfolio performance and net investment, following the methodology of Barber and Odean (2001), this work puts forward two assumptions to calculate monthly returns for each investor, (i) that all stocks are purchased or sold at the end of the month, and (ii) that we do not consider intra-month trades. Barber and Odean (2000, 2002) suggest that this method would not lead to biases of portfolio performance:

$$R_{ht} = \sum_{i=1}^{S_{ht}} \rho_{it} R_{it} \tag{2}$$

Where R_{it} is the gross monthly return of stock i and ρ_{it} is the market value of stock i held at the first trading day of month t scaled by the total market value of an individual's portfolio. Compared with the US stock market, trading costs in China, e.g., stamp tax, transfer fee and, commission fee, are relatively low. Thus, only the monthly gross return for each investor is calculated.

3.3 Summary statistics

Table 1 reports the summary statistics of investors and stocks traded in our sample. NIT is the net individual trading that captures the net investment of each investor in a given month. Age is an investor's age at a given month – the exact date of birth is available in our database.

[9] For a given month, we first identify the stock holdings of an individual investor at the beginning of the month. The monthly sell turnover is calculated as: $\sum_i^{S_{ht}} \rho_{it} \min(1, {S_{it}}/{N_{it}})$, where ρ_{it} is the market value of stock i held at the first trading date of month t divided by the entire market value of an individual's portfolio. S_{it} is the total number of shares of stock i sold during month t, while N_{it} is the number of shares of stock i held at the beginning of month t.

[10] To obtain the monthly buy turnover, these stocks purchased during month t are matched with the stock holdings at the beginning of next month. Specifically, the monthly buy turnover is: $\sum_i^{S_{ht}} \rho_{i,t+1} \min(1, {B_{it}}/{N_{i,t+1}})$, where B_{it} is the total number of shares of stock i purchased in month t, while $\rho_{i,t+1}$ and $N_{i,t+1}$ are the same as the previous part. Considering the motivation of selling activities, a benefit of the Chinese Stock market policy is that individuals do not need to pay tax for their capital gains. Therefore, we do not consider tax-motivated selling activities.

Similarly, trading experience is calculated based on the difference between the account opening date and each trading month. Male refers to the proportion of male investors, while portfolio turnover is the average of monthly buy and sell turnover, calculated following the method of Barber and Odean (2001). The number of transactions is the sum of buy trades and sell trades each investor made monthly. Portfolio value is the sum of the market value of stocks held by each investor, while account size is the wealth allocated in the stock market, which equals the sum of their portfolio value and the money in their account at a given month.

Panel A of Table 1 comprises the summary statistics of all investors on the stock market between 1st January 2007 and 31st July 2009, while Panel B reports details of investors who traded during the financial crisis period, from the beginning of November 2007 to the end of October 2008. After matching four files of our dataset and applying restrictions as mentioned in *Section 3.1*, the remaining dataset contains 1,549,468 individual investors from all over the country, including 1,233,684 investors who traded when the market crashed.[11] Overall, we find that investors in the Chinese stock market have a positive NIT, which goes up to 0.129 during the financial crisis period, as shown in Panel B.

To provide a clearer picture of the net individual trading ratio, Figure 2 shows the mean and median value of investors' NIT ratio from January 2007 to July 2009. Generally, the NIT fluctuates over the sample period, while both mean and median values of monthly NIT of individual investors are greater than zero during the financial crisis period (Nov 2007- Oct 2008), indicating that investors act as net buyers on average when the market crashed. By contrast, we find that investors do not act as net buyers constantly during the bull market and recovery periods. In particular, the average monthly NIT is significantly lower than zero in January, February, July of 2007, and five months after October 2008. Similar findings are

[11] The distribution of age and portfolio value of investors is very similar to the data on individual investors declared in the Stock Market Yearbook 2007-2009. In addition, the sex ratio of investors in our sample is very close to the ratio in the whole market. According to the Shanghai Stock Exchange Statistics Annual, the proportion of females is 45.85%, 45.37%, and 45.17% in 2007, 2008, and 2009, respectively. Besides, an investigation of individual investors from the Shenzhen Stock Exchange shows that female investors accounted for 40% in 2009. For more details, see http://www.sse.com.cn/aboutus/publication/yearly/ and https://www.szse.cn/market/periodical/year/index.html.

recorded by Hoffmann et al. (2013) and Ben-David, Franzoni, and Moussawi (2012), who argue that individual investors tend to provide liquidity while institutional investors are more likely to sell their stock positions during the market downswing.

Panel C comprises the descriptive statistics of 1,571 A-share stocks traded by investors in our sample between November 2007 and October 2008. Market Capitalization is the average daily market value. The average daily market capitalization is RMB 4,630.18 million, while the average closing stock price is RMB 14.10. Turnover ratio is the average daily stock turnover, calculated as the number of shares traded on a given day divided by the number of outstanding shares on the same day. Trading volume is the mean value of daily trading value. Compared to the market's trading volume, we find that, on average, the trading volume of investors in our dataset accounts for more than 5% of the whole market's daily trading volume.

Although we cannot observe whether investors change their risk-bearing capacity, by plotting the aggregate trading volume in total market-wide volume and investors' positions, we are able to identify how they trade and adjust their positions during the volatile period. In Figure 3, we show the trading volume of investors as a percentage of the total volume alongside the investors' positions. The figure shows that both the proportion of trading volume and position significantly increased during the crisis period. Noticeably, those two numbers dropped during the recovery period. This result indicates that individual investors increase their portfolio holdings by continuing to trade actively, particularly when the market crashed.

More detailed summary statistics of the financial crisis period are presented in Table 2 since we primarily focus on this subsample. Compared to females, male investors have relatively smaller portfolios and more trading experience, and they also trade more aggressively. Older and experienced investors are wealthier and have a lower portfolio turnover than their counterparts. Investors who allocate more wealth in the stock market also have larger portfolios and more trading experience. The wealthiest investors exercise more transactions but have a lower turnover than others. Combining the descriptive statistics from Tables (Figures) 1 – 2, we find that most Chinese investors are small, inexperienced, and trade exceptionally actively, especially during the market downswing.[12]

4. Results

4.1 Who are net buyers during the financial crisis period?

Table 3 presents the relationship between investors' characteristics and NIT using the financial crisis subsample. Specifications (1) and (2) show the results of the OLS regression, while Specifications (3) and (4) report the outcomes of the logit model in which the dependent variable equals 1 if NIT>0. Independent variables in all specifications and dependent variables in Specifications (1) and (2) are standardized. Time-fixed effects are controlled in all specifications, and standard errors are double-clustered at month and investor levels. We include a dummy variable $Gender$ in regressions, which equals 1 if a male, otherwise 0. Age is an investor's age at a given month. $Experience$ is trading experience, measured by the difference between account open date and each trading month. $Turnover$ is the average of buy and sell turnover, based on Barber and Odean's (2001) methodology. $Account\ size$ is the sum of the portfolio value and money in the stock market account each month.[13]

We find males have a significantly higher NIT than females indicating that male investors have a relatively higher buying intensity during the financial crisis period,[14] an explanation for

[12] In an unreported table, we find inexperienced investors (less than three years' trading) account for more than 61% of our data. The account size of more than 59% of investors is smaller than 50,000 RMB. The trading frequency is around 12 and 10 during the whole period and the subperiod, respectively. This result is slightly higher than Feng and Seasholes' findings (2003), which show 6.1 trades per month between 1999 and 2000 from individual Chinese investors. The relatively higher trading frequency in the current data perhaps reflects the emergence of online trading (Choi, Laibson, & Metrick, 2002; Barber & Odean, 2002; Zhang & Zhang, 2015).

[13] Our model explains net investment in terms of subjectively measured variables, mainly capturing socio-demographic characteristics. Therefore, we do not address the issue of the endogeneity of these variables. The underlying conceptual model of our analysis is rather simple: individual characteristics (gender, age, experience) are given, portfolio value and turnover may vary within these characteristics. Particularly, we primarily focus on how net individual trading in financial matters is driven by individual characteristics.

[14] The coefficients on gender in Specifications (1) – (2) suggest that the net individual trading of males is significantly larger than females. Alternatively, the results in Specifications (3) – (4) suggest that, although males have a higher likelihood to be net buyers, but the coefficient on gender is not significantly. The difference in significance of gender coefficients in Specifications (1) – (2) and Specifications (3) – (4) could be driven by the influence of observations in the tails. Suppose we have an A that follows a standard normal density and that the larger the value of A, the less risky the outcome is, with a modestly positive trend. In a logistic regression model, the impact of one observation for (A=1, B=0) will be more significant than in a linear regression model. This is because the effect of such an observation can be

which could be greater optimism, which concurs with previous studies that show males to be more optimistic than females regarding the economy and financial markets (Jacobsen, Lee, Marquering, & Zhang, 2014). Puri and Robinson (2007) find optimism is positively highly correlated with risk-taking; consequently, males would be more likely to invest during market downturns. Jacobsen et al. (2014) also find that risk perception differs along gender lines in that males tend to perceive lower levels of risk than females under similar circumstances. Meanwhile, males' higher level of net investments during stock market crashes can be driven by the fact that they interpret risk differently from females. Males view risk as a challenge they would like to face, while females believe it is a threat they must avoid (Arch, 1993).

Trading experience is significantly and negatively correlated with the NIT, indicating that investors with more trading years in the stock market show lower buying intensities. This finding accords with Hoffmann et al. (2013), suggesting that buy-sell imbalance decreases with account tenure during the crisis period; however, they find the coefficient on that variable not to be significant. Experienced investors' behaviour tends to be more in line with finance theories, whereby they are less likely to engage in biases, such as endowment and disposition effects, and also are likely to be better forecasters (Campbell et al., 2014; List, 2003; Feng & Seasholes, 2005; Nicolosi, Peng, & Zhu, 2009). Consequently, experienced investors tend not to buy or sell aggressively when the market index drops or their portfolios' profitability decreases during downswings.

Turnover is significantly and negatively related to net individual trading measurement as well, a possible explanation being that the effect of sell-side turnover outweighs its importance. In order to explore this interpretation further, we compare investors' sell turnover with the buy turnover and find, on average, that the sell turnover of more than 65% of investors is higher, or at least equals, to the buy turnover. Investors with larger accounts have a lower NIT than their counterparts during the crisis period. Similar findings are uncovered by Hoffmann et al. (2013), who report that investors with larger portfolios in the previous month have a lower buy-sell imbalance the following month. Wealthier investors are also deemed better informed and more

arbitrarily high in a logistic model.

sensitive towards the increased market risks, making them less likely to buy during a market downswing (Hoopes et al., 2016; Li, Geng, Subrahmanyam, & Yu, 2017).

Given the possible nonlinear relationship between the aging process and net investment, we also add the squared age in the regression (Dohmen et al., 2011; Korniotis & Kumar, 2011; Sicherman, Loewenstein, Seppi, & Utkus, 2016). The coefficients on age and squared age are significantly positive and negative, respectively, suggesting an inverted U-shaped relationship between age and NIT. This relationship may reflect changes in the importance of retirement savings over the life cycle (Sicherman et al., 2016). Additionally, the transition to retirement might trigger greater sensitivity towards risk, a relationship that Riley and Chow (1992) suggest is not linear, in that risk aversion at first decreases with age and then increases after 65. Similarly, Lee, Rosenthal, Veld, and Veld-Merkoulova (2015) uncover that the return expectation of older investors appears lower than that of younger generations, which explains the lower proportion of risky assets in older people's portfolios.

To further understand the relationship between buying behaviour and age, age and squared age are replaced by a $Young$ dummy variable in Specifications (2) and (4), which equals 1 if an investor is younger than 60.[15] The positive coefficient suggests that younger investors tend to have a higher NIT than older investors, either retired or approaching retirement. The insensitivity to perceived risk could also result from the fact that relatively younger investors do not have stronger concerns about future income uncertainty (Hoopes et al., 2016). Combining the outcomes from these regression models, we can conclude that the buying intensity varies across investors with different personal characteristics during the financial crisis.

4.2 Market returns, portfolio performance and NIT

[15] The dummy variable *Young* is set to one when an investor's age is below 60 since the retirement age in China is 55 for females and 60 for males during our sample period. Therefore, to investigate the possible effect of retirement on net individual trading during the financial crisis period, this study uses age 60 as a benchmark. Feng and Seasholes (2005) define those above the age of 55 as older investors in their analysis of the impact of age on stock market decisions in China. Our results are consistent when using age below 55 as a young dummy variable.

In Table 4, we perform OLS regressions to investigate whether the past performance of the market index and investors' portfolios would have an impact on net individual trading the following month. Portfolio performance is the gross return of an investor's portfolio at the beginning of month $t-1$, while the market return is the return of the SSEC Index at month $t-1$. We ignore intra-month trading when evaluating portfolio performance. Barber and Odean (2000, 2002) suggest that this method would not lead to biases of portfolio performance. The data of market index return is obtained from the CSMAR database. We also try other measurements of index returns, and the results remain robust.

Specifications (1) to (4) give the results in the financial crisis period. For comparison, in Specifications (5) to (8), we perform the same regression but use the data of the bull market subsample (from Jan to Sep 2007). The personal characteristics – i.e., age, squared age, gender, trading experience, portfolio turnover, and account size, are controlled in all regressions. The sign and significance of controlled variables, except experience, remain the same after including past portfolio returns and market returns. In Specification (1), we find investors' portfolio returns in the previous month do not significantly impact net individual trading in the following month. This outcome also holds in the bull market period, as shown in Specification (5). In contrast, lagged value of market index returns significantly affects net individual trading in two subsample periods. Individuals invest more in the face of the short-term reversal of stock markets, probably because investors believe the market trend has reversed, which they regard as signalling the end of the crisis period. By comparison, investors tend to believe the momentum of markets, therefore investing more when the index increases during the bull market period.

To further explore the relationship between investors' portfolio performances and their tendency to buy in different market conditions, in Specifications (2) – (4) and (6) – (8), we add three different dummy variables, respectively, (i) the positive return dummy, which equals 1 if the portfolio return has a positive value at month $t-1$, otherwise it equals 0, (ii) the excess return dummy equals 1 if the portfolio performance of an investor is better than the market index at month $t-1$, otherwise it equals 0, (iii) the positive return and excess return dummy equals 1 if the portfolio return is higher than the market index return and it is a positive value at month $t-1$.

The results of Specifications (2) – (4) and (6) – (8) can be summarized as follows: first, we find those investors who, during the crisis period, experienced a positive return in the previous month, have a significantly higher tendency to invest in the following month. This outcome is consistent with the findings of Malmendier and Nagel (2011, 2016), suggesting that investors rely more on their personal past experiences than on rational expectations when making decisions. Also, in line with the overconfidence theory, investors with high past returns tend to become overconfident, hence they trade more aggressively (Hilary & Menzly, 2006; Glaser & Weber, 2009). Individual investors who have performed well in the past tend to exhibit a self-attribution bias, using their past portfolio performance as an indicator of their investing ability and therefore exhibiting more aggressive trading behaviour in the following month (Hoffmann & Post, 2014). However, during the bull market period, we do not observe the same results: Specification (6) shows that investors do not invest significantly more the following month even though their portfolio returns have been positive. These results are consistent with the findings of Duxbury (2012), which uses experiments to investigate the re-investment behaviour. The outcomes of his study show that, in the face of a poor investment opportunity, individuals are more likely to make a re-invest decision following a sunk benefit than a sunk cost; while there is no significant difference in the propensity to re-invest between sunk costs and sunk benefits, given a good investment opportunity.

Secondly, we note that investors do not invest more in either sub-sample even if they outperform the previous month's market. This result implies that investors do not directly use the returns of the market index as a benchmark when making purchase decisions for the following month. Third, investors tend to buy more if their portfolios experience positive returns and outperform the market only when the market crashed. Overall, Table 4 suggests that the crash period plays a role in amplifying the overconfidence of well-performed investors: investors who had done well, especially when most other investors suffered losses during the market downturn, are more likely to be overconfident and exhibit a bias in self-attribution, thereby increasing their investment.

4.3 Stock-level analysis

In this part, we use the Wermers (1999) method of constructing the stock-day level buy-sell imbalance to capture aggregate investors' buying and selling intensity across stocks. The buy-sell imbalance is calculated each day as the volume bought by aggregate investors, minus the volume sold and divided by the total volume traded for a given stock:

$$IMB_{i,t} = \frac{Buy_{i,t} - Sell_{i,t}}{Buy_{i,t} + Sell_{i,t}} \quad (3)$$

Where $Buy_{i,t}$ is the share volume of stock i purchased by investors at day t, while $Sell_{i,t}$ is the number of shares of stock i sold at day t. $IMB_{i,t}$ captures the net investment of aggregate investors in our sample. The positive value of $IMB_{i,t}$ indicates that individual investors act as net buyers of stock i at a given day, and vice versa.

Previous studies document that the purchasing and selling behaviour could be affected by stocks' past performance characteristics. In particular, Ji, Zhang, and Guo (2008) identify the cultural differences in stock picking in terms of the trend in share prices, in that Chinese investors tend to believe in mean reversion and are more likely to buy stocks with poor past performance. Likewise, Ng and Wu (2007) find that individual investors in the Chinese stock market, especially those middle and small investors, are prone to sell stocks with positive past returns and buy stocks with negative past returns. Also, individual investors could be attracted by extremely high trading volume stocks; consequently, they are more likely to concentrate on the same side of stocks that have better market liquidity (Barber & Odean, 2008; Hsieh, 2013).

Based on these findings, therefore, our study adopts a panel data regression to investigate whether past stock returns and stock characteristics have an impact on intentions to buy during the crisis period. Table 5 reports the results of the regression model. To ensure the consistency of our dataset, the sample period is set from the beginning of November 2007 to the end of October 2008. IMB is the buy-sell imbalance of stocks. We include the market capitalization and turnover of stocks in all regressions to control for valuation uncertainty across stocks and for investors being attracted to attention-grabbing events (Zhang, 2006; Barber & Odean, 2008;

Kumar, 2009a; Barrot et al., 2016). $LogMarketCap$ is calculated as the logarithm of closing market value for stock i at day $t-1$. $Turnover$ is measured by using the method of Hou, Kuo and Lee (2012), as the trading volume at day t divided by the outstanding shares on that day. $CAR[x,y]$ is the cumulative abnormal return of a given stock from x days before to y days before the transaction day.[16] The abnormal return of each stock is measured as the raw stock return minus a market index return.[17] Similarly, $Return[x,y]$ is the cumulative return from x days before to y days before the transaction day.

We exclude the return on the trading day (the day that buy-sell imbalance measurement is constructed) since it is impossible to distinguish the impact of intraday return on the aggregate buy-sell imbalance from the effect of individual trading on the trend of share prices. Also, we allow the effects of past returns on trading imbalance to persist up to one month before the transaction day, given that the impact of past long-run returns on investors' trading is very limited (Ng & Wu, 2007).[18] We include the time-fixed effects in all regressions, and standard errors are clustered at the stock level.[19]

Specification (1) shows a significant negative correlation between past cumulative abnormal returns and buy intensity during the crisis period. The result is unaffected by using holding returns as a proxy for the past performance of stocks, as shown in Specification (3). These outcomes are consistent with previous findings of individual investors in the French stock market and middle and small investors in the Chinese stock market (Barrot et al., 2016; Ng &

[16] For instance, $CAR[-1]$ is the abnormal return one day before the trading day, $CAR[-5,-2]$ denotes the cumulative abnormal return from five days before to two days before the construction of buy-sell imbalance measurement.

[17] The abnormal return is calculated by subtracting the return of the SSEC Index from the return of a given stock. The results are consistent by using CSI 300 index, CSI Small-cap 500 index, and CSI 800 index as a proxy for the market return.

[18] We also add the holding period returns and cumulative abnormal returns from 60 days before to 28 days before the trading day in an unreported regression. However, the coefficient is insignificantly and negatively correlated to the buy-sell imbalance on day 0.

[19] Barrot et al. (2016) use the same method to cluster standard errors, allowing them to be correlated within a given stock, but not correlated across stocks on the same day. In an unreported table, the standard errors are double-clustered at stock and day level, and the results remain the same.

Wu, 2007). Specifically, investors at the aggregate level tend to have a lower buying intensity on stocks with a relatively better past performance.

In Specifications (2) and (4), the change of the coefficients and significance of past returns are very slight after adding stock fixed effects, indicating that the unobserved characteristics embedded across stocks do not have a considerable influence on the relationship between buy-sell imbalance and past stock performance. The positive coefficient estimates on the $LogMarketCap$ and $Turnover$ are significant across all regressions. Stocks with higher turnover and market capitalization tend to have better information quality and market liquidity (Zhu, Sun, Yung, & Chen, 2020). Investors who have a higher buy intensity on those stocks could be driven by attention-grabbing bias, as documented in Barber and Odean (2008), who argue that individuals are more inclined towards securities with a high trading volume. Overall, we find individual investors tend to have a higher buying intensity on stocks with better liquidity and higher market capitalization. They also believe in the mean-reversion strategy, given the negative correlation between buy-sell imbalance and past returns. The higher buying intensity after the price decreases during the crisis indicates that individual investors at an aggregate level tend to be exposed to the opposite position by the other competitors in the market.

5. Alternative explanations and Robustness

5.1 Do stocks with a higher buying intensity perform better in the short horizon?

In addition to exhibiting self-attribution bias after performing well in the past, one possible reason investors engage in buying is that they have better stock-picking abilities. If so, then stocks with a higher buy-side tendency should outperform those sold during the crisis. To verify this alternative explanation, we first divide stocks into buy and sell categories:

$$Buy_{side}IMB_{i,t} = IMB_{i,t}|IMB_{i,t} > 0 \tag{4}$$

$$Sell_{side}IMB_{i,t} = -IMB_{i,t}|IMB_{i,t} < 0 \tag{5}$$

Stocks are grouped into the buy-side if the IMB is a positive value on a given day; otherwise, they are regarded as the sell-side. Thereafter, for each category, stocks are further classified into several portfolios based on the magnitude of IMB. Particularly, in Panel A, portfolio B contains all stocks with a positive IMB, while portfolio S includes all sell-side stocks. To ensure the robustness of the outcomes, in Panels B, C, and D, for each category, stocks are further grouped into tertile, quintile, and decile portfolios, respectively. This procedure results in the construction of twenty portfolios in Panel D – i.e., ten buy-side and ten sell-side portfolios. In Panel B (C and D), portfolio B1 comprises stocks with the highest buy-side pressure, while portfolio S1 includes stocks with the highest selling intensity. Furthermore, we compute the abnormal return for each portfolio as equal-weighted portfolio returns minus the return of the SSEC Index on the day they are constructed. Also, for each portfolio, we calculate the cumulative abnormal returns from five days before to twenty days after the trading day.

Table 6 shows the cumulative market-index adjusted abnormal returns concerned with buy-sell imbalance.[20] The first and second rows of each panel report cumulative abnormal returns of buy-side and sell-side portfolios, respectively. To compare the performance of stocks with the highest buy-side and sell-side tendencies, the last row of each panel reports the cumulative abnormal returns of a zero-investment portfolio by holding the buy-side portfolio and shorting the sell-side portfolio. Consistent with our previous findings that buy-sell imbalance is negatively correlated with past short-run returns in *Section 4.3*, stocks allocated on the buy-side underperform those investors sold before the formation day. This outcome is more pronounced in stocks with the highest trading intensity (see the last row in Panels C and D). Also, the significant and negative coefficient estimates of zero-investment portfolios in Panels B, C and D, on one-day abnormal returns before the formation day indicate that the effects of past returns on buy-sell imbalance are much stronger in a very short run.

The cumulative abnormal return of portfolio B (B1) in Panel A (Panels B, C, and D) is a negative value (but insignificant) on the portfolio formation day.[21] Barber, Odean, and Zhu (2009) argue that retail investors could move the market, consequently, stocks with the highest

[20] The cumulative abnormal returns before the trading day, for instance, are equal to the sum of abnormal returns from 5 days before formation day to 1 day before it. By comparison, CARs after trading contain the abnormal return on the formation day. Indeed, the result is consistent when abnormal returns on the formation day are excluded.

[21] In fact, the CARs of portfolio B1 in Panel D are significantly negative on the trading day if we extend our sample period to 17th October 2007 (one day after the market index hit the historical highest) and 28th October 2008 (the day market index reach the lowest during the crisis period).

buying tendency would experience positive returns and vice versa. However, different from the US and other matured stock markets, small investors account for a massive proportion of the Chinese stock market. Therefore, investors are unlikely to move the market even if they gather on the buy-side of a given stock. Also, small investors are hard to beat the market when institutional investors are on the opposite side. Chen, Chow, and Shiu (2015) and Ng and Wu (2007) also reveal that stocks that are highly crowded by small investors on the buy-side experienced a significantly negative return on their portfolio formation day.

Contrarily, stocks experienced a significant positive abnormal return on the day that individual investors sold them. This result remains consistent, no matter how the sell-side portfolio is constructed, and it persists from one day after the trading day to at least twenty days after it. Interestingly, this significantly positive CAR is more pronounced in portfolios with higher sell-side tendencies. In Panel D, the cumulative abnormal return one day after the intense selling period is 1.326%, rising to 4.109% until twenty days after. The evidence from the zero-investment portfolio tells a clear story: the (intense) buying portfolios significantly underperform the (intense) selling portfolios from the trading day to at least 10 days after it. Again, this effect appears more remarkable when comparing portfolios with the highest selling and buying intensities (Panel D). Overall, the outcomes reject the alternative hypothesis that individual investors buy during the crisis period due to their stock-picking abilities, since the stocks they purchased underperform those they sold in the short term.

5.2 IMB and relatively long-run stock performance

In this part, we develop a regression model to investigate the impact of buy-sell imbalance on stock returns from one day to eighty days after trading following Barrot et al. (2016):

$$Return[1,\mathrm{y}]_{i,t} = \beta_0 + \beta_1 IMB[0]_{i,t} + \beta_2 Return(-1,0]_{i,t} + \beta_3 Return[-1,-5]_{i,t} + \beta_4 Return[-6,-27]_{i,t} + \beta_5 LogMarketCap_{i,t} + \beta_6 Turnover_{i,t} \quad (6)$$

and

$$CAR[1,y]_{i,t} = \beta_0 + \beta_1 IMB[0]_{i,t} + \beta_2 CAR(-1,0]_{i,t} + \beta_3 CAR[-1,-5]_{i,t} + \beta_4 CAR[-6,-27]_{i,t} +$$

$$\beta_5 LogMarketCap_{i,t} + \beta_6 Turnover_{i,t} \tag{7}$$

We use three methods to estimate holding period returns from day one to day y: (i) cumulative raw returns, (ii) market-index adjusted cumulative abnormal returns, and (iii) benchmark-portfolio adjusted cumulative abnormal returns, following the method of Daniel, Grinblatt, Titman, and Wermers (1997). β_1 captures the relationship between buy-sell imbalance on the trading day and future returns. Standard errors are double clustered at the day and stock level.

At a first step, we estimate Eq. (6) and Eq. (7) by using cumulative (abnormal) returns from day one to day y, where y takes values from one to eighty, as the dependent variable. Figure 4 reports eighty β_1 coefficients based on three different return measurements. The result is consistent with our findings in Table 6: the trend of β_1 suggesting that, when using cumulative raw returns or market-adjusted cumulative abnormal returns as the dependent variable, stocks with higher buy-sell imbalance significantly experienced lower cumulative (abnormal) returns in either a short-run or a relatively long run. The negative impact of buy-sell imbalance disappears until at least sixty days subsequently; however, we do not observe the β_1 to be significantly positive until eighty days. This outcome is more pronounced using the benchmark-adjusted portfolio CARs as the dependent variable. Overall, the alternative method shows that stocks investors purchased intensively underperform the stocks they sold during the crisis period in either the short or relatively long term.

5.3 Do net buyers gamble in the stock market?

Compared to the US and European stock markets, the Chinese stock market is characterized by the frequent trading of individual investors, who also account for more than 80% of the market's total trading volume (Allen et al., 2020). Liu et al. (2021) find that gambling behaviour is one of the key motivations for investors to engage in trading. Thus, the provision of liquidity by individual investors during the crisis period may also be driven by gambling. To explore the existence of a positive connection between net individual trading and the tendency to gamble, we use Kumar's (2009b) method to identify lottery-type stocks in which stocks belonging to the lowest n^{th} price percentile, the highest n^{th} idiosyncratic volatility, and the highest n^{th}

idiosyncratic skewness are considered to be lottery-types.[22] Here the idiosyncratic volatility of each stock is calculated by using a three-factor model: we start by saving the residuals of the regression and then calculate the standard deviation for each stock as a proxy for the idiosyncratic volatility. The idiosyncratic skewness is a scaled measure of the third moment of the residual, which is obtained by fitting a two-factor model to the daily stock returns time series – excess market returns and squared excess market returns.[23] Following this procedure, we identify lottery-type stocks and then investigate whether the propensity to gamble can explain the high net investment of investors during the crisis period.

Additionally, we use four measurements to examine individual investors' lottery preferences. The first measurement is the raw proportion of wealth allocated in lottery-type stocks:

$$Lottery\ Preference_{i,t}^{(1)} = \frac{\sum_{j\in A_{t-1}} n_{i,j,t} P_{j,t}}{\sum_{j=1}^{N_{i,t}} n_{i,j,t} P_{j.t}} \tag{8}$$

where A_{t-1} is a set of lottery-type stocks at the end of month $t-1$, $n_{i,j,t}$ is the number of shares held by investor i on stock j at the end of month t, $N_{i,t}$ is the total number of stocks held by investor i at the end of month t. $P_{j,t}$ is the share price of stock j at the end of month t. The first lottery preference measurement captures the proportion of lottery-type stocks in the portfolio of each investor.

The second measurement is the lottery preference adjusted by portfolio value at the end of each month. Investors with a larger portfolio size are more likely to hold lottery-type stocks. To ascertain that the propensity of holding lottery-type stocks is not due to the larger portfolio size, Kumar (2009b) compares the real proportion of lottery-type stocks with an expected value, which is a condition of portfolio size:

$$Lottery\ Preference_{i,t}^{(2)} = \frac{NLW_{i,t} - ENLW_{i,t}}{ENLW_{i,t}} \tag{9}$$

Where $NLW_{i,t}$ and $ENLW_{i,t}$ is the real and expected normalized lottery-preference weight for a given investor i at the end of month t, respectively, in that:

[22] For our study we choose n=50 as Kumar (2009b) did.

[23] The calculation of idiosyncratic volatility and idiosyncratic skewness is based on factor models by using daily return data of the previous 180 days. The results are consistent by using the previous 90 days of daily return data to compute idiosyncratic volatility and idiosyncratic skewness.

$$NLW_{i,t} = \frac{Lottery\ Preference_{i,t}^{(1)} - \min(Lottery\ Preference_{i,t}^{(1)})}{\max(Lottery\ Preference_{i,t}^{(1)}) - \min(Lottery\ Preference_{i,t}^{(1)})} \tag{10}$$

and

$$ENLW_{i,t} = \frac{Portfolio\ Size_{i,t}^{(1)} - \min(Portfolio\ Size_{i,t}^{(1)})}{\max(Portfolio\ Size_{i,t}^{(1)}) - \min(Portfolio\ Size_{i,t}^{(1)})} \tag{11}$$

Where $Portfolio\ Size_{i,t}^{(1)}$ is the portfolio value of investor i at the end of month t, $\min(Portfolio\ Size_{i,t}^{(1)})$ is the minimum portfolio value of all investors who hold stocks at the end of month t, and $\max(Portfolio\ Size_{i,t}^{(1)})$ is the maximum portfolio value of all investors who hold stocks at the end of month t. Likewise, $\min(Lottery\ Preference_{i,t}^{(1)})$ and $\max(Lottery\ Preference_{i,t}^{(1)})$ are the minimum and maximum $Lottery\ Preference_{i,t}^{(1)}$ of all investors at a given month t.

The third lottery-preference measurement is the market portfolio adjusted lottery preference:

$$Lottery\ Preference_{i,t}^{(3)} = \frac{Lottery\ Preference_{i,t}^{(1)} - Lottery\ Preference_{t}^{market\ index}}{Lottery\ Preference_{t}^{market\ index}} \tag{12}$$

$Lottery\ Preference_{t}^{market\ index}$ captures the proportion of lottery-type stocks allocated to the market index.

Lastly, we construct a transaction-based measure of lottery preferences. The previous three measurements are determined by the stock holdings at the end of each month; however, investors who have lottery-type stocks may not intend to buy them. Also, lottery-type stocks are rebalanced every month, therefore stocks may not hold that lottery property when they are purchased. Therefore, we add another measurement to analyse whether investors buy lottery-type stocks deliberately:

$$Lottery\ Preference_{i,t}^{(4)} = \frac{\sum_{j \in A_{t-1}} Buy\ Volume_{i,j,t}}{\sum_{j=1}^{n} Buy\ Volume_{i,j,t}} \tag{13}$$

Where the numerator is the total number of shares of lottery-type stocks purchased by investor i at month t, while the denominator is the total number of shares of all stocks purchased by investor i at month t.

Table 7 reports the outcomes of regression models. The sample period is from the beginning of November 2007 to October 2008. The dependent variable is one of the lottery preference measurements defined previously. Individual characteristics, portfolio turnover, and account size are controlled in all specifications. Specifications (1) to (4) present the correlation between NIT and gambling behaviour. To ensure the robustness of results, NIT is replaced by a dummy variable in Specifications (5) to (8) which equals 1 if an investor is a net buyer ($NIT > 0$), otherwise it equals 0. Time-fixed effects are controlled, and standard errors are double-clustered for all specifications at individual and month levels.

The results from Specifications (1) to (3) indicate that investors with a higher buy intensity do not hold a portfolio with a higher proportion of lottery-type stocks during the crisis period. Notably, the coefficient estimate on NIT in Specification (2) indicates that, after adjusting for portfolio size, the proportion of lottery stocks declines significantly with the intensity of buying in the period of the market downturn. Investors with a higher NIT tend to be more active and might purchase lottery-type stocks deliberately rather than hold them passively. However, the significantly negative coefficient on NIT in Specification (4) reveals that the proportion of lottery-type stocks purchased also reduces as investment increases.

Our findings regarding the relationship between buying intensity and gambling behaviour are not influenced by employing the net buyer dummy in regressions, as shown in Specifications (5) to (7). The significantly negative coefficients on $Net\ Buyer\ Dummy$ show that both portfolio-size adjusted and market-index adjusted lottery preferences are lower for net buyers. Besides, consistent with the finding in Specification (4), net buyers are less prone to seeking lottery-type stocks, as shown in Specification (8). The association between control variables and the tendency to gamble is generally in line with Kumar's (2009b) findings, in that males and younger investors show a higher propensity to gamble. In addition, we find that individuals with less stock market wealth are more likely to buy or hold lottery-type stocks. Investors with less personal wealth are more likely to exhibit behavioural biases such as gambling (Jones, Shi, Zhang, & Zhang, 2021). Additionally, previous studies document that individuals with less personal wealth are more likely to gamble in order to escape poverty (Brenner, 1986; Herring & Bledsoe, 1994; Kumar, 2009b). The results from Table 7 indicate that net buyers, or investors with higher levels of buying intensity, do not engage in gambling. In other words, gambling behaviour cannot explain intense buying during the crisis period.

5.4 Robustness check using different definitions of bear and bull markets

Although stock prices typically experience sustained rises or falls, however, there is no consensus on how to define bull and bear markets (Candelon, Piplack, & Straetmans, 2008). To ascertain the robustness of our results, we first use a nonparametric approach by identifying peaks and troughs during our sample period to define bull and bear markets (Pagan & Sossounov, 2003; Candelon et al., 2008). Bry and Boschan (1971) adopt an algorithm to recognize turning points of business cycles. Pagan and Sossounov (2003) modify their algorithm and suggest that the essential feature of this dating algorithm is the choice of the turning points (peaks and troughs), which refer to the maximum and minimum values of a time scale. More specifically, the peak (trough) is the highest (lowest) point in an eight-month window on both sides of the point.[24] Accordingly, a peak must meet the following criteria:

$$P_t > \max(P_{t\pm1,\ldots,}P_{t\pm8}) \tag{14}$$

While a trough has to be:

$$P_t < \min(P_{t\pm1,\ldots,}P_{t\pm8}) \tag{15}$$

Where P_t is the market index at month t and $P_{t\pm n}$ is the market index n months before and after the market index at month t. Meanwhile, the dating algorithm imposes restrictions on the duration of the market state as well as on the magnitude of the rise and fall. In particular, the bull (bear) market requires a cumulative increase (drop) in the stock index of more than 20% and a duration of at least 4 months. Figure 1 gives a clear picture of a peak in October 2007 and a trough in October 2008. This means that the stock market was in a bull market from January 2007 until October 2007. The market was then in a bear state from November 2007 until the trough in October 2008, and then the market state was bullish until the end of the sample period.

[24] The results are consistent when using a six-month window on both sides of the point, following Candelon et al. (2008) and Chen (2012).

Therefore, the periods of the bear market determined by the non-parametric approach are consistent with the periods we defined in *Section 3.1*.

Apart from the nonparametric approach, we also use a simple moving average method to define bull and bear market (Chen, 2012):

$$r_t = \frac{r_{t-1}+r_{t-2}+\cdots+r_{t-n}}{n} \tag{16}$$

r_t is the moving average of the index returns during the previous n months. The market status at month t is defined as a bull market when $r_t>0$, otherwise, it is defined as a bear market. This naïve moving average approach is very similar to the cumulative return method used by Daniel and Moskowitz (2016). Edwards, Biscarri and Pérez de Gracia (2003) suggest that market states in developing countries tend to be shorter in duration but greater in the magnitude of change than those in developed countries. Therefore, we choose n=3, 6, 9 as the duration when calculating the moving average index returns.[25]

Lastly, we define bull and bear market over the sample period by using the method of Klein and Rosenfeld (1987) as well as Fabozzi and Francis (1977). Specifically, a month is defined as the upswing (downswing) category when the return of the market index is positive (negative) and higher than one-half of the market's standard deviation of monthly return over the sample period (31 months). Besides, a market status must consist of at least two consecutive up or down months. Following this method, March 2007 – October 2007 and October 2008 – July 2009 is defined as a bullish market, while January 2008 – October 2008 is a bearish market.

Table 8 reports the results by defining the bear market of our sample in three different ways. Overall, the outcomes are consistent with those in Table 3. In addition, the results in Tables 4 – 7 are not affected by the periods over which we use different approaches to measure bull and bear markets.

[25] We use the SSEC Index as a proxy for the market index. The results are consistent when using the SSEC A-Share Index and the CSI 300 Index as proxies for the market indices. When n=3, the duration of the bear market was from December 2007 to January 2009; when n=6, the bear market was from March 2008 to March 2009; and when n=9, the bear market was from April 2008 to May 2009. The outcomes are consistent when choosing n=3, 6, and 9. For simplicity, we only report the results of n=3.

6 Conclusion

This study investigates the trading behaviour of individual investors in the Chinese stock market by using a unique dataset with daily transaction records from 1^{st} January 2007 to 31^{st} July 2009. We focus on net buying by investors during the financial crisis period and develop an individual-level net investment measurement, matching it to investors' characteristics to examine who tends to have a higher buying tendency. The evidence shows that individual investors, on average, act as net buyers during the market downswing and that male and younger investors buy more aggressively than their counterparts. The higher buying intensity of those investors maybe because they have lower perceptions of risk and lower sensitivity towards risk increases.

Furthermore, we uncover that market and portfolio returns influence the tendency to buy in the following month differently. During the crisis period, investors use the rise of index returns as proxies for market recovery and increase their investment in the next month. The past portfolio performance does not directly influence net buying, whereas individuals buy more aggressively if they experienced positive portfolio returns in the previous month. Such a result of positive past performance causing an increase in future investment does not exist in a bull market. We argue, therefore, that market turmoil is instrumental in reinforcing the overconfidence of well-performing investors, which in turn leads them to invest more and show a self-attribution bias.

Next, we conduct a stock-day level analysis of the dynamic relationship among past stock returns, stock characteristics, and buying tendencies. Consistent with previous studies, we find that, during the financial crisis, investors at an aggregate level show negative feedback trading behaviour in that stocks with worse short-run returns experienced higher buy-side pressures. Lastly, we put forward two alternative explanations for the net buying behaviour: (i) a superb stock-picking ability where stocks with higher buy-side intensity outperform stocks sold, and (ii) a higher propensity to gamble. However, buy-side stocks, especially those with the highest buying intensity, significantly underperform sell-side stocks until at least ten days after trading. Also, the regression model reveals that stocks with higher buy-sell imbalance experience lower cumulative (abnormal) returns over a relatively long run. Again, gambling behaviour does not explain high net individual trading during the crisis period since net buyers neither hold a portfolio with a higher proportion of lottery-type stocks nor intentionally pursue lottery-type stocks.

Reference

Allen, F., Qian, J. Q. J., Shan, C., & Zhu, J. L. (2020). The development of the Chinese stock market. *In The Handbook of China's Financial System*. Princeton University Press.

Andersen, S., Hanspal, T., & Nielsen, K. M. (2019). Once bitten, twice shy: The power of personal experiences in risk taking. *Journal of Financial Economics*, 132(3), 97-117.

Arch, E. C. (1993). Risk-taking: A motivational basis for sex differences. *Psychological Reports*, 73(1), 3-11.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, 29(3), 155-173.

Barber, B., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2), 773-806.

Barber, B., & Odean, T. (2001). Boys will be boys: gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1), 261-292.

Barber, B., & Odean, T. (2002). Online investors: Do the slow die first? *The Review of Financial Studies*, 15(2), 455-488.

Barber, B., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2), 785-818.

Barber, B., Odean, T., & Zhu, N. (2009). Systematic noise. *Journal of Financial Markets*, 12(4), 547-569.

Barberis, N., & Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *The American Economic Review*, 98(5), 2066-2100.

Barrot, J., Kaniel, R., & Sraer, D. (2016). Are retail traders compensated for providing liquidity? *Journal of Financial Economics*, 120(1), 146-168.

Ben-David, I., Franzoni, F., & Moussawi, R. (2012). Hedge fund stock trading in the financial crisis of 2007–2009. *The Review of Financial Studies*, 25(1), 1–54.

Benjamin, D. J., Brown, S. A., & Shapiro, J. M. (2013). Who is 'behavioral'? Cognitive ability and anomalous preferences. *Journal of the European Economic Association*, 11(6), 1231-1255.

Benos, A. V. (1998). Aggressiveness and survival of overconfident traders. *Journal of Financial Markets*, 1(3-4), 353-383.

Boin, A. (2004). On financial crises. *British Journal of Management*, 15(2), 191-195.

Brenner, G. (1986). Why do people gamble? Further Canadian evidence. *Journal of Gambling Behavior*, 2(2), 121-129.

Bry, G., & Boschan, C. (1971). Interpretation and Analysis of Time-Series Scatters. *The American Statistician*, 25(2), 29-33.

Bucciol, A., & Miniaci, R. (2011). Household portfolios and implicit risk preference. *Review of Economics and Statistics*, 93(4), 1235-1250.

Candelon, B., Piplack, J., & Straetmans, S. (2008). On measuring synchronization of bulls and bears: The case of East Asia. *Journal of Banking & Finance*, 32(6), 1022-1035.

Chai, J., Horneff, W., Maurer, R., & Mitchell, O. S. (2011). Optimal portfolio choice over the life cycle with flexible work, endogenous retirement, and lifetime payouts. *Review of Finance*, 15(4), 875-907.

Campbell, J., Ramadorai, T., & Ranish, B. (2014). Getting better or feeling better? How equity investors respond to investment experience. *NBER Working Paper* No. 20000.

Chan, K., Wang, B., & Yang, Z. (2019). Why investors do not buy cheaper securities: Evidence from a natural experiment. *Journal of Banking & Finance*, 101(C), 59-76.

Chang, E., Cheng, J., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679.

Chen, H., Chow, E., & Shiu, C. (2015). The informational role of individual investors in stock pricing: Evidence from large individual and small retail investors. *Pacific-Basin Finance Journal*, 31(C), 36-56.

Chen, S. (2012). Revisiting the empirical linkages between stock returns and trading volume. *Journal of Banking & Finance, 36*(6), 1781-1788.

Chiang, Y.-M., Hirshleifer, D., Qian, Y., & Sherman, A. E. (2011). Do investors learn from experience? Evidence from frequent IPO investors. *The Review of Financial Studies*, 24(5), 1560-1589.

Choi, J., Laibson, D., & Metrick, A. (2002). How does the internet affect trading? Evidence from investor behavior in 401(k) plans. *Journal of Financial Economics*, 64(3), 397-421.

Cronqvist, H., Siegel, S., & Yu, F. (2015). Value versus growth investing: Why do different investors have different styles? *Journal of Financial Economics*, 117(2), 333-349.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, 47(2), 448-474.

Da, Z., Huang, X., & Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1), 175-196.

Dhar, R., & Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5), 726-740.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, 52(3), 1035-1058.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122(2), 221-247.

Diener, E., Sandvik, E., & Larsen, R. (1985). Age and sex effects for emotional intensity. *Developmental Psychology*, 21(3), 542-546.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522-550.

Dorn, D., & Weber, M. (2013). Individual investors' trading in times of crisis: Going it alone or giving up? *Working Paper*.

Duxbury, D. (2012). Sunk costs and sunk benefits: A re-examination of re-investment decisions. *The British Accounting Review*, 44(3), 144-156.

Edwards, S., Biscarri, J., & Pérez de Gracia, F. (2003). Stock market cycles, financial liberalization and volatility. *Journal of International Money and Finance*, 22(7), 925-955.

Fabozzi, F., & Francis, J. (1977). Stability tests for alphas and betas over bull and bear market conditions. *The Journal of Finance*, 32(4), 1093-1099.

Feng, L., & Seasholes, M. (2003). A profile of individual investors in an emerging stock market. *Working paper*, University of California at Berkeley.

Feng, L., & Seasholes, M. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, 9(3), 305-351.

Frydman, C., & Wang, B. (2020). The impact of salience on investor behavior: Evidence from a natural experiment. *The Journal of Finance*, 75(1), 229-276.

Glaser, M., & Weber, M. (2009). Which past returns affect trading volume? *Journal of Financial Markets*, 12(1), 1-31.

Greenwood, R., & Nagel, S. (2009). Inexperienced investors and bubbles. *Journal of Financial Economics*, 93(2), 239-258.

Herring, M., & Bledsoe, T. (1994). A model of lottery participation. Demographics, context, and attitudes. *Policy Studies Journal*, 22(2), 245-257.

Hilary, G., & Menzly, L. (2006). Does past success lead analysts to become overconfident? *Management Science*, 52(4), 489-500.

Hirshleifer, D., & Luo, G. Y. (2001). On the survival of overconfident traders in a competitive securities market. *Journal of Financial Markets*, 4(1), 73-84.

Hoffmann, A., & Post, T. (2014). Self-attribution bias in consumer financial decision-making: How investment returns affect individuals' belief in skill. *Journal of Behavioral and Experimental Economics*, 52, 23-28.

Hoffmann, A., Post, T., & Pennings, J. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, 37(1), 60-74.

Hoopes, J., Langetieg, P., Nagel, S., & Stuart, B. (2016). Who sold during the crash of 2008-9? Evidence from tax-return data on daily sales of stock. *NBER Working Paper* No. 22209.

Hou, W., Kuo, J., & Lee, E. (2012). The impact of state ownership on share price informativeness: The case of the Split Share Structure Reform in China. *The British Accounting Review*, 44(4), 248-261.

Hsieh, S. (2013). Individual and institutional herding and the impact on stock returns: Evidence from Taiwan stock market. *International Review of Financial Analysis*, 29(C), 175-188.

Huang, X. (2019). Mark twain's cat: Investment experience, categorical thinking, and stock selection. *Journal of Financial Economics*, 131(2), 404-432.

Jacobsen, B., Lee, J., Marquering, W., & Zhang, C. (2014). Gender differences in optimism and asset allocation. *Journal of Economic Behavior & Organization*, 107(PB), 630-651.

Ji, L., Zhang, Z., & Guo, T. (2008). To buy or to sell: Cultural differences in stock market decisions based on price trends. *Journal of Behavioral Decision Making*, 21(4), 399-413.

Jiang, Z.-Q., Zhou, W.-X., Sornette, D., Woodard, R., Bastiaensen, K., & Cauwels, P. (2010). Bubble diagnosis and prediction of the 2005–2007 and 2008–2009 Chinese stock market bubbles. *Journal of Economic Behavior & Organization*, 74(3), 149-162.

Jones, C. M., Shi, D., Zhang, X., & Zhang, X. (2021). Understanding retail investors: Evidence from China. *Working Paper*.

Kaniel, R., Saar, G., & Titman, S. (2008). Individual investor trading and stock returns. *The Journal of Finance*, 63(1), 273-310.

Kaustia, M., & Knüpfer, S. (2008). Do investors overweight personal experience? Evidence from IPO subscriptions. *The Journal of Finance*, 63(6), 2679-2702.

Klein, A., & Rosenfeld, J. (1987). The Influence of Market Conditions on Event-Study Residuals. *The Journal of Financial and Quantitative Analysis*, *22*(3), 345-351.

Korniotis, G., & Kumar, A. (2011). Do older investors make better investment decisions? *Review of Economics and Statistics*, 93(1), 244-265.

Kumar, A. (2009a). Hard-to-value stocks, behavioral biases, and informed trading. *The Journal of Financial and Quantitative Analysis*, 44(6), 1375-1401.

Kumar, A. (2009b). Who gambles in the stock market? *The Journal of Finance*, 64(4), 1889-1933.

Larsen, R. J., & Diener, E. (1987). Affect intensity as an individual difference characteristic: A review. *Journal of Research in Personality*, 21(1), 1-39.

Lee, B., Rosenthal, L., Veld, C., & Veld-Merkoulova, Y. (2015). Stock market expectations and risk aversion of individual investors. *International Review of Financial Analysis*, 40(C), 122-131.

Li, X., Geng, Z., Subrahmanyam, A., & Yu, H. (2017). Do wealthy investors have an informational advantage? Evidence based on account classifications of individual investors. *Journal of Empirical Finance*, 44(C), 1-18.

Liao, J., Peng, C., & Zhu, N. (2021). Extrapolative bubbles and trading volume. *The Review of Financial Studies*, forthcoming.

List, J. (2003). Does market experience eliminate market anomalies? *The Quarterly Journal of Economics*, 118(1), 41-71.

Liu, H., Peng, C., Xiong, W. A., & Xiong, W. (2021). Taming the bias zoo. *Journal of Financial Economics*, forthcoming.

Lleo, S., & Ziemba, W. T. (2018). Predicting stock market crashes in China. *The Journal of Portfolio Management*, 44(5), 125-135.

Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, 126(1), 373-416.

Malmendier, U., & Nagel, S. (2016). Learning from inflation experiences. *The Quarterly Journal of Economics*, 131(1), 53-87.

Ng, L., & Wu, F. (2007). The trading behavior of institutions and individuals in Chinese equity markets. *Journal of Banking & Finance*, 31(9), 2695-2710.

Nicolosi, G., Peng, L., & Zhu, N. (2009). Do individual investors learn from their trading experience?. *Journal of Financial Markets*, 12(2), 317-336.

Pagan, A., & Sossounov, K. (2003). A simple framework for analysing bull and bear markets. *Journal of Applied Econometrics*, *18*(1), 23-46.

Puri, M., & Robinson, D. (2007). Optimism and economic choice. *Journal of Financial Economics*, 86(1), 71-99.

Riley, W., & Chow, K. (1992). Asset allocation and individual risk aversion. *Financial Analysts Journal*, 48(6), 32-37.

Seru, A., Shumway, T., & Stoffman, N. (2010). Learning by trading. *The Review of Financial Studies*, 23(2), 705-739.

Shen, P.-L., Li, W., Wang, X.-T., & Su, C.-W. (2015). Contagion effect of the European financial crisis on China's stock markets: Interdependence and pure contagion. *Economic Modelling*, 50, 193-199.

Sicherman, N., Loewenstein, G., Seppi, D. J., & Utkus, S. P. (2016). Financial attention. *The Review of Financial Studies*, 29(4), 863-897.

Browning, E. (2008). Stock Investors Lose Faith, Pull Out Record Amounts. *The Wall Street Journal*, December 22. https://www.wsj.com/articles/SB122990642933825357.

Wang, G.-J., Xie, C., Lin, M., & Stanley, H. E. (2017). Stock market contagion during the global financial crisis: A multiscale approach. *Finance Research Letters*, 22(C), 163-168.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance*, 54(2), 581-622.

Yu, H., & Hsieh, S. (2010). The effect of attention on buying behavior during a financial crisis: Evidence from the Taiwan stock exchange. *International Review of Financial Analysis*, 19(4), 270-280.

Zhang, X., & Zhang, L. (2015). How does the internet affect the financial market? An equilibrium model of internet-facilitated feedback trading. *MIS Quarterly*, 39(1), 17-38.

Zhang, X. F. (2006). Information uncertainty and stock returns. *The Journal of Finance*, 61(1), 105-137.

Zhao, Y., Lee, C., & Yu, M. (2020). Does equity market timing have a persistent impact on capital structure? Evidence from China. *The British Accounting Review*, 52(1), 100838.

Zhao, Z., Li, S., & Xiong, H. (2014). Short sale constraints, disperse pessimistic beliefs and market efficiency—Evidence from the Chinese stock market. *Economic Modelling*, 42, 333-342.

Zhu, Z., Sun, L., Yung, K., & Chen, M. (2020). Limited investor attention, relative fundamental strength, and the cross-section of stock returns. *The British Accounting Review*, 52(4), 100859.

Table 1 Summary statistics

This table presents the summary of statistics for individual investors and stocks. The study's dataset comes from a large anonymous Chinese brokerage firm comprising of more than two million individual accounts. To ensure dataset compliance, we conduct a 'clean-up' process as described in *Section 3.1*. The remaining dataset amounts to 1,549,468 individual investors, in which 1,233,684 traded during the financial crisis period. Panel A comprises the summary statistics of the whole sample, from 1st January 2007 to 31st July 2009, while Panel B details investors trading during the financial crisis period from the beginning of November 2007 to the end of October 2008. *NIT* is the average net individual trading measurement across the whole sample (financial crisis subsample for Panel B) period. *Age* (*trading experience*) is based on the difference between an investor's birthday (account opening date) and each trading month. *Male* refers to the percentage of male investors. *Portfolio turnover* is the average of monthly buy and sell turnover, calculated following the method of Barber and Odean (2001). *Number of transactions* is the sum of buys and sells made by investors over the sample period (financial crisis subsample for Panel B). *Portfolio value* is the sum of market value of stocks held by each investor. *Account size* is the mean of monthly wealth allocated in the stock market; specifically, this equals each portfolio's value plus money in their account at the end of a month. Panel C comprises the descriptive statistics of 1,571 A-share stocks traded by investors in our sample between November 2007 and October 2008. *Market Capitalization* (in million RMB) is the average daily market value. *Share price* (in RMB) is the daily closing stock price. *Turnover ratio* is calculated as the number of shares traded over the number of outstanding shares, and *trading volume* (in million RMB) is the daily transaction value.

Variables	Mean	Standard Deviation	Mini	25%	Median	75%	Max
Panel A. Whole period (Number of Accounts=1,549,468)							
NIT	0.063	0.54	-1.000	-0.102	0.002	0.262	1.000
Age	41.17	11.79	18	32	40	49	91
Male	53.44%	-	-	-	-	-	-
Trading experience	4.32	4.21	0.00	0.75	1.92	7.83	16.75
Portfolio turnover	0.56	0.34	0.00	0.26	0.50	0.99	1.00
Number of transactions	12.53	30.88	1	2	6	13	42,298
Portfolio value	105,990.7	582,956.1	0.00	7,536.00	27,150.00	80,502.65	4.70e+08
Account size (in RMB)	142,699.7	716,562.5	0.00	14,476.38	41,081.68	110,786.40	4.71e+08
Panel B. Financial Crisis period (Number of accounts=1,233,684)							
NIT	0.129	0.58	-1.000	-0.008	0.019	0.453	1.000
Age	40.54	11.69	18	32	39	48	90
Male	53.53%	-	-	-	-	-	-
Trading experience	3.83	4.17	0.08	0.67	1.17	7.58	16.00
Portfolio Turnover	0.49	0.34	0.00	0.18	0.50	0.81	1.00
Number of transactions	10.78	23.59	1	2	5	11	17,597
Portfolio value	109,332.80	556,984.50	0.00	8,865.00	29,375.00	84,024.00	2.30e+08
Account size (in RMB)	146,474.40	726,554.00	0.00	14,873.96	41,293.08	110,932.30	2.33e+08
Panel C. Descriptive statistics of stocks traded during the financial crisis period							
Market capitalization	4,630.18	13,507	61.39	846.89	1,661.04	3,609.14	325,272.38
Share price	14.10	13.84	1.13	6.57	10.14	16.56	291.62
Turnover ratio (%)	2.38	3.05	0.00	0.88	1.55	2.78	93.26
Trading volume	79.02	239.84	0.00	11.52	28.35	72.03	16,398.07

Table 2 Summary of individual accounts on the financial crisis subsample period sorted by investors' characteristics
This table reports a detailed summary of individual investors' trading during the financial crisis period, from the beginning of November 2007 to the end of October 2008. To ensure dataset compliance, the following accounts are deleted, those (i) that only hold security investment funds, index funds, or B-share stocks, (ii) where age and gender are unrecorded, (iii) where stock holdings or balances show negative values, (iv) which are cancelled during the sample period, (v) where investors do not trade or hold at least one stock during the sample period. *Age* is at a given month (exact dates of birth are in our database). *Trading experience* is the difference between the account opening date and each trading month. *Portfolio value* is the sum of the market value of stocks held at a given month. The *number of purchases* and the *number of sales* are the buy and sell transactions made in a given month. *Portfolio turnover* is the average value of the monthly buy and sell turnover ratio. *Account size* is the monthly wealth allocated in the stock market, which equals the sum of the portfolio value and money in an account at a given month. For comparison purposes, each month investors are divided into groups based on gender, age, trading experience, and account size.

	Portfolio Value (in RMB)	Number of purchases	Number of sales	Portfolio turnover	Trading experience
All investors	109,332.8	5.99	4.79	0.49	3.83
By gender					
Male	108,333.4	6.21	5.04	0.51	3.93
Female	110,537.1	5.71	4.50	0.46	3.71
By age					
<=30	52,797.81	4.93	3.97	0.52	1.32
31-60	121,182	6.27	5.00	0.48	4.38
>60	159,997.8	6.16	5.10	0.44	5.87
By trading experience					
Open year <3	84,766.05	6.09	4.84	0.51	0.82
Open year >=3	149,136.3	5.82	4.72	0.44	8.72
By account size					
<=50,000	15,229.74	4.18	3.51	0.53	2.97
50,000-500,000	117,547.5	7.57	5.86	0.44	4.80
>500,000	1,063,034	13.17	10.41	0.40	5.63

Table 3 NIT and personal characteristics

This table presents the relationship between NIT and investors' characteristics. The financial crisis subsample period is from the beginning of November 2007 to the end of October 2008. We only consider investors with identifiable gender and age, holding A-share stocks at a large brokerage firm. For each trading month we calculate age, investment experience, portfolio turnover, account size, matching those variables with their monthly net individual trading measurement. $Gender$ is a dummy variable which equals 1 if a male and 0 if a female. Age is an investors' age at a given month. $Turnover$ is the average value of buy and sell turnover based on the method of Barber and Odean (2001). $Experience$ is the number of years of trading based on the difference between the account opening date and each trading month. $Account\ size$ is the portfolio's market value and money in an account at a given month. $Young$ is a dummy variable equals 1 if the age is lower than 60, and 0 otherwise. The dependent variable in Specifications (1) – (2) is the net individual trading, while it is replaced by a dummy variable equals 1 if $NIT > 0$ in the logit model. Independent variables in all specifications and dependent variables in Specifications (1) – (2) are standardized. We include the time fixed effects and double-clustered standard errors at the individual and time levels. Standard errors are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	OLS Regression		Logit Model	
	Specification (1)	Specification (2)	Specification (3)	Specification (4)
	NIT	NIT	NIT	NIT
$Gender$	0.0152**	0.0150*	0.0070	0.0067
	(0.0072)	(0.0080)	(0.0154)	(0.0169)
Age	0.0447**		0.0806**	
	(0.0176)		(0.0392)	
Age^2	-0.0529***		-0.0951***	
	(0.0104)		(0.0265)	
$Experience$	-0.0391***	-0.0392***	-0.1049***	-0.1050***
	(0.0139)	(0.0130)	(0.0262)	(0.0240)
$Turnover$	-0.2018***	-0.2017***	-0.3389***	-0.3387***
	(0.0302)	(0.0301)	(0.0431)	(0.0429)
$Account\ size$	-0.0181***	-0.0181***	-0.0251***	-0.0250***
	(0.0039)	(0.0040)	(0.0086)	(0.0089)
$Young$		0.0370**		0.0695***
		(0.0156)		(0.0256)
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R-square	0.04	0.04		
Pseudo R-square			0.02	0.02

Table 4 NIT and past returns during the bull market and financial crisis periods

This table presents the relationship between NIT and past returns of the market index and investors' portfolios. The sample period of the bull market is from the beginning of January 2007 to the end of September 2007, while the financial crisis period is from the beginning of November 2007 to the end of October 2008. We only consider investors who hold A-share stocks at a large brokerage firm and who have identifiable gender and age. $Gender$ is a dummy variable which equals 1 if a male and 0 if a female. Age is an investors' age at a given month. $Turnover$ is the average value of buy and sell turnover based on the method of Barber and Odean (2001). $Experience$ is the number of years of trading based on the difference between the account opening date and each trading month. $Account\ size$ is the portfolio's market value and money in an account at a given month. $Positive\ return\ dummy$ is a dummy variable equals 1 if the lagged return of an investor is a positive value, 0 otherwise. $Excess\ return\ dummy$ is a dummy variable equals 1 if the lagged return is higher than the lagged market return, 0 otherwise. $Positive\ return$ & $Excess\ return\ dummy$ is a dummy variable equals 1 if the lagged return is a positive value, and it is higher than the lagged market return, 0 otherwise. Independent and dependent variables are standardized in all regressions. We include the time fixed effects and double-clustered standard errors at the individual and time levels. Standard errors are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Financial crisis period				Bull market period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NIT	NIT	NIT	NIT	NIT	NIT	NIT	NIT
$Gender$	0.0119*	0.0119*	0.0119*	0.0119*	0.0011	0.0011	0.0011	0.0011
	(0.0067)	(0.0067)	(0.0067)	(0.0067)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
Age	0.0949***	0.0951***	0.0949***	0.0951***	0.0413*	0.0412*	0.0413*	0.0413*
	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0235)	(0.0235)	(0.0235)	(0.0235)
Age^2	-0.0960***	-0.0961***	-0.0960***	-0.0961***	-0.0564***	-0.0563***	-0.0564***	-0.0564***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0171)	(0.0171)	(0.0171)	(0.0171)
$Experience$	-0.0078	-0.0076	-0.0078	-0.0078	-0.0268***	-0.0268***	-0.0268***	-0.0268***
	(0.0081)	(0.0081)	(0.0081)	(0.0082)	(0.0086)	(0.0086)	(0.0086)	(0.0086)
$Turnover$	-0.1994***	-0.1997***	-0.1995***	-0.1998***	0.0046	0.0046	0.0046	0.0046
	(0.0318)	(0.0317)	(0.0317)	(0.0317)	(0.0247)	(0.0247)	(0.0247)	(0.247)
$Account\ size$	-0.0088**	-0.0089**	-0.0088**	-0.0088**	0.0145***	0.0145***	0.0145***	0.0145***
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
$Lagged\ portfolio\ return$	0.0014	-0.0170	0.0023	-0.0145	-0.0097	-0.0110	-0.0123*	-0.0129*
	(0.0152)	(0.0155)	(0.0094)	(0.0152)	(0.0085)	(0.0093)	(0.0065)	(0.0066)
$Lagged\ market\ return$	0.0777***	0.0788***	0.0772***	0.0815***	0.0268***	0.0263***	0.0275***	0.0269***
	(0.0078)	(0.0075)	(0.0051)	(0.0076)	(0.0094)	(0.0091)	(0.0086)	(0.0090)
$Positive\ return\ Dummy$		0.0542***				0.0118		
		(0.0127)				(0.0173)		
$Excess\ retrun\ Dummy$			-0.0019				0.0085	
			(0.0188)				(0.0110)	
$Positive\ return$ &				0.0460**				0.0113
$Excess\ return\ Dummy$				(0.0207)				(0.0132)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-square	0.05	0.05	0.05	0.05	0.01	0.01	0.01	0.01

Table 5 Aggregate buy-sell imbalance and stock characteristics

This table reports the stock-day level OLS regressions of aggregate investors' buy-sell imbalance on previous stock returns, market capitalization, and turnover. The sample period is from 1st November 2007 to 31st October 2008. IMB is the buy-sell imbalance of individual stock, using the volume bought minus the volume sold by aggregate investors divided by the total volume traded. $LogMarketCap$ is the logarithm of stocks' closing market values one day before the trading day. $Turnover$ is computed as the trading volume at day t divided by the outstanding shares on that day. $CAR[x,y]$ ($Return[x,y]$) is the cumulative abnormal return (holding period return) from x days before to y days before the transaction day. The abnormal return for each stock is measured as the raw stock return minus the return of the SSEC Index. We include time fixed effects in all regressions, and standard errors are clustered at the stock level. For comparison, stock fixed effects are included in Specifications (2) and (4). Standard errors are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Specification (1)	Specification (2)	Specification (3)	Specification (4)
	IMB	IMB	IMB	IMB
$CAR[-1]$	-0.2860***	-0.2786***		
	(0.0342)	(0.0335)		
$CAR[-5,-2]$	-0.1057***	-0.0949***		
	(0.0148)	(0.0142)		
$CAR[-27,-6]$	-0.0449***	-0.0315***		
	(0.0055)	(0.0057)		
$Return[-1]$			-0.2768***	-0.2688***
			(0.0333)	(0.0325)
$Return[-5,-2]$			-0.1029***	-0.0915***
			(0.0150)	(0.0142)
$Return[-27,-6]$			-0.0420***	-0.0283***
			(0.0055)	(0.0057)
$LogMarketCap$	0.0018**	0.0225***	0.0018**	0.0219***
	(0.0009)	(0.0049)	(0.0009)	(0.0049)
$Turnover$	0.6441***	0.7111***	0.6396***	0.7048***
	(0.0358)	(0.0397)	(0.0359)	(0.0397)
Time fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	No	Yes	No	Yes
Number of Observations	349,654	349,654	349,654	349,654
R-square	0.01	0.02	0.01	0.02

Table 6 Buy-sell imbalance and cumulative abnormal returns

This table reports cumulative abnormal returns (CARs) for the portfolios of stocks traded, sorted by the buy-sell imbalance of aggregate investors. The sample period is from 1st November 2007 to 31st October 2008. Stocks are grouped into buy-side and sell-side based on the sign of the IMB on each day. The daily portfolios are constructed based on the value of IMB. In Panel A, stocks are grouped into buy (sell) categories based on the value of IMB. Specifically, portfolio B comprises stocks that have a positive IMB, while portfolio S includes stocks with a negative IMB. To ensure the robustness of results, stocks are grouped into buy (sell) tertiles, quintiles, and deciles in Panels B, C, and D respectively, based on the value of IMB. Portfolio B1 in Panels B, C, and D includes stocks that experienced the highest buy-side pressure, while portfolio S1 contains stocks with the highest sell intensities. The equal-weighted portfolios are constructed on the formation day, and market-index adjusted abnormal returns are aggregated from 5 days before to 20 days after their formation days. The t-values are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% levels.

Portfolios	T-5	T-3	T-1	Formation day	T+1	T+3	T+5	T+10	T+15	T+20
Panel A. Aggregate investors order imbalance – sorted equal-weighted portfolio excess returns (daily, in percent)										
Intense buying Portfolio	0.549**	0.353*	0.132	-0.069	-0.070	0.050	0.195	0.642*	1.157**	1.592***
(B)	(2.19)	(1.88)	(1.45)	(-0.73)	(-0.47)	(0.22)	(0.71)	(1.84)	(2.58)	(3.04)
Intense Selling Portfolio	0.670***	0.425**	0.184*	0.361***	0.561***	0.805***	0.979***	1.466***	1.983***	2.467***
(S)	(2.64)	(2.22)	(1.96)	(3.93)	(3.78)	(3.61)	(3.65)	(4.31)	(4.52)	(4.74)
B-S	-0.121	-0.072	-0.052	-0.430***	-0.631***	-0.755**	-0.784**	-0.824*	-0.826	-0.876
	(-0.34)	(-0.27)	(-0.39)	(-3.27)	(-2.99)	(-2.38)	(-2.04)	(-1.69)	(-1.32)	(-1.19)
Panel B. Aggregate investors order imbalance – sorted equal-weighted portfolio excess returns (daily, in percent)										
Portfolio B1	0.144	0.074	0.018	-0.096	-0.106	0.037	0.222	0.743**	1.339***	1.846***
(Highest buy tendency)	(0.58)	(0.39)	(0.20)	(-0.94)	(-0.67)	(0.16)	(0.79)	(2.11)	(2.99)	(3.53)
Portfolio S1	0.582**	0.380**	0.187*	0.578***	0.943***	1.309***	1.562***	2.179***	2.758***	3.273***
(Highest sell tendency)	(2.28)	(2.00)	(1.97)	(6.47)	(6.50)	(5.86)	(5.91)	(6.59)	(6.46)	(6.42)
B1-S1	-0.438	-0.306	-0.169	-0.674***	-1.048***	-1.272***	-1.340***	-1.436***	-1.419**	-1.426*
	(-1.23)	(-1.15)	(-1.30)	(-4.98)	(-4.89)	(-3.95)	(-3.47)	(-2.97)	(-2.29)	(-1.95)

Panel C. Aggregate investors order imbalance – sorted equal-weighted portfolio excess returns (daily, in percent)

Portfolio B1	0.021	-0.037	-0.019	-0.128	-0.147	-0.003	0.211	0.734**	1.323***	1.850***
(Highest buy tendency)	(0.09)	(-0.20)	(-0.22)	(-1.22)	(-0.93)	(-0.01)	(0.74)	(2.08)	(2.98)	(3.56)
Portfolio S1	0.634**	0.415**	0.205**	0.669***	1.095***	1.515***	1.814***	2.479***	3.085***	3.609***
(Highest sell tendency)	(2.49)	(2.18)	(2.20)	(7.51)	(7.54)	(6.70)	(6.81)	(7.48)	(7.26)	(7.09)
B1-S1	-0.613*	-0.452*	-0.225*	-0.797***	-1.242***	-1.518***	-1.603***	-1.745***	-1.762***	-1.760**
	(-1.73)	(-1.70)	(-1.75)	(-5.79)	(-5.79)	(-4.67)	(-4.11)	(-3.61)	(-2.87)	(-2.42)

Panel D. Aggregate investors order imbalance – sorted equal-weighted portfolio excess returns (daily, in percent)

Portfolio B1	-0.129	-0.169	-0.101	-0.151	-0.211	-0.174	0.007	0.506	1.099**	1.620***
(Highest buy tendency)	(-0.52)	(-0.91)	(-1.14)	(-1.35)	(-1.26)	(-0.71)	(0.02)	(1.39)	(2.48)	(3.09)
Portfolio S1	0.730***	0.486**	0.236***	0.796***	1.326***	1.841***	2.175***	2.927***	3.581***	4.109***
(Highest sell tendency)	(2.85)	(2.56)	(2.63)	(8.86)	(8.95)	(8.01)	(8.13)	(8.82)	(8.54)	(8.07)
B1-S1	-0.859**	-0.656**	-0.338***	-0.948***	-1.537***	-2.015***	-2.168***	-2.422***	-2.482***	-2.490***
	(-2.41)	(-2.47)	(-2.67)	(-6.59)	(-6.87)	(-5.97)	(-5.38)	(-4.92)	(-4.07)	(-3.41)

Table 7 NIT and gambling

This table shows the relationship between NIT and investors' tendency to gamble after controlling personal characteristics. The subsample period of the financial crisis is from the beginning of November 2007 to the end of October 2008. We only consider investors who hold A-share stocks at a large brokerage firm and whose gender and age are identifiable. For each month, we calculate investors' net investment, personal characteristics, and matching these variables with their gambling tendencies. The dependent variable in Specifications (1)-(8) is one of the lottery-preference measurements ($Lottery(1) - Lottery(4)$) which we defined in *Section 5.3*. NIT is estimated as the transaction value bought, minus the transaction value sold and divided by the total transaction value of the investor at a given month. $Net\ Buyer\ Dummy$ is a dummy variable equals 1 if the $NIT > 0$, otherwise 0. $Gender$ is a dummy variable equals 1 if an investor is a male, otherwise 0. Age is an investors' age each month. $Turnover$ is calculated based on the method of Barber and Odean (2001). $Experience$ is the number of years of trading based on the difference between the account opening date and each trading month. $Account\ size$ is portfolio value plus money in an account. Independent and dependent variables are standardized in all regressions. We include the time fixed effects and double-clustered standard errors at the individual and time levels. Standard errors are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Specification (1)	Specification (2)	Specification (3)	Specification (4)	Specification (5)	Specification (6)	Specification (7)	Specification (8)
Dependent Variable	$Lottery$ (1)	$Lottery$ (2)	$Lottery$ (3)	$Lottery$ (4)	$Lottery$ (1)	$Lottery$ (2)	$Lottery$ (3)	$Lottery$ (4)
NIT	-0.0024	-0.0067***	-0.0046	-0.0222***				
	(0.0035)	(0.0023)	(0.0038)	(0.0043)				
$Net\ Buyer\ Dummy$					-0.0075	-0.0149***	-0.0112*	-0.0191***
					(0.0061)	(0.0049)	(0.0067)	(0.0048)
Age	-0.0121***	-0.0138***	-0.0115***	-0.0111***	-0.0121***	-0.0138***	-0.0115***	-0.0105***
	(0.0020)	(0.0023)	(0.0015)	(0.0022)	(0.0020)	(0.0023)	(0.0015)	(0.0022)
$Gender$	0.0002	0.0080***	-0.0001	0.0018	0.0001	0.0079***	-0.0001	0.0014
	(0.0024)	(0.0016)	(0.0024)	(0.0028)	(0.0024)	(0.0016)	(0.0024)	(0.0028)
$Experience$	0.0003	-0.0076***	0.0015	-0.0029	0.0002	-0.0077***	0.0014	-0.0026
	(0.0024)	(0.0017)	(0.0025)	(0.0025)	(0.0024)	(0.0017)	(0.0025)	(0.0026)
$Turnover$	0.0322***	0.0136***	0.0313**	0.0160***	0.0321***	0.0137***	0.0313**	0.0220***
	(0.0055)	(0.0024)	(0.0070)	(0.0033)	(0.0054)	(0.0025)	(0.0070)	(0.0038)
$Account\ size$	-0.0154**	-0.0060**	-0.0153***	-0.0158***	-0.0154**	-0.0059**	-0.0153***	-0.0152***
	(0.0019)	(0.0009)	(0.0017)	(0.0023)	(0.0019)	(0.0009)	(0.0017)	(0.0023)

Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6,263,171	6,254,033	6,263,171	6,018,882	6,263,171	6,254,033	6,263,171	6,018,882
Number of Clusters	1,192,107	1,191,834	1,192,107	1,177,346	1,192,107	1,191,834	1,192,107	1,177,346
R-square	0.0044	0.0070	0.0057	0.0055	0.0044	0.0070	0.0057	0.0053

Table 8 Robustness check

This table presents the relationship between NIT and investors' characteristics. We only consider investors with identifiable gender and age, holding A-share stocks at a large brokerage firm. For each trading month we calculate age, investment experience, portfolio turnover, account size, matching those variables with their monthly net individual trading measurement. $Gender$ is a dummy variable which equals 1 if a male and 0 if a female. Age is an investors' age at a given month. $Turnover$ is the average value of buy and sell turnover based on the method of Barber and Odean (2001). $Experience$ is the number of years of trading based on the difference between the account opening date and each trading month. $Account\ size$ is the portfolio's market value and money in an account at a given month. $Young$ is a dummy variable equals 1 if the age is lower than 60, and 0 otherwise. The bear market in Specifications (1) – (2) is from November 2007 to October 2008, defined using Pagan and Sossounov's (2003) approach, while in Specifications (3) – (4) the bear market is from December 2007 to January 2009, using Chen's (2012) approach instead. In Specifications (5) – (6), the bear market is determined by using the method of Klein and Rosenfeld (1987), from January 2008 to October 2008. Independent and dependent variables in all specifications variables are standardized. We include the time fixed effects and double-clustered standard errors at the individual and time level. Standard errors are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Turning points (Peak & Trough points)		Chen's (2012) method		KR's (1987) method	
	Specification (1)	Specification (2)	Specification (3)	Specification (4)	Specification (5)	Specification (6)
	NIT	NIT	NIT	NIT	NIT	NIT
$Gender$	0.0152**	0.0150*	0.0147**	0.0142**	0.0215***	0.0223***
	(0.0072)	(0.0080)	(0.0062)	(0.0070)	(0.0076)	(0.0083)
Age	0.0447**		0.0463***		0.0308**	
	(0.0176)		(0.0157)		(0.0137)	
Age^2	-0.0529***		-0.0505***		-0.0460***	
	(0.0104)		(0.0096)		(0.0083)	
$Experience$	-0.0391***	-0.0392***	-0.0262***	-0.0253**	-0.0273*	-0.0298**
	(0.0139)	(0.0130)	(0.0123)	(0.0118)	(0.0148)	(0.0142)
$Turnover$	-0.2018***	-0.2017***	-0.1552***	-0.1552***	-0.2192***	-0.2190***
	(0.0302)	(0.0301)	(0.0360)	(0.0358)	(0.0283)	(0.0282)
$Account\ size$	-0.0181***	-0.0181***	-0.0114***	-0.0112***	-0.0167***	-0.0169***
	(0.0039)	(0.0040)	(0.0036)	(0.0038)	(0.0029)	(0.0030)
$Young$		0.0370**		0.0284*		0.0508***
		(0.0156)		(0.0148)		(0.0137)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-square	0.04	0.04	0.04	0.04	0.05	0.05

Figure 1 Performance of market indices

This graph shows the SSEC Index, SSEC A-share Index, and CSI 300 Index from the beginning of January 2007 to the end of July 2009. The crisis period is from November 2007 to the end of October 2008.

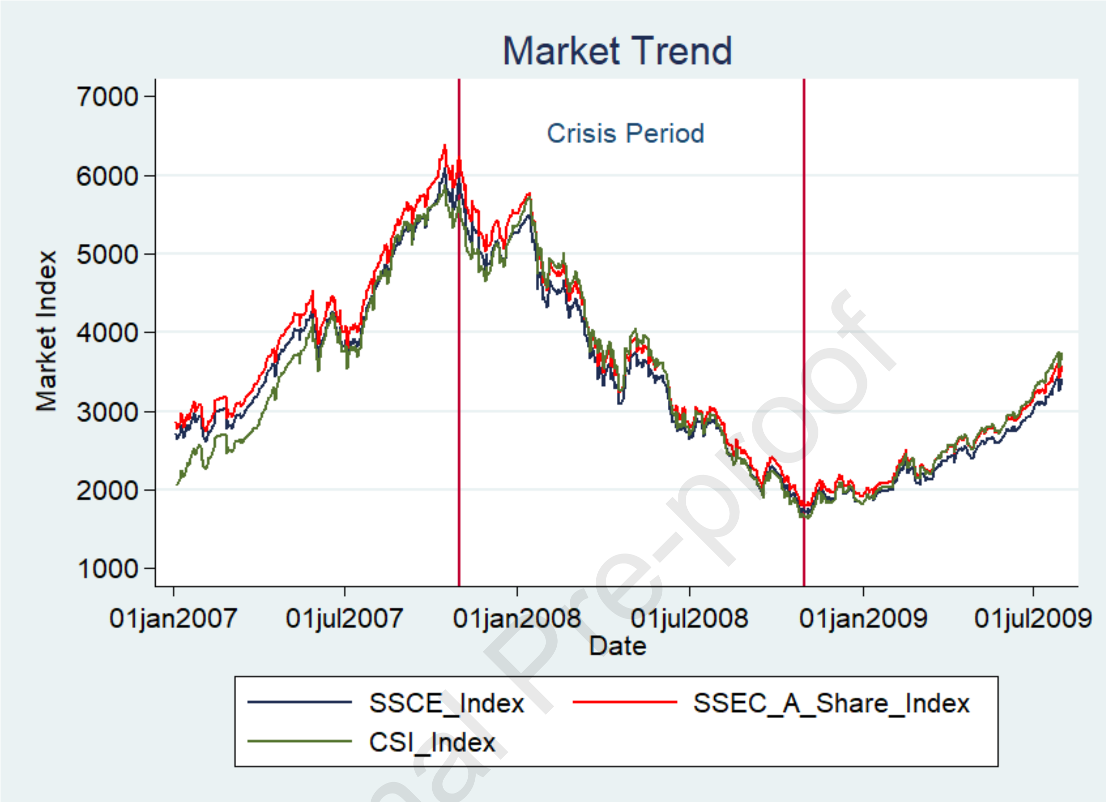


Figure 2 Investors' monthly NIT ratio

This graph plots the mean and median value of monthly *NIT* for individual investors who traded A-share stocks during the period from January 2007 to July 2009. *NIT* is the net individual trading measurement, computed as the transaction value bought, minus the transaction value sold and divided by the total transaction value. We only consider investors who hold A-share stocks at a large brokerage firm and whose gender and age are identifiable.

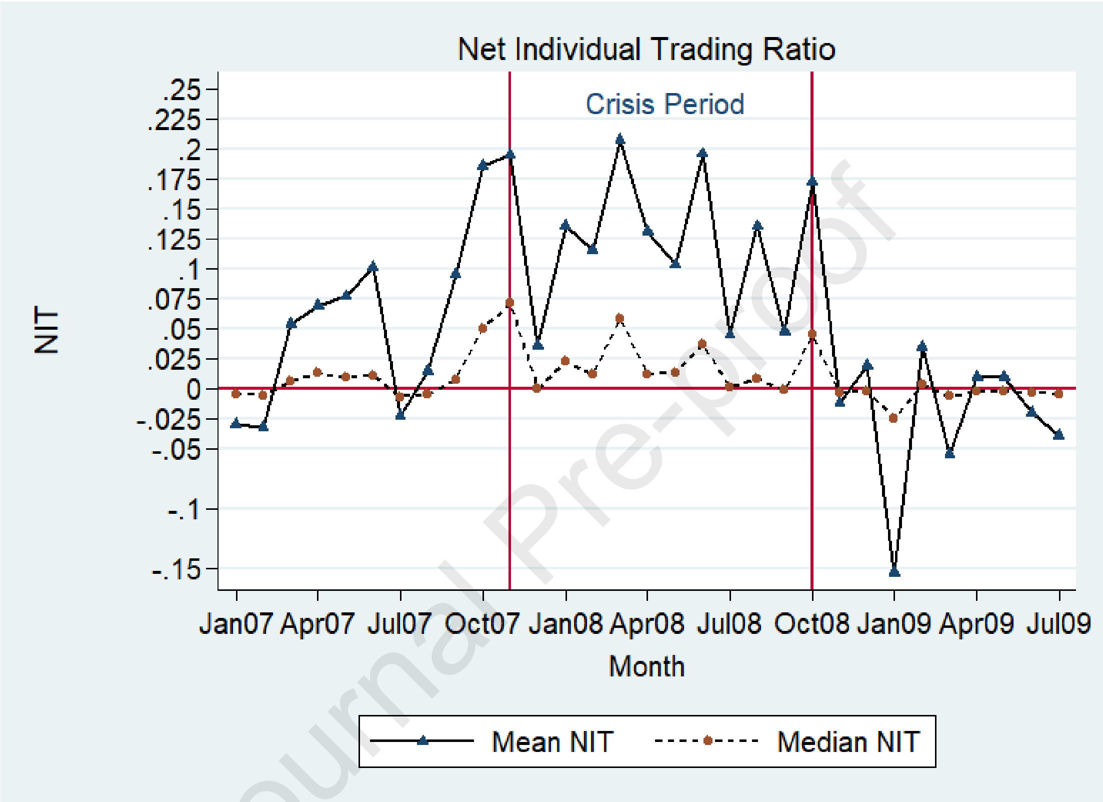
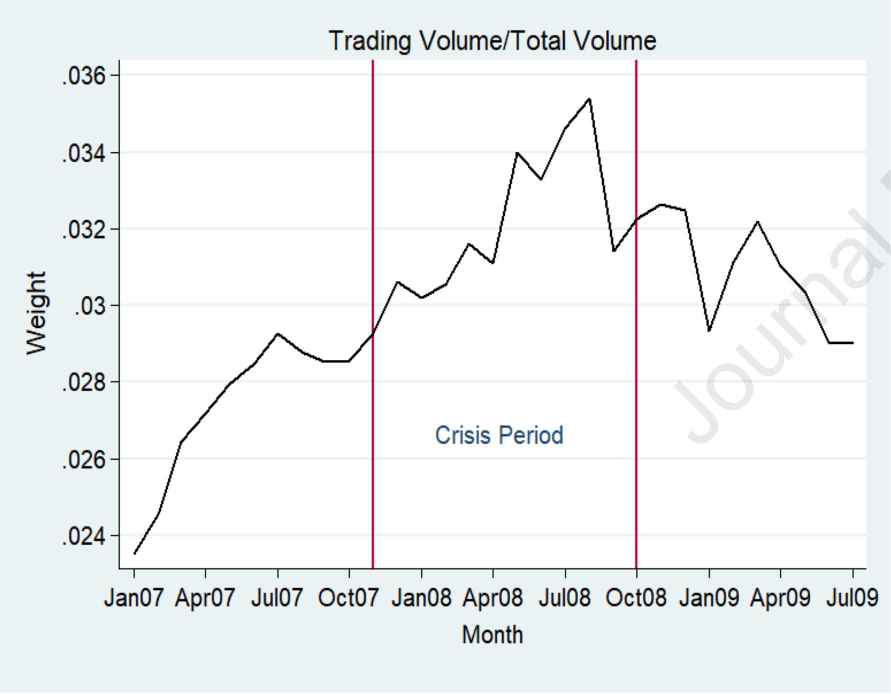


Figure 3 Proportion of trading volume and investors' positions

This graph plots the trading volume of investors as a percentage of total market-wide trading volume and their monthly average positions. The proportion of trading volume is computed as the aggregate share of total market-wide volume traded (Panel A). Investors' positions are calculated as the ratio of portfolio value to total account value (portfolio value plus the money in an account) at the beginning and end of each month (Panel B). The sample includes individuals trading A-share stocks from the beginning of January 2007 to the end of July 2009. The crisis period is from the beginning of November 2007 to the end of October 2008. The SSEC Index decreased to 1,664 from 6,124 during this period.

Panel A. Proportion of trading volume



Panel B. Investors' positions

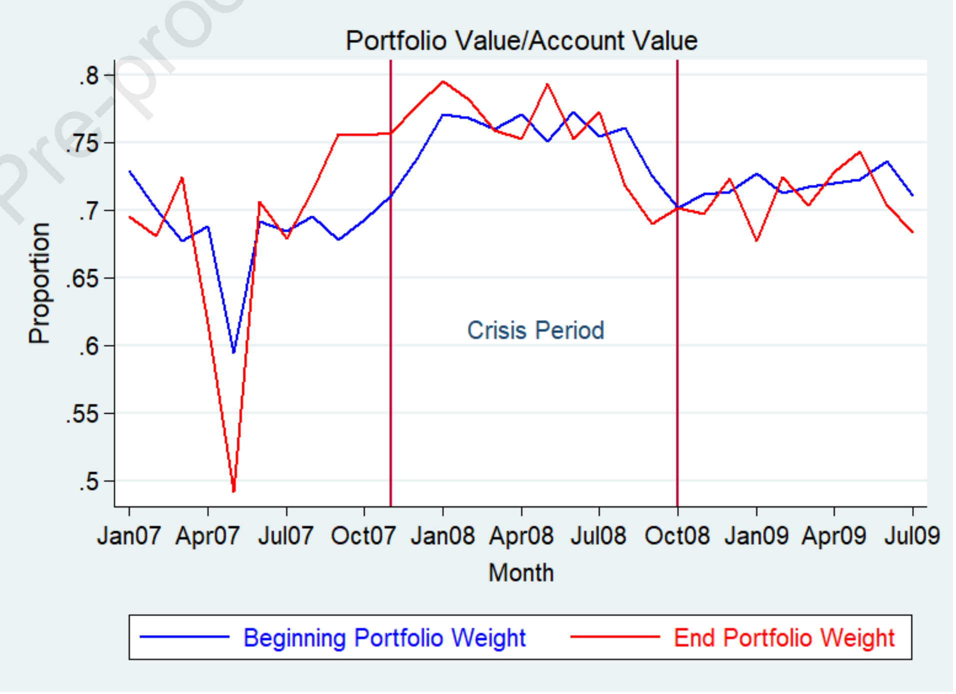
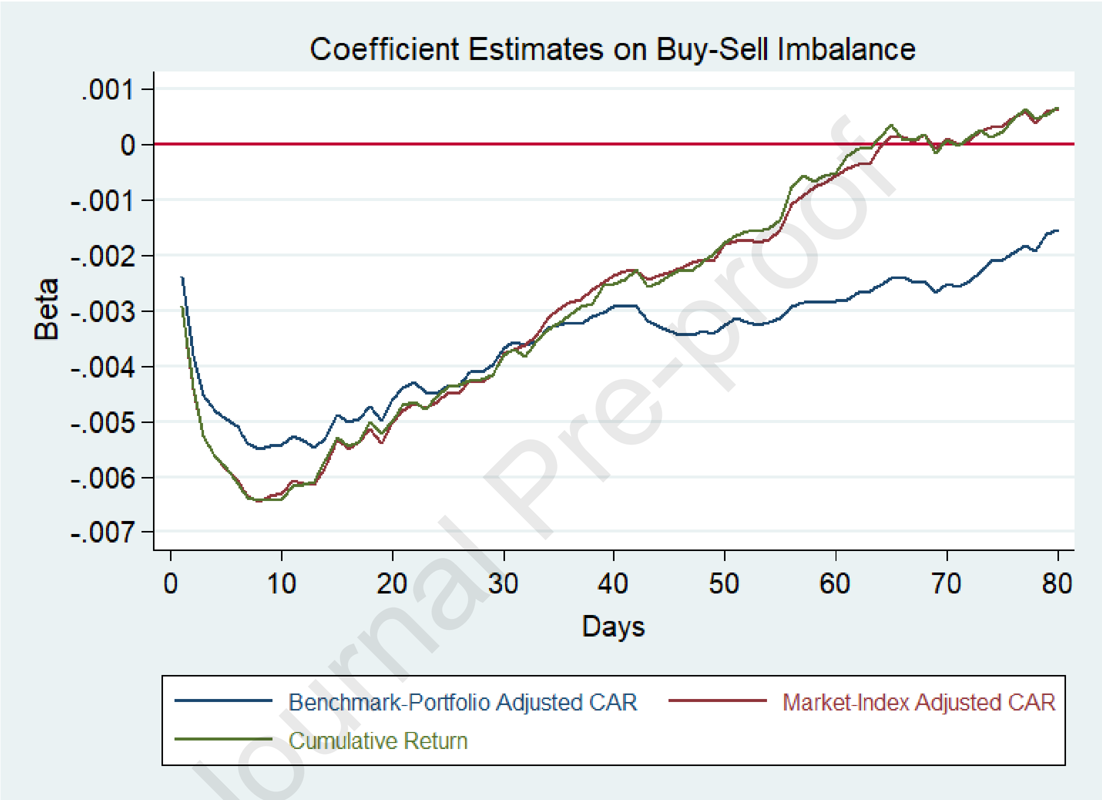


Figure 4 Stock returns and buy-sell imbalance

This figure shows the coefficients on the aggregate buy-sell imbalance in stock-day level regressions where the dependent variables are the cumulative returns, market-index adjusted cumulative abnormal returns, and benchmark-portfolio adjusted cumulative abnormal returns from one day after to eighty days after the trading day. The sample period is from 1st November 2007 to 31st October 2008. Control variables in the regression include past returns, market value, and turnover of stocks. The buy-sell imbalance for a given stock is constructed by using the volume bought minus the volume sold by aggregate investors and divided by the total volume traded.



Highlights

1. Male and younger investors are more likely to be net buyers during the financial crisis period.

2. Individual investors exhibit a self-attribution bias when the market crashed.

3. The superb stock-picking ability or the tendency to gamble cannot explain the net purchase behavior of investors.