THREE ESSAYS ON THE TRADING BEHAVIOUR OF INDIVIDUAL INVESTORS

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ABSTRACT

This thesis contains three stand-alone empirical chapters dedicated to contributing to the field of behavioural finance by exploring the behavioural differences among investors and the factors that influence their trading behaviour.

The first empirical chapter analyses the existence of gender difference in herding, the possible causes, and the consequences of the higher herding tendency. The main findings suggest that female investors herd more intensively and lose more than males, especially during bull markets. Market conditions and stock characteristics affect females and males in similar ways, and the lower portfolio turnover of females is the primary source of gender effect on herding.

The second empirical chapter of this thesis examines investors' buying behaviour with an emphasis on the financial crisis period beginning in October 2007. The results show that individual investors, especially males and the younger investors, tend to provide liquidity by acting as net buyers when the market crashes. The findings also indicate that better performance during the financial crisis encouraged investors to be overconfident, thus exhibiting self-attribution bias. The results of the stock-level analysis suggest that investors tend to purchase stocks with poor short-term past performance, higher liquidity, and larger market capitalization. Lastly, we do not find evidence that a superior stock-picking ability or a higher propensity to gamble can explain the intensive buying during market downturns.

The final empirical chapter focuses on investors' reactions to earnings surprises. The outcomes suggest that individual investors increase (reduce) their holdings on stocks with positive (negative) earnings surprises. This chapter also explores to what extent the media tone could influence investors' reactions, and the evidence shows that investors overreact to good (bad) earnings news for firms with positive (negative) media tone than for those with negative (positive) media tone. The media effect is also more pronounced for firms with negative earnings surprises and for investors with lower wealth and poorly diversified portfolios.

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A thesis presented for the degree of Doctor of Philosophy

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DECLARATION

This thesis has not been submitted in any part for any other degree or qualifying examination at this or any other university. Unless the manuscript indicates otherwise, this thesis is entirely my own work.

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Dedicated to my family

Chapter One: Introduction

In recent decades traditional financial theories have been continuously challenged, primarily because human beings are not fully rational when making investment decisions, and their behaviour can be influenced by psychological factors as well as the external environment. Numerous theories have been developed to help explain why investors fail to respond to fundamental market information promptly and properly, such as prospect theory (Kahneman and Tversky, 1979), risk-as-feeling theory (Loewenstein et al., 2001), limited attention theory (Kahneman, 1973), and mental accounting (Thaler, 1985). The theories above, and various hypotheses yet to be mentioned, applied psychological and sociological concepts to address anomalies and behavioural biases in financial markets, including overconfidence, herding effects, calendar effects, non-standardized preferences, etc., which later emerged independently as behavioural finance/economics.

As one of the most sizeable components of the capital markets, individual investors have received considerable attention from academics in recent years. In the extensive behavioural finance literature, individual investors are also recognized as noise traders because their decisions are highly susceptible to external events and changes in sentiment, resulting in irrational investment behaviour. To gain a more comprehensive understanding of individual investors' behaviour, Chapter 2 presents an overview of the literature, which documents factors that may affect the decisions of individual investors and their behavioural biases. Although existing studies have identified various behavioural biases of individual investors, many remain unexplained. This thesis endeavours to contribute to this field by exploring the behaviour of individual investors and the factors that influence their trading behaviour in the stock market.

Stock trading in China began in the late nineteenth century, at the end of the Qing Dynasty. As a result of the Westernization Movement, some commercial organizations began to adopt the form of joint-stock companies, and stock trading emerged (Chen, 2006). However, a centralized stock market could not be established due to the extremely limited number of shares and joint-stock companies. With the reform and opening up after 1978, China gradually became the world's second-largest economy due to its broad geographical area and huge and cheap labour market. The stock market in mainland China was established in 1990, and it consists of two independently domestic stock exchanges: the Shanghai Stock Exchange (SSE), which was formed on 26th November and started its operations on 19th December, and the Shenzhen Stock Exchange (SZSE), which was opened on 1st December 1990. From then on, thousands of private and state-owned enterprises have been listed on the SSE and SZSE. At the end of 2020 there were 4,154 listed companies, and the total market capitalization of SSE and SZSE reached $12.21 trillion, making it the largest equity market except for the US stock market.

Stocks traded on the Chinese stock market can be divided into two categories: A-share stocks, which are quoted in RMB and traded by domestic and qualified foreign institutional investors (QFII); and B-share stocks, which are issued in foreign currencies (US and HK dollars) and are available for purchase by offshore investors as well as domestic investors who have foreign currency accounts. Compared to the US stock market, the Chinese A-share stock market has two distinct differences in terms of trading mechanism. 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. In a sense, this approach can mitigate speculative trading and provide more stability to the market (Allen et al., 2020). 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%.[1]

In addition to the trading mechanism, 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. Based on the estimates from CICC Research, individual investors' ownership accounts for 54% of the market's free-floating shares at this time. Given the enormous impact of individual investors in the Chinese stock market, it is exceptionally worthwhile to investigate their trading behaviour, including trading biases and factors influencing their decision, from a behavioural finance perspective.

To achieve this, the thesis uses three stand-alone essays and specializes in studying individual investors in the Chinese stock market. The primary dataset used in this study is from a large anonymous Chinese brokerage firm. This unique dataset contains the account information of more than two million individual investors and allows us to retrieve daily stock holdings, transaction records, cash balances, and personal information related to Chinese investors. The

[1] 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.

sample period of this dataset is between 1st January 2007 and 31st July 2009, and consists of three phases: i) the bull-market period from the beginning of January 2007 to mid-October 2007, when the SSE Composite Index (SSEC) hit its historically highest peak, rising from 2,675 points to 6,124 points; ii) the financial crisis period from mid-October 2007 to the end of October 2008, during which the SSEC dropped sharply to 1,664 points; and iii) the recovery period from November 2008 to July 2009, in which the SSEC more than doubled from the bottom to 3,412 points. This database is ideal for the research because it also enables us to explore how investors trade in different market conditions.

The data from each investor's account included, (i) the customer's profile, (ii) the balance after each transaction day, (iii) the stock holdings, and (iv) the transaction file. The customer's profile allowed for the retrieval of each investor's personal information, including a unique account number, account-open date, gender, nationality, birth date, and personal National Identity Number. The dataset also includes information about daily cash balances for each investor after a trading day. Additionally, the stock holding file contains information regarding the stock code and the total number of shares held by each investor. It is also possible to identify the market value of each stock based on investors' current holdings.

Finally, the transaction file provides the trading history of individual investors, including the, (i) transaction date, (ii) stock traded, (iii) the number of shares purchased or sold, (iv) price of stock traded, (v) total number of shares after each transaction, (vi) transaction type, such as whether selling or purchasing, (vii) pre-tax and post-tax costs of each trade. Information about the account balance, stock holdings, and trading records are updated daily.

Chapter 3 of this thesis examines the gender differences in herding. Herding can be defined as a form of correlated behaviour when an agent ignores the available information set and imitates the decision of others (Avery and Zemsky, 1998). Previous literature on herding behaviour can be classified into two broad categories. The first type of study uses the cross-sectional standard (absolute) deviations to analyse the existence of herding behaviour across the stock market (Christie and Huang, 1995; Chang et al., 2000; Demirer and Kutan, 2006). Alternatively, Lakonishok et al.'s (1992) approach (known as the LSV approach) is used to shed light on the herding behaviour of a specific investor group (Nofsinger and Sias, 1999; Choe et al. 1999; Wermers, 1999).

The impact of gender on investment has been extensively documented in behavioural finance research. These studies have mainly found gender to play a role in various factors, such as risk appetite (Arch, 1993; Croson and Gneezy, 2009; Jacobsen et al., 2014), overconfidence (Barber and Odean, 2001; Hirshleifer and Luo, 2001; Chuang and Lee, 2006), and gambling (Kumar, 2009). However, there is still a lack of literature that clearly explains whether herding is more likely to be a female or male preference and the mechanisms and consequences underlying the gender differences in herding. Indeed, psychological findings show that women are more likely to change their beliefs and behaviours under social pressure and show a higher degree of conformity (Eagly, 1978; Eagly and Carli, 1981). Bond and Smith (1996) find that individuals living in collectivist states (e.g., China and Japan) are more likely to exhibit a greater degree of conformity than those living in non-collectivist states. Inspired by psychological research, we first investigate whether there is a difference in herding between females and males.

In fact, Merli and Roger (2013) construct an individual-level herding measurement and report that although females, on average, herd more intensively than males, the difference is not significant in most quarters. Despite this, their study leaves a number of open questions in investigating gender differences in herding. In comparison, our study also empirically addresses the following questions: i) do female investors herd more than males? ii) do market conditions and stock characteristics affect the gender difference in herding? iii) what are the consequences of the higher herding tendency of females, and iv) what induces females to herd more intensively?

We first use the LSV method to develop a daily herding measurement for each stock from female and male investors' groups to answer these research questions. Chapter 3 shows that although both females and males herd intensively in the Chinese stock market, females exhibit a somewhat higher degree of herding than males, especially during bull-market periods. Furthermore, the regression model indicates that stock characteristics have a similar effect on the herding behaviour of female and male investors but are more noticeable in the female group, potentially because females as a group are inclined to use similar risk management strategies (Daníelsson, 2008). Regarding the impact of herding on trading performance, the outcomes suggest that behavioural factors drive the herding of individual investors. In particular, females lose more than males because of their intensive herding, especially in a market upswing. This is consistent with the findings of Hsieh (2013), who argues that individual investors experience losses when engaging in behaviour-driven herding. Finally, to understand the main source of gender difference in herding, we construct an individual-level herding measurement by following the method of Merli and Roger (2013). The evidence is in line with the overconfidence hypothesis, suggesting that females, especially those with a lower portfolio turnover, exhibit a higher herding tendency.

Chapter 4 of this thesis focuses on the trading behaviour of individual investors during the financial crisis period. When facing a financial crisis, it is appropriate to sell off assets as much as possible to hedge the risk. However, recent French and German stock market findings show that individual investors provide liquidity and do not take a lower risk when the market crashes (Barrot et al., 2016; Dorn and Weber, 2013). Likewise, Hoffmann et al. (2013) reveal that individual investors do not change from risky stocks to cash and continuously trade actively during the market downswing. Hoopes et al. (2016) suggest that investors who provide liquidity in times of financial crisis must have an incentive to do so, e.g., in order to obtain a higher risk premium. This chapter examines four research questions to provide a better understanding of how investors react to financial crises.

Firstly, considering that previous studies have found that investors' trading styles have a biological basis and can also be influenced by hedging demands, behavioural biases, and life experiences (Cronqvist et al., 2015; Benos, 1998; Korniotis and Kumar, 2011; Malmendier and Nagel, 2011), we address the question of whether personal characteristics may affect their buying when the market crashes. This chapter also investigates whether past trading performance affects net investment. In particular, we compare whether the past portfolio performance in the market upswing and downswing has the same effect on the buying tendency. Furthermore, the stock-day level buy-sell imbalance is used to examine which types of stocks had a higher buying intensity during the financial crisis. Lastly, we investigate whether superb stock-picking skills or the gambling tendency can explain the net buying of individual investors.

Our study constructs an individual-level measurement to identify the net investment of investors. We mainly concentrate on 1,233,684 investors who held or traded stocks during the crash period. The empirical outcome confirms that individual investors, on average, acted as net buyers during the crash period. The evidence from the panel regression model suggests that male and younger investors exhibit a higher intensity of buying than female and older investors. Those investors' relatively higher propensity to buy during market downturns can be explained by their lower sensitivity to increased market risk (Jacobsen et al., 2014; Hoopes et al., 2016). Our results also demonstrate that in the crisis period, the previously positive performance of portfolios boosts investor confidence and lead to a significant increase in the propensity to buy. Such a result does not exist during the bull-market period, suggesting that a better performance in times of financial crisis encourages investors to buy more aggressively and thus exhibit a self-attribution bias. In addition to the self-attribution bias of individual investors induced by a combination of the financial crisis and past investment performance, we also attempt to explain their net buying by a superior stock-picking ability and gambling behaviour. However, the results show that stocks with higher buying intensity underperform stocks with lower buying intensity in both the short and relatively long term. In addition, net buyers do not hold more or actively purchase lottery stocks. Finally, Chapter 4 shows that stocks with poorer past performance, better liquidity, and larger market capitalization have a higher buy-side pressure during market downturns.

Chapter 5 explores how individual investors will react to major public information and whether their reactions will be influenced by distracting external information. The earnings announcement contains essential information about the company's recent operations, and therefore it can correct for previous price movements. In addition, nearer the earnings announcements, share prices may be vulnerable to excessive fear and greed due to the increased information asymmetry (Jansen and Nikiforov, 2016). While a growing body of literature contributes to understanding investors' trading behaviours around earnings announcements, the conclusions are not uniform (Lee, 1992; Vieru et al., 2006; Hirshleifer et al., 2008; Luo et al., 2020). Aside from the fact that investors' limited attention leads them to ignore the information in firms' announcements, their reactions may also be influenced by market and media sentiment (Mian and Sankaraguruswamy, 2012; Cahill et al., 2017; Seok et al., 2019).

In light of the mixed results regarding the relationship between investors' reactions and earnings surprises, and the potential impact of media tone on this relationship, this study empirically addresses the following research questions: How do investors react to earnings surprises? Does pre-announcement media tone influence investors' reactions to earnings surprises? Does the impact of media tone vary across investor groups? Following Li et al. (2019) and García (2013) and collecting media news data from the *Genius Finance Database*, Chapter 5 constructs two media tone measurements. Similar to the method of Ekholm (2006), we use the average of standardized holding changes to capture investors' reactions after earnings announcements. Our final sample includes 202,580 articles reported between 30 days and one day before earnings announcements. It also contains 12,652 earnings announcements released by 1,452 firms and 1,486,477 investors who traded within 15 days after the quarterly earnings announcements from 1st January 2007 to 31st July 2009.

The findings of Chapter 5 suggest that, on average, individual investors increase (reduce) their holdings on stocks with positive (negative) earnings surprises. Additionally, our study finds an asymmetric effect of media tone on positive and negative earnings surprises. Specifically, the evidence shows that investors react more strongly to positive (negative) earnings surprises with high (low) media tone than those with low (high) media tone. In line with Mian and Sankaraguruswamy (2012), we also detect that the effect of media tone is more pronounced for investors' reactions to negative earnings surprises than to positive earnings surprises. Chapter 5 also investigates the influence of media tone on different types of investors and demonstrates that investors in well-diversified and high-wealth groups are less likely to be affected by it. This outcome implies that investors who are more likely to have private information or be distracted by information about other stocks in their hands are less likely to be affected by the tone of the media.

This thesis contributes to the behavioural finance literature in the following ways. First, it provides new evidence on the behavioural biases of individual investors. Chapter 3 explores the possible linkage between gender and herding behaviour and uncovers that females herd more intensively than males. Chapter 4 investigates the buying behaviour of individual investors and shows that males and younger investors traded more aggressively when the market crashed. The findings in Chapter 5 suggest that investors who allocated less wealth or have poorly diversified portfolios in the stock market are more likely to be influenced by media tone. Second, this thesis provides insight into trading behaviour in different market conditions since our dataset allows bull-market and financial-crisis periods to be viewed separately. The evidence from Chapter 3 suggests that investors herd more and, accordingly, lose more during the upswing market. Chapter 4, unlike all previous studies, uses an individual-level analysis and finds that compared to positive past performance in the bull market, only a positive past performance during a bear market amplifies buying inclinations. Lastly, this thesis extends the literature on learning the behaviour of individual investors in the Chinese stock market. Due to the restriction of the dataset, literature that examines Chinese investors has rarely focused on individual investors, yet they are an important part of the Chinese stock market (Chen et al., 2007; Feng and Seasholes, 2003; Feng and Seasholes, 2005; Li et al., 2017b). By focusing on individual investors, this thesis provides insights into the behavioural differences among investors and the factors that influence their trading behaviour.

The rest of this thesis is structured as follows. Chapter 2 reviews previous literature on the factors that determine individuals' investment decisions and their behavioural biases. Chapter 3 investigates the existence of differences in herding between genders, the sources of such differences, and the consequences of intensive herding. Chapter 4 analyses the trading behaviour of individual investors during the financial crisis period. Chapter 5 examines investors' reactions to earnings surprises and the role of media tone in influencing the relationship between investors' trading and earnings surprises. Chapter 6 emphasizes the primary findings as well as the limitations of this thesis and offers suggestions for future research.

Chapter Two: Literature Review

As one of the essential components in the financial markets, over the past few decades individual investors have attracted a large number of researchers to investigate their behaviour. Although existing studies have made tremendous contributions in detecting the behavioural biases of individual investors and factors that determine their behaviour, there are still many behavioural biases that have not been identified and anomalies that remain unexplained. This thesis endeavours to understand individual investors' behaviour and contribute to this area by using a unique dataset, including holding and transaction records. Section 2.1 reviews the literature concerning the determinants of investors' behaviour and Section 2.2 presents the behavioural biases of individual investors.

2.1 What could influence investors' behaviour?

Most traditional financial theories, such as the efficient market hypothesis (EMH) and expected utility theory, are based on certain rigorous hypotheses. For instance, these theories require that every individual is rational and informed and can make decisions quickly and correctly, or even that there are no transaction costs. However, most of these assumptions are unrealistic in the real world, and individual decisions differ from theoretical expectations. In this part, this thesis discusses factors documented in the existing literature that have an impact on the decision-making process and the behaviour of individuals.

2.1.1 Personal characteristics

Investment style has a biological basis, although it can be affected by hedging demand, behavioural bias, and investors' personal life experiences (Cronqvist et al., 2015). This part looks at how genetic factors, personal life experiences, and cognitive abilities influence the behaviour of investors.

2.1.1.1 Gender

Gender differences in individual behaviour have been widely documented in the financial literature. These investigations focus primarily on the different risk preferences and risk-taking between females and males. Theoretical studies offer explanations for why the risk-taking behaviour of males differs from that of females. First, the gender difference in risk-taking behaviours relates to investment knowledge. Dwyer et al. (2002) find that the risk-taking behaviour of female investors is similar to males when controlling for investment knowledge. Additionally, the risk-as-feeling theory posits that risk-taking behaviours also depend on individuals' emotional experiences from results (Loewenstein et al., 2001). In particular, psychologists note that females exhibit higher affect intensity than males; thus, females naturally perceive a greater degree of risk (Larsen and Diener, 1987; Diener et al., 1985). Arch (1993) suggests that males and females interpret risks in different ways. More specifically, males regard risks as challenges they need to face, while females consider risks as threats they have to avoid. Jacobsen et al. (2014) offer several interpretations of why females are more risk-averse than males on the stock markets. Their finding suggests that males are more optimistic about economic conditions as well as stock markets. Also, the female respondents report a higher level of stock market risk than males. Indeed, after controlling for optimism about the economy and financial markets, female and male investors behave very similarly.

The overconfidence theory offers another mechanism for why males are more risk-seeking than females. It elaborates why male investors are willing to take more risks: males are more likely to be overconfident than female investors; hence, they tend to underestimate the risk of their portfolios (Hirshleifer and Luo, 2001; Chuang and Lee, 2006). Barber and Odean (2001) collected trading data and information about personal characteristics (e.g., gender, marital status, age, and income) of 78,000 households from a large discount brokerage firm from February 1991 to the beginning of 1997. They argue that males tend to be more overconfident than females, and thus exercise more trades than females. Overall, the results indicate that males trade more excessively (about 45%) than females, and this frequent trading activity reduces the trading performance of men.

A few studies provide new explanations on gender differences in risk-taking behaviour. For instance, according to Carr and Steele (2010), the different risk-taking behaviour between genders derives from stereotypes. In their experimental settings, subjects in the experimental group are told that the task they are about to complete will be used to evaluate their mathematical and logical talent. Subjects are required to point out their gender before the task. In the control group, subjects are informed that they are completing puzzle-solving tasks and need to declare their gender after completing the task. Overall, the outcomes indicate that females in the treatment group tend to be more loss-averse and risk-averse than males. At the same time, there is no significant difference in risk aversion and loss aversion between females and males in the control group. In addition, the magnitude of lottery choice plays a critical role in determining risk-taking behaviours. Holt and Laury (2002) suggest that males become less risk-seeking, and the gender difference disappears when the stake of lotteries increases. Similar outcomes are uncovered by Rieger et al. (2015). Their findings show that whether females are more risk-averse than males depends on the payback of lotteries.

Finally, the gender difference in risk-taking behaviours could be task-specific. Schubert et al. (1999) indicate that the relative risk attitude of men and women strongly depends on the circumstance of the decision-making since they fail to find evidence that males and females have different risk attitudes when subjects confront contextual decisions. Furthermore, after collecting data from experimental studies following Holt and Laury's (2002) risk elicitation method, Filippin and Crosetto (2016) argue that only a relatively small proportion of these studies find females to be more risk-averse than males. Besides, by using Cohen's D as an effect size measurement and constructing a new dataset with pooled data from previous literature, they suggest that the magnitude of gender differences is comparatively small.

2.1.1.2 Aging process, IQ, and cognitive ability

Hoopes et al. (2016) find that investors approaching retirement are more sensitive to increased risk since they are likely to have fewer earning opportunities in the future. However, the impact of the aging process on financial behaviour is not conclusive in academia for various reasons. Firstly, although most psychological and experimental studies show that older investors are more risk-averse than the younger generation, several studies argue that the relationship between age and risk aversion might not be linear (Barsky et al., 1997; Bucciol and Miniaci, 2011; Korniotis and Kumar, 2011; Dohmen et al., 2011). Frijns et al. (2008) report a positive relationship between the aging process and risk-taking behaviours. However, their study also finds that males reduce their highly risk-taking behaviours along with the aging process to a greater extent than females. Not only that, Davydov et al. (2017) examine the trading behaviours of individual investors in the ETFs market, and they find that the portfolio risk of older females is higher than younger females. Riley and Chow (1992) indicate that risk aversion declines with age until 65 and increases remarkably after that. Likewise, Cohn et al. (1975) suggest that older investors are prone to invest a greater proportion of their savings in risky assets. Interestingly, middle-aged investors (45–55 years old) with above-average wealth invest most in risky assets.

Second, various researchers note that the age effect on investment behaviour could be influenced by cognitive ability (Burks et al., 2009; Benjamin et al., 2013). Bonsang and Dohmen (2015) claim that the main reason for the negative relationship between age and risk-taking behaviour is the inferior cognitive abilities of elders. Finke et al. (2017) show that the financial literacy of subjects peaked at age 49, then decreased gradually. The decline in cognitive ability increases the unwillingness to take risks. Christelis et al. (2010) use survey data to investigate relationships among age, cognitive ability, and willingness to take financial risks. By employing stock-market participation as a proxy for financial risk-taking behaviours, their results show that it is cognitive ability rather than aging that affects the willingness for stock-market participation. Also, studies in brain and cognitive science report that older people indeed make more mistakes in their risk-seeking choices as their ability to measure expected value is poor (Samanez-Larkin et al., 2010; Li et al., 2001; Samanez-Larkin and Knutson, 2015).

Korniotis and Kumar (2011) investigate the stock market performance of individual investors. They argue that older investors may have more trading experience, which could benefit their portfolios. However, due to the aging process, their cognitive abilities decrease with age. The outcomes of their study illustrate that, although older and experienced traders show better knowledge of investment (e.g., lower trading frequency, well-diversified portfolio), the portfolio performance is worse than their counterparts due to the deterioration of cognitive ability. Furthermore, some researchers investigate the impact of cognitive abilities on financial decision-making. Grinblatt et al. (2012) examine the influence of individuals' intelligence quotient on their stock market performance. The evidence shows that retail traders with higher IQs are less likely to exhibit the disposition effect. As a result of distinctive market timing and stock-picking ability, individual investors with higher IQs experience a higher abnormal return. Another study conducted by Grinblatt et al. (2011) uses a similar dataset to investigate whether high-IQ individuals have a higher propensity to participate in the stock market. Indeed, they find that high-IQ investors are not only more likely to hold mutual funds and stocks, but their portfolios also have a higher Sharpe ratio and are better diversified.

2.1.1.3 Life experiences

The life-course theory proposes that personal experiences can explain people's later behaviour. Early personal experiences can be traced back to an individual's prenatal period as an unborn child in the mother's womb. Cronqvist et al. (2016) find that a high level of prenatal testosterone exposure leads to higher risk-taking and more trading as an adult. In addition, individuals with higher birth weights have a greater likelihood of stock market participation. Conversely, investors with lower birth weights are more likely to hold portfolios with higher volatility and skewness. These findings are consistent with compensatory behaviour. In the later stages of life, investors may be transformed by personal life experiences. Malmendier and Nagel (2011) suggest that investors' experiences of economic fluctuation could shape their willingness to take additional risks.

Previous trading experience can also have an impact on the future investing behaviour of individuals. Some researchers argue that individuals with more investment experience outperform those with less experience because they are better at decision-making and market timing (Arrow, 1962; Grossman et al., 1977; Nicolosi et al., 2009; Seru et al., 2010; Feng and Seasholes, 2005; Dhar and Zhu, 2006). On the other hand, studies also document that investors overestimate their previous investment experience or are influenced by good investment experiences that they had in the past, such as buying stocks that earned profits (Madrian and Shea, 2001). Strahilevitz et al. (2011) investigate repurchase behaviour and find that investors are unwilling to repurchase stocks that they sold at a loss and that increase in price after the sale. To some extent, their study demonstrates that investors are trying to stay away from stocks that have brought them frustration and regret. Chan et al. (2019) find that investors with more trading experience tend to exhibit a higher degree of portfolio inertia when facing a better investment opportunity in the B-share stock market. Choi et al. (2009b) find that different experiences of past 401(K) savings returns can shift investors' future savings rates. This outcome indicates that individual investors tend to be affected by their prior experience in similar investments when making a portfolio decision.

2.1.1.4 Other external environment-related social demographics

The financial behaviour of individual investors can also be influenced by some external environment-related social demographics, such as income, wealth, financial literacy, and marital status. The evidence of wealth effects influencing investor decisions has been widely documented in the empirical behavioural finance literature. For instance, Vissing-Jorgensen (2003) reviews the empirical evidence for the dependence of a range of behavioural biases on investor wealth and finds that most of these irrational behaviours have diminished significantly as wealth increases. Massa and Simonov (2006) argue that an investor's wealth can be used to measure the quality of their information. Simply put, a wealthier investor will be less likely to rely on public information and more likely to rely on his private sources of information. In other words, wealthy investors should have more information to make financial decisions. Brunnermeier and Nagel (2008) indicate that, unlike consumption levels and long-term habits that vary with wealth, the share of liquid assets that households invest in risky investments is less susceptible to changes in wealth. In particular, households rebalance their allocation of risky assets extremely slowly following inflows and outflows of funds or capital gains and losses. Differences in wealth levels may also result in varying risk-taking of investors. For instance, Dorn and Huberman (2005) find that investors with more wealth have better diversification in their equity portfolios, while Calvet et al. (2007) show that wealthy investors tend to hold a larger share of equities. Income also matters for financial decision making and trading behaviour. Viceira (2001) claims that an increase in idiosyncratic labour income risk raises investors' propensity to save, bringing their equity portfolios down towards the level of retired investors. In addition, the positive correlation between labour income and equity returns can cause investors' equity holdings to fall back below the level of retired investors. Shive (2010) studies the impact of social influence on the trading behaviour of investors and finds that individuals with more income tend to place more buys and sells.

It is also well documented that individual investors are more likely to exhibit behavioural biases in their trading than institutional investors due to their poor financial literacy. For example, Barber et al. (2007) compare the disposition effect for individuals and various types of institutional investors. They find that the disposition effect is strong for individual investors, who are almost four times more likely to sell winners than losers. Indeed, Behrman et al. (2012) find evidence that both financial literacy and educational attainment have a strong linear positive relationship with wealth accumulation, with the effect of financial literacy being even more substantial. Lusardi (2008) shows that low literacy and, in particular, a lack of financial literacy can affect an individual's choice of saving plans and wealth accumulation. Financial or savings-related education can, to some extent, assist illiterate individuals in improving their ability to choose savings plans and thus improve their financial situation in retirement. By contrast, using meta-analysis, Fernandes et al. (2014) uncover that financial literacy education interventions explain only about 0.1% of the variance in the financial behaviours studied. Particularly, the average effect of the financial education intervention on their sample of low-income people was even weaker.

Lastly, the marital status of individual investors can also influence their financial decision-making process. Barber and Odean (2001) investigate the relationship between overconfidence, trading frequency, and stock market performance. They find that men, especially single men, trade more frequently than women and that their aggressive trading behaviour hurts the performance of their portfolios. Kumar (2009) uses individual-level trading data and defines lottery-style stocks. The findings of this study show that single or divorced, less educated, and lower-income retail investors have a greater tendency to buy and hold lottery stocks.

2.1.2 Psychological factors

This part of the literature review provides both psychological and empirical evidence that individuals' attention, moods, and emotions can influence their risk attitudes in decision-making processes. As a result, changes in the risk preferences of retail traders would impact their stock market performance.

2.1.2.1 Attention

There is a huge variety of financial assets available, and the number of stocks is too great for individual investors to analyse thoroughly. Therefore, the individual investor's decision-making process is likely to be influenced by their attention. Kahneman (1973) proposes limited attention theory, which states that attention to an item necessarily reduces attention to another thing. Engelberg et al. (2012) argue that due to constraints on investors' time and energy, they cannot effectively process all the available information, which means they may not immediately respond to information related to stock fundamentals. Specifically, investors may delay their reaction to crucial information if they pay too little attention to it. At the same time, they may overreact to irrelevant news if they spend too much attention on this information (Barber and Odean, 2013).

Previous studies document that attention has a more significant impact on purchase decisions than selling decisions due to sorting bias (Barber and Odean, 2008; Engelberg et al., 2012). Barber and Odean (2008) use extreme stock returns, abnormal trading volumes, and stock-specific news as attention measures. They find that investors act as net buyers on attention-grabbing stocks. Also, buying is more likely to be affected by attention than selling. Lou (2014) uses advertising expenditure as a representative of attention, and he argues that increasing advertising expenditure leads to a contemporaneous rise in net buying and abnormal returns. Similarly, according to the asymmetrical attention theory, good news contributes to heavy pressure on the buy-side of stocks with positive signals (Barber et al., 2019). Li et al. (2014) explore the mechanism of information percolation on stock markets. Their findings suggest that firm-specific news can enhance investors' knowledge and further impact their trading. Baker and Wurgler (2007) argue that stocks of low market-cap, young, unprofitable, high volatile, non-dividend paying, growing firms, or stocks of firms in financial distress have a higher probability of being affected by changes in investors' attention. The rationale behind this is that 'speculative' stocks tend to experience a higher return when sentiment increases. Accordingly, stocks with speculative characteristics are more likely to be influenced by waves of investors' attention.

Hirshleifer et al. (2009) propose the distraction theory and find that the number of earnings announcements plays a crucial role in distracting investors. The evidence of their study shows that post-earnings announcement drift is more significant on days with more earnings announcements. Similarly, Dellavigna and Pollet (2009) argue that investors' attention is more likely to be disturbed on Fridays. As a result, they find that limited attention significantly impacts earnings announcements, especially those released on Friday. Peress (2008) uses media coverage to proxy investors' attention and investigates how it affects trading during earnings announcements. He finds that price and trading volume changes more when the *Wall Street Journal* reports an earnings surprise for the stock. Also, the post-earnings announcement drift is smaller for stocks covered by the *Wall Street Journal* than for the same stock without media coverage. In other words, the underreaction is less pronounced when investors pay attention.

Hillert et al. (2014) find that media coverage could exacerbate investor biases since the return predictability is most robust for firms with high levels of public attention. Da et al. (2011) use the Google search volume index to measure investor attention directly. They discover that stocks with abnormal SVI have a positive price pressure in the short run, and price reversals can be observed within a year. Likewise, Zhang and Wang (2015) use the Baidu search index to measure investor attention in the Chinese stock market. They find that individual investors' attention on non-trading days leads to price jumps in market opening quotes on the next trading day. Sicherman et al. (2016) use online account logins as a proxy for investors' attention. They show that investor demographics and financial position are strongly correlated with the level of attention.

The effect of media tone may differ for different firms and market conditions. Karlsson et al. (2009) identify the ostrich effect; that is, investors pay more attention to stocks during market upswings, while they put their heads in the sand when market volatility is low or during market downswings. Following this theory, Hou et al. (2009) find that the underreaction-driven earnings momentum is more pronounced when the market crashes, while the overreaction-driven price momentum is stronger during a bull market. Yang et al. (2017) detect an asymmetrical effect of media news on investors' trading decisions. In particular, investors tend to pay more attention to positive news and underreact to negative news during a market upswing, while they are more likely to be affected by negative news during a market downswing.

2.1.2.2 Mood, emotion, and sentiment

Isen and her colleagues develop the mood maintenance hypothesis (MMH), which uncovers a negative relationship between risk-taking behaviour and mood (Isen and Patrick, 1983; Isen and Geva, 1987; Isen et al., 1988). One explanation for this result is that subjects in a good mood tend to maintain their positive feelings, and thus they are more likely to avoid a high-risk gamble or bet. By comparison, subjects in a bad mood are more willing to take risks since they hope that the positive outcome of a risky gamble will change their bad moods. Studies in behavioural finance provide empirical evidence to support MMH. For instance, Kliger and Levy (2003) use cloud cover to proxy traders' emotions and adopt the S&P500 call option price to obtain traders' absolute risk aversion (ARA). The results of their study indicate that people in a good mood have a lower propensity to undertake risks in the capital market. To ascertain the relation between risk-taking and emotion (happiness), Guven and Hoxha (2015) first analyse happiness's determinants. After controlling personal characteristics, geographic location, and year-fixed effects, the results demonstrate that sunshine positively interacts with happiness. Their further outcomes provide evidence for MMH in that individuals with a positive mood have a lower propensity to take risks.

In comparison, Forgas (1995) develop the affective infusion model (AIM) and find opposite results to the MMH. According to Forgas (1995), individuals tend to make decisions through substantive processing when the target is sophisticated, unfamiliar, and highly relevant. Indeed, an investor's decisions in the stock markets, such as purchasing and selling securities, and market timing, meet these criteria precisely. A body of literature has provided supportive evidence for AIM. For example, Yuen and Lee (2003) perform a two-way analysis of variance (ANOVA) to examine whether mood states could significantly impact risk-taking behaviour. Their findings indicate that although risk-taking behaviour does not differ significantly between individuals in positive and neutral moods, individuals who are depressed proved to be less willing to take risks than those in a neutral mood or positive mood. Kuhnen and Knutson (2011) argue that risk aversion is positively related to negative emotions (e.g., anxiety) and negatively associated with strong positive emotions (e.g., excitement). Indeed, the rationale behind these outcomes is that the nucleus accumbens will be activated if individuals are in a good mood; consequently, they are more likely to make a riskier choice. Conversely, people tend to avoid risky investments when the anterior insula, associated with negative emotions, is activated (Bjork et al., 2004).

Investor sentiment, as an indication of investors' feelings, is also related to their mood. It is often used as a measure of incorrect beliefs or preferences exhibited by investors as a group. Baker and Wurgler (2006, 2007) define investor sentiment as a belief about future cash flows and investment risks that the fundamentals cannot explain. Their study uncovers that investor sentiment affects stock markets contemporaneously, with this effect reversing on the following trading day as investors become aware of deviations from fundamentals. Zhou (2018) summarizes measures of investor sentiment, including the Baker-Wurgler method, measures based on survey data, and textual analysis of media data. He argues that it is not conclusive how to evaluate the trend of sentiment and what lag length should be employed.

Lutz (2016) uses returns on lottery-type stocks and a dynamic factor model to develop a novel investor sentiment index. The evidence suggests that when the investor sentiment starts to experience a downswing (peak-to-down), high sentiment forecasts low future returns for speculative stocks. Qiu and Welch (2006) compare the effect of survey-based sentiment and sentiment extracted from the closed-end fund discount. They find that survey-based sentiment can be used to interpret the small-firm return spread and the return spread between stocks held by individual and institutional investors. By employing social media platform (Sina) data, Dong and Gil-Bazo (2020) construct a stock-level media sentiment measurement. They demonstrate that positive investor sentiment predicts higher stock risk-adjusted returns in the very short term, though price reversals follow it. The result remains stable when they control for social media coverages.

2.1.3 Other factors

2.1.3.1 Culture

The impact of culture on economic phenomena and investments has not been discussed extensively in the literature, perhaps because culture is a very general concept and its relationship with finance is too ambiguous to allow the construction of testable hypotheses. Guiso et al. (2006) find that individuals from different races and religions vary in their beliefs about trust and preferences for education and politics. Consequently, different beliefs about trust are correlated with the probability of being an entrepreneur or self-employed. At the same time, different preferences for education and politics are associated with personal savings and the redistribution policies of governments.

Psychological studies report that people in collectivistic countries like China are more likely to display greater conformity than in non-collectivistic countries (Eagly, 1978; Bond and Smith, 1996). In reality, we also find that only investors in Asia, such as the Chinese DAMA and Japanese Mrs. Watanabe, are deemed to form a group as they show similar economic behaviour.[2] More recently, various studies suggest that Chinese DAMA tend to get together and mimic others' behaviour in their group (Li, 2017). Compared to the other groups, the Chinese DAMA has a specific social community, and they are more likely to gather together through their similar interests, such as square dancing. Also, Li (2017) claims that the Chinese DAMA have a higher propensity to be deceived since the emergence of social media.

According to Grinblatt and Keloharju (2001), Finnish investors are more likely to engage in stock trading among firms that use the investors' native language for communication and have CEOs with the same cultural context. Kumar et al. (2015) find that the name of fund managers can influence fund flows as well as the sensitivity to performance. Foreign-named financial managers receive 10% lower fund flows annually compared to financial managers with a local name. With respect to funds operated by these managers, investors show more sensitivity to poor performance. Another study by Kumar (2009) shows that, compared to investors living in Protestant countries, those living in Catholic counties have a higher propensity to buy and hold lottery-type stocks.

2.1.3.2 Social connections and peer effects

Individual investors may not be independent in decision-making when it comes to investment since they have social connections with others, such as their family members, friends, community neighbourhoods, and financial consultants. Li (2014) argues that investors with parents or children who invested in stocks for the first time in the preceding five years have a higher probability of participating in stock markets themselves in the following five years. An individual may be influenced by those nearby who already have similar investment experiences before making decisions to open an account or trade. Hong et al. (2004) posit a strong

[2] Both Chinese DAMA and Japanese Mrs.Watanabe refer to elderly females in a respectful way.

connection between social interaction and the likelihood of entering stock markets. Their study shows that individuals who actively socialize with neighbours or attend church, especially in cities with high stock market participation rates, are more likely to trade in the stock market.

Similar results are documented in Brown et al. (2008a), who report a causal relationship between individuals and their community's participation in the stock markets. Moreover, peer effects are detected in the probability of entering retirement plans by Duflo and Saez (2002), who find that saving decisions can be affected by others in the same department. Besides, individuals might learn financial knowledge or investment opportunities through socializing and thus engage in stock market trading (Guiso and Jappelli, 2005). Interestingly, although participation in the stock market increases with the returns experienced by neighbours, no evidence suggests that the undesirable investment outcomes of peers would affect market participation, meaning that individuals are unwilling to share negative experiences when socializing (Kaustia and Knüpfer, 2012).

2.1.3.3 Weather, calendar effects, and seasonal effects

The relationship between weather conditions and stock market returns has been widely explored since 1993. Saunders (1993) first investigates the correlation between weather and stock market performance. His study finds that stock market returns are significantly higher when sunny than on trading days with more clouds. However, this relation is found to be much weaker when more recent data is used. It is possible that the modern stock markets have become more efficient or that individual investors are more rational than before. Also, he argues that the sunshine effect can partially offset the Monday effect and enhance the Friday and January effects on stock returns. Hirshleifer and Shumway (2003) find that sunshine has a significant positive association with stock market performance and that positive stock returns are more likely to occur on sunny days. In contrast, weather conditions such as rain and snow are not relevant to stock returns after controlling for the sunshine effect. They suggest that although it is possible to earn abnormal returns by constructing a weather-based strategy by short-selling indices with cloud cover and longing indices with sunshine, the payoff depends on the stock market trading frequency and transaction costs.

Cao and Wei (2005) argue that psychological outcomes show that individuals' behaviours tend to be more aggressive at a low temperature, while their behaviours can be apathetic or aggressive when the temperature is relatively high. Overall, the evidence of their study indicates that temperature is negatively associated with stock market performance. Chang et al.

(2008) analyse the association between the weather in New York City and daily stock returns and trading patterns of NYSE stocks. The evidence suggests that lower stock returns accompany days with more clouds, yet this relationship is only statistically significant at the beginning of the trading day. Moreover, on days with more clouds, seller-initiated trades dominate the stock market at the beginning of the market open. Additionally, trading days with more clouds have greater volatility and less market depth, while the bid-ask spreads and turnover are not significantly associated with cloud coverage.

Schmittmann et al. (2015) investigate the effect of weather on stock market returns and trading behaviours by using the data of retail traders in the German stock market. They find that individual traders have a lower trading frequency and are more likely to purchase on good-weather days. In addition, the relation between weather and the tendency to purchase is much stronger for assets with higher risks. Similarly, by merging the survey data of institutional investors and cloud cover values, Goetzmann et al. (2015) find that institutional traders are significantly more optimistic on days with lower cloud cover. Investors are more likely to believe the stock market is undervalued when the cloud cover is relatively low.

Goetzmann and Zhu (2005) use the change in bid-ask spreads as a proxy for market liquidity and find that the association between weather and stock market returns is insignificant. However, they argue that market makers tend to be less risk-seeking on cloudy days since the bid-ask spreads become much wider during the cloud cover days. Loughran and Schultz (2004) argue that most of the studies in weather finance cannot link the location of investors to their local weather. To address this puzzle, they investigate the association between weather conditions and stock market performance by using the cloud cover in the cities where Nasdaq firms are located to represent the local investors’ mood. According to their empirical outcomes, traders invest heavily in the local firms listed on the Nasdaq. However, there is no evidence that cloud cover around a firm affects its market performance.

In addition to the weather effect, air quality also impacts the behaviour of individual investors. Levy and Yagil (2011) use the AQI (air quality index) to proxy air condition. The outcomes show that stock market returns are highly negatively associated with air pollution. Also, the relationship between air quality and stock market returns is weaker if the stock exchange is far from the polluted regions. More recently, Li and Peng (2016) use ten years of the stock market and AQI data to explore the relationship between air pollution and Chinese stock market performance. The empirical evidence shows that air pollution has a significantly negative impact on stock returns. This effect exists only after 2010, as air pollution attracted more public attention after this. Likewise, Zhang et al. (2017) analyse whether haze pollution in Beijing impacts the stock performance of Beijing-based listed firms. The findings demonstrate that haze pollution is highly negatively associated with the performance of stocks, while stock volatility increases with the level of haze pollution, even after controlling for Seasonal Affective Disorder (SAD) and other well-known stock market anomalies.

The seasonal effect is a systematic, calendar-related effect. Some examples include the Monday effect, the Friday effect, the holiday effect, and depression in winter due to reduced daylight hours. Using the Dow Jones Industrial Average as the market return, Lakonishok and Smidt (1988) find that the stock market performs better at the end of the month, in the second half of December, and on the last trading day before holidays (e.g., Christmas), while the stock market returns are lower on Mondays. Kamstra et al. (2003) argue that investors tend to be more depressed in the autumn and winter than in the spring and summer, and hence investors are less willing to undertake risks in the stock market. They find that the SAD effect is positively correlated with most of the stock market returns, and the magnitude of this effect depends on the latitude of each country. More recently, Kamstra et al. (2017) use mutual funds data and uncover that retail investors tend to redeem their investments in riskier mutual funds (equity funds) in the fall, while they reinvest in equity mutual funds in the spring.

Jacobsen and Marquering (2008) cast doubt on the relevance of weather-induced mood effects and claim that it is due to the data-driven consequence. Their study finds that SAD and temperatures are strongly correlated with Halloween factors. Besides, they find that 'Sell in May' is the main driving force of stock market returns, while the effect of SAD is the weakest. Indeed, the *Financial Times* first identified the May effect in 1964. However, after using stock market data from nineteen countries, Bouman and Jacobsen (2002) find that this phenomenon still exists, and investors have noticed it.

2.2 Behavioural biases of individual investors

This section of the literature review summarizes those behavioural biases that can harm individual investors' stock market performance.

2.2.1 Overconfidence, gambling, and sensation seeking

Overconfidence, one of the most compelling discoveries in psychology, can be defined as the propensity of individuals to overvalue the accuracy of their private information, financial literacy, or individual abilities (De Bondt and Thaler, 1994; Daniel et al., 1998; Daniel and Hirshleifer, 2015). Overconfident investors take it for granted that they can perform exceptionally well in trading and thus make a profit. The theoretical study of Daniel et al. (1998) points out that investors tend to exhibit self-attribution bias when they overestimate their private information, and the private information coincides with forthcoming public information. There will be a short-term momentum effect on the stock price in these circumstances, while we can observe a price reversal in the long run. Similarly, Gervais and Odean (2001) imply that overconfidence is highly correlated with self-attribution bias and is persistent in the stock market.

Odean (1999) investigates trading patterns of individual investors by using data from a discount brokerage for the period between 1987 and 1993. Overall, the results show that individual traders who invest extremely actively in stock markets lose money. One of the interpretations of frequent trading is overconfidence. According to the overconfidence hypothesis, retail traders believe that they have more private information than others or have better trading skills and cognitive abilities than the population average (Barber and Odean, 2013). Barber and Odean (2001) examine the relationship between overconfidence, trading frequency, and stock market performance. They argue that males tend to be more overconfident than females. Indeed, the results demonstrate that males, especially single males, trade more frequently than females, and their aggressive trading behaviour hurts the performance of their portfolios. They also find that males are more likely to hold stocks with higher market risks and smaller firm sizes. The evidence from German stock markets also supports the overconfidence assumption as traders who believe they know more than others display a higher transaction frequency. However, their performance is worse than other individual traders (Dorn and Huberman, 2005). Likewise, Kuo and Lin (2013) find that day traders tend to be overconfident, misinterpret private information, and consequently experience considerable losses in Taiwan's futures market.

Chen et al. (2007) use trading frequency as a proxy for overconfidence and show that individual Chinese investors are more overconfident than those in the US stock market. They attribute this to the lack of critical thinking in Chinese culture and education, which causes people to be more overconfident (Yates et al., 1989). In a more recent study, Forman and Horton (2019) suggest that the relative position size (RPS), a transaction value to total account size ratio, is a more representative measure of overconfidence. Their findings show that investors with a high RPS underperform those with a lower RPS since they cannot manage the timing of entrance and exit from the market. By contrast, as another proxy for overconfidence, more frequent trading is accompanied by better trade timing.

Another interpretation for the frequent trading of retail traders is that they trade for entertainment and exhibit sensation-seeking behaviours. Using traffic tickets as an example of sensation-seeking, evidence from Finnish stock markets proves that both sensation-seeking and overconfidence could impact trading activities (Grinblatt and Keloharju, 2009). Although sensation-seeking investors do not necessarily have to hold a portfolio with higher volatility and skewness, they can simultaneously hold a well-diversified portfolio and trade for entertainment. Kumar (2009) collects individual-level trading data and uses three stock-specific characteristics (price, volatility, and skewness) to define lottery-style stocks. To be more specific, securities with low price, high idiosyncratic volatility, and high idiosyncratic skewness are considered to be lottery-style stocks. Kumar's study finds that individual-specific characteristics determine the propensity to gamble. To be more specific, retail traders with a lower education level, lower income, and certain religious beliefs are more likely to gamble on the stock markets. Another study conducted by Chen et al. (2020) applies the search volume of keywords related to the lottery in Google as a proxy for investors' gambling sentiments. They point out that retail traders have a higher propensity to purchase lottery-type stocks when the gambling sentiment is high. Also, gambling sentiment is positively related to IPO stock returns.

2.2.2 Herding behaviour

The herding behaviour of investors has been extensively analysed over recent decades. Contemporary studies divide herding into 'rational' and 'irrational' categories in relation to 'intrinsic herding motivation' (Bikhchandani and Sharma, 2001). Devenow and Welch (1996) declare that rational herding can be explained by, (i) payoff externalities, (ii) reputation concerns, and (iii) information cascades. Considering the benefit of market liquidity, herding may be considered to be rational if its payoff is an increasing function of the number of customers pursuing it (Merli and Roger, 2013; Dow, 2004). Regarding reputation concerns, herding happens when institutional investors suppress their own private information sets and follow the action of others in order to avoid being punished because of differing insights (Scharfstein and Stein, 1990; Rajan, 1994; Wermers, 1999). Herding may also be a rational decision if it is induced by information cascades and where investors optimally and intentionally imitate others' actions instead of using the available information (Bikhchandani et al., 1992; Welch, 1992; Bikhchandani and Sharma, 2001; Hirshleifer and Teoh, 2003a; Lao and Singh, 2011). Chang et al. (2000) regard herding as irrational behaviour if investors ignore their information sets and indiscreetly imitate the decisions of others.

Herding behaviour can also be distinguished by whether investors intentionally mimic others' decisions (Bikhchandani and Sharma, 2001; Kremer and Nautz, 2013). Specifically, unintentional or spurious herding occurs if investors make a similar decision due to identical information, trading strategies, or educational backgrounds, while intentional herding refers to that purely induced by behavioural factors or investors having an intention to imitate the trading decision of other investors (Bikhchandani and Sharma, 2001; Goodfellow et al., 2009; Hsieh, 2013). Intentional herding may be considered rational if it is driven by information cascades or reputation concerns (Avery and Zemsky, 1998; Scharfstein and Stein, 1990).

Herding behaviour has also been witnessed in emerging stock markets. Choe et al. (1999), who use an LSV herding measurement, find that foreign investors in South Korea displayed a significant herding tendency, especially before the financial crisis. The herding behaviour in the South Korean stock market is also documented by Kim and Wei (2002), who report that foreign investors are more engaged in herding than domestic investors. Similarly, by using stock return dispersion as a proxy for aggregate market herding, Chang et al. (2000), in revealing that herding takes place in the Taiwan and South Korean stock markets, also report that security return dispersion drops when markets experience extreme conditions. More recent evidence from Chen et al. (2015) also supports the existence of herding in the Taiwan stock market. They conclude that herding by small individual investors destabilizes the stock market since a price reversal is detected following its occurrence. Similarly, Hsieh (2013) summarizes a negative feedback trading strategy of individual investors in the Taiwan stock market; she argues that individual investors show a higher propensity to engage in behavioural-driven herding than do institutional investors.

The literature on herding in the Chinese stock market is primarily focused on the scope of aggregate markets, rather than on different types of investors, due to the absence of a viable dataset. Herding in the Chinese stock market was first investigated by Demirer and Kutan (2006), however, they failed to find evidence of it in either the SSE or the SZSE. By contrast, evidence from Tan et al. (2008) suggests that herding does take place in the Chinese stock market and that it is more pronounced during the bull-market period. Their study also uncovers that the herding tendency of domestic investors in the A-share market is more likely to be influenced by trading volume and market volatility. Likewise, Lee et al. (2013) find a significant industry-level herding tendency in the Chinese stock market, and they also report that herding was more prevalent in some industries during the bull-market period. Conversely, although the herding behaviour in the Chinese stock market was detected by Lao and Singh (2011), their findings uncover more intensive herding during the market downswing. More recently, Li et al. (2017a) find that the magnitude of trading volume dispersion of individual investors is lower than that of institutional investors, hence, individual investors are more inclined to herd. They also find that herding by individual investors becomes more intensive in times of market stress.

2.2.3 Familiarity

Since Zajonc (1968) finds evidence that the attitudes of individuals towards things depend on how familiar they are with them, the “mere exposure effect” has prompted much discussion in academia. In the context of finance, the literature provides substantial findings on the familiarity preference of professional and individual investors, which might be explained by attention (Huang et al., 2016), ambiguity aversion (Baltzer et al., 2015), and information superiority (Coval and Moskowitz, 1999; Bernile et al., 2015). Coval and Moskowitz (1999) find that investment managers tend to buy stocks of firms close to their fund’s location. One explanation is that managers have an information advantage among local firms since the local stock in the portfolio typically has a small market capitalization, a relatively higher leverage ratio, and tends not to export products to foreign countries. As another manifestation of familiarity bias, Pool et al. (2012) show that fund managers, especially inexperienced ones and those who have lived a long time in their home states, overweight stocks in their home states. Their study also shows that the home-state bias has a more substantial impact on asset allocation than the impact of fund locations. Furthermore, there is no evidence to suggest that fund managers’ information advantage drives such a portfolio selection strategy because home-state stocks do not significantly outperform other stocks in their portfolios. Huberman (2001) suggests that the company’s shareholders are often clients, employees, or people who live in the region served by the company.

Regarding the preference for the familiarity of individual investors, it may indeed be a rational decision if it is induced by information. For example, Massa and Simonov (2006) argue that individual investors in the Finland stock market tend to buy stocks that they are familiar with in terms of geographic location and field of expertise. This preference for familiarity is a result of information-driven behaviour rather than a behavioural bias. Similar results are detected by Ivković and Weisbenner (2005), who state that local stocks held by individual investors outperform non-local stocks. More recently, Ben-David et al. (2019) show that although industry insiders do not have private information, they can gain excess payoffs when trading their own industry stocks by taking advantage of industry familiarity. However, preference for familiarity can also be a purely behaviourally driven bias when an individual does not have any information advantage but overweight assets familiar to them in some sense, such as local-name stocks (Ackert et al., 2005). Seasholes and Zhu (2010) report that individual investors' buy-and-hold portfolio of local stocks does not experience excess returns. Also, the transaction-based portfolios show that the local stocks that investors bought perform significantly worse than those they sold.

2.2.4 Disposition effect

The disposition effect refers to the tendency of investors to sell assets that earn profits and retain assets that lose value (Shefrin and Statman, 1985). In fact, the disposition effect can be interpreted by prospect theory (Kahneman and Tversky, 1979): (1) individuals estimate profits and losses by a reference point; (2) investors are more likely to be risk-seeking when they are in loss positions and to be risk-averse when they have already obtained profits. A variety of studies verify the existence of the disposition effect. Shefrin and Statman (1985) argue that the disposition effect also relates to the mental account, regret aversion, self-control, and tax motivation.

Weber and Camerer (1998) perform several experiments under different scenarios to examine the disposition effect. Under their experimental designs, subjects made choices (sell or buy) regarding six risky assets before each period. Two different methods are performed to calculate gains and losses (FIFO and LIFO). The evidence from their study suggests that subjects will repurchase losing assets if they assume the price of these assets will increase in the future. Finally, they also find that the disposition effect is generated from reluctance to sell rather than optimism related to keeping the losing assets, as subjects would not repurchase losers. Shapira and Venezia (2001) use detailed trading information from a large Israeli bank to analyse disposition effect, stock market performance, and other trading behaviours of individual investors and professionally institutional traders. The results suggest that the disposition effect is more persistent in individual investors.

In order to ascertain the motivation in trading stocks, Grinblatt and Keloharju (2001) employ a unique dataset from Finland, which contains transaction records of individual and institutional investors. Overall, their study demonstrates the existence of the disposition effect in retail traders. More specifically, after eliminating the influence of tax-loss selling, individual traders are unwilling to realize losses. In addition, compared with professional traders, both anchoring prices and past stock performance significantly impact the trading decisions of retail investors. Kaustia (2004) argues that the reference price is essential in the disposition effect and trading activities since both new maximum and minimum prices could impact the trading volume.

2.2.5 Mental accounting and narrow framing

Mental accounting refers to the system individuals use to document and summarize their daily affairs, which encompasses how people feel and process the results of events and how their decisions are made and assessed (Thaler, 1999). Barberis and Huang (2001) argue that an individual tends to engage in narrow framing when carrying out mental accounting, i.e., the profit or loss of a single stock can affect their subsequent decision-making. Choi et al. (2009a) find that when individuals make a new investment, they tend to ignore its correlation with the existing assets in the portfolio, which is consistent with the prediction of mental accounting that investors have a separate pre-determined account for each asset, rather than treating all assets as a whole portfolio. Also, the outcomes detected by the model of Barberis et al. (2006) suggest that an individual who is first-order risk-averse and under the context of narrow framing is unwilling to pursue a small and independently profitable gamble.

Indeed, mental accounting and narrow framing have made significant contributions to many behaviour anomalies, such as the disposition effect (Niehaus and Shrider, 2014), the puzzle of insufficient annuities (Brown et al., 2008b), consumption choice (Thaler, 1985; Thaler, 1990; Shafir and Thaler, 2006), and stock market participation (Barberis et al., 2006). Bailey et al. (2011) indicate that an agent tends to engage in narrow framing if he or she uses longer intervals when executing multiple transactions. Moreover, their empirical evidence shows that investors in the context of narrow framing are more likely to place a relatively small portion of their investment in mutual funds and index funds. At the same time, their portfolios underperform those who do not engage in narrow framing. Frydman et al. (2018) show that with the interaction of the disposition effect and mental accounting, investors would use the newly purchased asset to replace the mental account of the recently sold asset. Subsequently, the benchmark for gains and losses is updated as the sold asset cost rather than the newly purchased asset.

2.2.6 Representativeness and conservatism bias

Representativeness bias refers to the characteristic that people use small samples as an overall sample, while conservatism bias refers to the tendency to underweight new information relative to previous information. Barberis et al. (1998) attribute investor underreaction and overreaction to a psychological bias in mankind, that is, the conservatism and representativeness, in which investors react incorrectly to a cascade of news, such as earnings announcements. Ritter (2003) argues that these two behavioural biases often exist in opposition to each other. For example, representativeness bias causes investors to overreact and drive prices up too much after a succession of good public messages. By contrast, conservatism can lead to an inadequate response from investors after positive news, resulting in an increase in stock prices in the future (e.g., post earnings announcement drift).

Representativeness bias involves an over-reliance on stereotypes, which results in people forming probabilistic judgments that systematically violate Bayes' rule (Tversky and Kahneman, 1974). Additionally, investors may incorrectly attribute certain characteristics of a company as a sign of a good investment, and such misconceptions can induce cognitive errors (Lakonishok et al., 1994). Dhar and Kumar (2001) examine the price trends of stocks purchased by households in a discount brokerage firm over five years. The results of their study reveal that investors prefer to buy stocks that have experienced positive prior abnormal returns, which is consistent with the belief that past price trends represent the future. Wu et al. (2009) find some evidence of conservatism bias in investor responses to earnings per share in the medium-term horizon; however, their study provides little support for the misuse of the representativeness heuristic. On the contrary, Chen et al. (2007) collect trading data of individual investors in the Chinese stock market and find that investors show representativeness bias as they believe that past returns are an indicator of future returns.

CHAPTER THREE: GENDER AND HERDING

This study uses a unique dataset from a large anonymous brokerage firm to examine the herding behaviour of Chinese individual investors. The empirical evidence reveals that females are more inclined to follow the behaviour of ‘same-sex’ investors. Market conditions and stock characteristics affect females and males similarly in that individual investors herd more intensively in the bull market, on stocks with better liquidity and larger market capitalization. Females lose more than males when they trade intensively, especially during a bull-market period. Outcomes from individual-level herding measurements imply that the lower portfolio turnover of females is the main source of the gender differences in herding.

3.1 Introduction

Herding, which is deemed to be a type of correlative behaviour, occurs when individuals ignore public or private information they have obtained and mimic the behaviour of others (Avery and Zemsky, 1998; Hwang and Salmon, 2004). Contemporary studies analysing herding behaviour generally follows one of two paths – firstly, Christie and Huang's (1995) findings and the study of Chang et al. (2000) use the cross-sectional standard, and absolute deviations (CSSD and CSAD) to explain the aggregate herding behaviour of the stock market (Demirer and Kutan, 2006; Goodfellow et al., 2009), and secondly, Lakonishok et al.'s (1992) (henceforth LSV) method of investigating herding behaviour among specific investor groups (e.g. Nofsinger and Sias, 1999; Choe et al., 1999; Wermers, 1999; Barber et al., 2009; Choi, 2016).

Apart from these studies, Merli and Roger (2013) construct a new individual-level herding measurement, suggesting that, to some extent, investors' characteristics could have an impact on herding tendency. The results of their study show that, on average, females have a higher herding intensity than males, while the difference is not significant for most quarters. In spite of this, their study is silent about three empirical questions when investigating the gender difference in herding: Why the difference in herding between females and males does not persist over time, is that because of market conditions? What is the consequence of the higher herding tendency of females? What drives a higher herding tendency of females?

Although gender differences in investment behaviour have been widely explored,[3] however, what remains unclear is whether herding is more likely to be a female or male preference, and what is the mechanism and consequence behind gender differences in herding. In a psychological sense, females show a higher degree of conformity (Cooper, 1979; Eagly, 1978; Eagly and Carli, 1981).[4] Consequently, they are more likely to change their behaviour and follow the decisions of other female investors. Besides, females are thought to be less overconfident and have lower trading experience compared to male investors; accordingly, they are more likely to follow others' behaviour. Motivated by studies in psychology and behavioural finance, we investigate the herding behaviour of Chinese investors.

[3] For instance, studies document that females are more risk-averse compared to their male counterparts (Sundén and Surette, 1998; Barber and Odean, 2001; Croson and Gneezy, 2009). Meanwhile, Barber and Odean (2001) and Kumar (2009) show that male investors tend to be more overconfident and have a higher propensity to gamble in the stock market.

[4] Conformity is a form of social force or pressure that could lead to a switch of belief or behaviour (Crutchfield, 1955; Cialdini and Goldstein, 2004).

Four research questions are addressed in this study. First, we analyse whether the herding tendency of female investors is more intensive than that of males. Second, we examine whether the gender difference in herding is because females tend to crowd on the same side of a certain set of stocks whereas males crowd on the same side of another set of stocks. Third, this study investigates abnormal returns in relation to herding. Finally, to understand the mechanism behind herding, we investigate whether overconfidence or trading experience dominates the gender effect.

To answer these research questions, the trading data of individual investors from a large anonymous Chinese brokerage firm has been collected. This unique dataset has made it possible to retrieve daily stock holdings, transaction records, cash balances, and personal information relating to Chinese investors between January 2007 and July 2009. To ensure its validity, only active investors' data has been used.[5] Also, only A-share stocks, traded or held by individual investors, listed on the SSE and SZSE have been included. In total, the final dataset used contains the transaction records of more than 1.6 million individual investors from across the country.

The LSV method is used to construct a daily herding measurement for each stock from female and male investors' groups. Overall, the empirical results demonstrate a strong herding tendency of individual investors in the Chinese stock market. During the sample period, as well as in the bull-market and financial-crisis-market conditions, females show a somewhat higher level of herding intensity than males. Besides, we find, in both female and male groups, herding is more prevalent during the bull-market period. Furthermore, evidence obtained from a regression model suggested that both females and males crowd more intensively on stocks with larger capitalization and higher market liquidity.

We also find that both investor groups herd less intensively on the sell side of stocks with high volatility and low past returns, while stock returns and volatility only have a significant impact on the buy-side herding of females. Additionally, the magnitude of past returns is found to affect females and males differently, in that females are less likely to be attracted by stocks with extreme past returns. The above outcomes indicate that stock characteristics have a similar effect on the herding behaviour of female and male investors, but is more pronounced in the

[5] Investors who have at least one transaction record or hold one stock are regarded as active investors.

female groups, probably because females as a group tend to use similar risk management strategies.

The relation of stock returns and herding indicates that herding by individuals tends to be caused by behavioural factors, and also that females lose more, especially in a bull market, because of their intensive herding. Lastly, we construct an individual-level herding measurement by following the method of Merli and Roger (2013) to further explore the mechanism behind herding. The evidence reveals that females have a higher herding tendency after controlling for investors' characteristics, especially those who have a lower portfolio turnover.

The contributions of this work are as follows. Firstly, it focuses on the gender differences in herding. Though we adopt the individual-level herding measurement constructed by Merli and Roger (2013), this study differs from theirs in a number of ways. Particularly, the research questions in this study are distinct – we investigate the sources and consequences of gender differences in herding. As a result, we highlight the outcome that compared to males, females experience larger losses due to their higher herding tendency. Besides, our investigation demonstrates that portfolio turnover is the main source that drives gender differences in herding. Meanwhile, our comprehensive analyses use three different herding measurements and report consistent results that show females tend to herd more than males.

Furthermore, our study extends the literature on learning the herding behaviour in the Chinese stock market along two dimensions. Firstly, previous studies primarily focus on the aggregate market or industry level when investigating the existence of herding behaviour in the Chinese stock market (Demirer and Kutan, 2006; Tan et al., 2008; Lao and Singh, 2011; Lee et al., 2013). However, due to the restriction of the dataset, these works are unable to differentiate trades between individual and institutional investors, accordingly, they do not find direct evidence of herding for individual investors. Benefiting from a unique dataset with the transaction records, we find individual investors intensively herd in the Chinese stock market. Secondly, compared to earlier literature, this study is based on more completed data when highlighting the impact of market conditions on herding. Tan et al. (2008), for instance, only focus on 87 firms in the Chinese stock market, within which 44 firms and 43 firms are dual-listed A- and B-shares on the SSE and SZSE, respectively. Likewise, Lao and Singh (2011) analyse the difference in herding between downswing and upswing market conditions by using 300 top stocks listed in the SSE. Our paper complements current published works by using all

A-shares stocks listed in SSE and SZSE and rules out the selection bias on the testing of herding effect in different market conditions.

This chapter will continue as follows: Section 3.2 presents our hypotheses. Section 3.3 includes the methodology and describes the data. Section 3.4 compares the herding tendencies of female and male investors in different market conditions. Section 3.5 summarizes the relation between herding and stock characteristics. Section 3.6 presents the stock returns around herding dates, and Section 3.7 tries to pin down what drives gender differences in herding. Section 3.8 and Section 3.9 contain the results of the robustness check and present the study's conclusions.

3.2 Hypothesis development

Psychological studies suggest that females exhibit a higher degree of conformity than males (Cooper, 1979; Eagly, 1978; Eagly and Carli, 1981). Hence, females are more likely to change their beliefs or behaviours in order to fit into a particular group. Meanwhile, Bond and Smith (1996) argue that individuals who live in a collectivistic country, like China, are more likely to display a greater level of conformity than those who live in non-collectivistic countries. Consistent with this argument, Asian females, such as Chinese DAMA and Japanese Mrs. Watanabe, are regarded as investor groups that show similar economic behaviours. In a psychological sense, females show a higher degree of conformity. Consequently, they are more likely to change their behaviour and follow the decisions of other female investors. Besides, females are thought to be less overconfident and have lower trading experience compared to male investors; accordingly, they are more likely to follow others' behaviour. Motivated by studies in psychology and behavioural finance, therefore, we expect that:

H1: Females tend to herd more intensively than males in the stock markets.

The gender difference in herding may be caused by the tendency of females to crowd on the same side of a particular set of stocks whereas males on the same side of another group of stocks. Previous studies verify that the herding tendency could be influenced by market conditions and stocks' characteristics; however, their results have been mixed (Wermers, 1999; Shyu and Sun, 2010). For instance, contrary outcomes have been reported in the Chinese stock market regarding whether herding is more pronounced during the market's upswing or downswing (Tan et al., 2008; Lao and Singh, 2011; Lee et al., 2013). Given the confounding results in the literature, we develop a contradictory hypothesis:

H2a: Gender differences in herding can be driven by market conditions and stock characteristics.

H2b: Market conditions and stock characteristics are not driven forces of gender differences in herding.

Additionally, when a group of investors 'crowd' on the same side of a stock, its price appears to move either upwards or downwards. Hirshleifer et al. (1994) suggest that if herding is information-based, it should be possible to observe a price continuation. By contrast, if behavioural factors cause herding, then a price reversal should be detectable. For instance, after Chinese investors crowded to buy gold and bitcoins, price reversals followed; hence we assume that similar outcomes may be reflected in the stock market:

H3: Investors will lose money when they herd intensively in the stock market.

Indeed, females and males differ along certain dimensions, and these differences may drive their different herding behaviours. Goodfellow et al. (2009) also suggest that overconfident investors are less likely to follow others' behaviour in the stock market since they trust their own capabilities. Evidence from either the U.S. or the emerging stock markets suggests that, compared to female investors, males are more likely to be overconfident (Barber and Odean, 2001; Niederle and Vesterlund, 2007; Hsu and Shiu, 2010). Hence, it is possible that male investors are less likely to follow the behaviours of others on the stock market. Apart from the overconfidence theory, investors might learn from trading and trust their judgments afterward. Merli and Roger (2013) demonstrate that investors rely more on their information and herd less in the stock market after acquiring trading experience. Considering previous arguments about the impact of the trading experience and overconfidence on herding, this study uses an individual-level herding measurement to pin down what drives gender differences in herding:

H4a: Overconfidence is the main source that drives gender differences in herding.

H4b: Trading experience is the main source that drives gender differences in herding.

3.3 Data and methodology

3.3.1 Data source

We first collect the individual-level trading data from a large anonymous Chinese brokerage firm. The sample period is between 1st January 2007 and 31st July 2009. This unique dataset is superb for our study since during the sample period, the Chinese stock market experienced both a bull-market period and a financial-crisis period. More details of the dataset used in this thesis can be found in the introduction part. In order to investigate the herding behaviour of individual investors, we primarily focus on the transaction file.[6] Apart from this primary dataset, we also collect the data on stock characteristics (e.g., stock prices, returns, market value, and trading volume) from the *China Stock Market and Accounting Research* (*CSMAR*). To ensure the accuracy of *CSMAR* data, a cross-check is conducted with the stock data in the *RESSET Financial Research Database* (*RESSET/DB*), which is another professional platform for Chinese financial markets.

[Insert Table 3.1 about here]

The summaries of stock characteristics and customer information are reported in Table 3.1. The sample contains 1,604 A-share stocks traded between 1st January 2007 and 31st July 2009 in SSE and SZSE. Panel A presents the summary statistics of stocks in the sample. The average daily market capitalization is RMB 4,304 million, while the average daily stock price is RMB 13.18.[7] The average turnover is the average daily turnover ratio, calculated as the number of shares traded on a given day divided by the number of outstanding shares on the same day. The average volume is the mean value of daily trading value. Compared to the trading volume of the market, we find that, on average, the trading volume of investors in our dataset accounts for around 6.56% of the whole market's daily trading volume.

Panel B of Table 3.1 presents the characteristics of individual investors. The proportion of males (53.38%) in the sample is slightly higher than that of females.[8] Investors' age is calculated by the difference between their birthday and 31st July 2009. Trading experience is measured by the average trading year, based on the difference between the account's open date and the end of July 2009. It can be seen that, on average, male investors are more experienced

[6] To develop the individual-level herding measurement, we use both transaction file and stock holding file, then match holding and trading records to calculate investors' portfolio turnover. For more details, see Section 3.7.

[7] Panel A of Table 3.1 presents the market value of the largest market-capitalization stock, which belonged to the Bank of China on 6th July 2009 accounting for RMB 839,305 million. On that day, 171.325 billion non-tradable shares turned out to be tradable and the Bank of China became the largest market cap stock on the Chinese stock market.

[8] The sex ratio of our dataset is very similar 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 http://www.sse.com.cn/aboutus/publication/yearly/.

in the stock market. The trading frequency is the average number of transactions each investor made in a month, while the turnover ratio is the mean of monthly turnover, calculated based on the method of Barber and Odean (2001).[9] Again, we find that male investors traded more during the sample period than females.

3.3.2 Methodology

To analyse whether females or males are more inclined to follow the behaviour of others in same-sex groups, the LSV method is used to construct the herding measurement, which is calculated daily, thus:

$$LSV(i,j,t) = \left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right| - E\left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right| \tag{3.1}$$

$$p(i,t) = \frac{\sum_{j=1}^{n} B(i,j,t)}{\sum_{j=1}^{n} B(i,j,t)+\sum_{j=1}^{n} S(i,j,t)} \tag{3.2}$$

For each day t, we first separate individual investors into two groups based on their gender. Where $LSV(i,j,t)$ is used to measure the daily herding tendency for a given investor group i, on stock j, at day t. $B(i,j,t)$ is the number of individual investors in group i who are net buyers of stock j at day t, while $S(i,j,t)$ defines the net sellers (number of investors that have decreased the holding) in group i on stock j at day t. Also, $p(i,t)$ is the average proportion of net buyers in group i across all securities. The second term of Equation (3.1) is an adjustment factor that captures the proportion of net buyers in group i on stock j at day t under the null hypothesis of no herding. If individual investors make their investments separately and randomly, then the proportion of net buyers should follow the binomial distribution:

$$E\left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right|$$

$$= \sum_{k}^{n(i,j,t)} \binom{n(i,j,t)}{k} p(i,t)^{k}(1-p(i,t))^{n(i,j,t)-k}\left|\frac{k}{n(i,j,t)} - p(i,t)\right| \tag{3.3}$$

Where $n(i,j,t)$ is the total number of active investors in group i on stock j at day t. The adjustment factor is a declining function of the number of active investors, and it should not significantly differ from zero.

[9] For more details, see Section 3.7.

A higher herding tendency implies that a greater proportion of investors crowd on the same side of a stock during a trading day. However, the LSV measurement ignores the direction of trades (purchases or sells). Therefore, this study follows Wermers' (1999) methodology by constructing the buy-side and sell-side herding measurements, respectively. More specifically, if stocks traded by group i have a higher (lower) proportion of net buyers than the average stock traded by the same group on a given day, those stocks are classified as buy-side (sell-side) herding stocks:

$$Buy\ LSV(i,j,t) = LSV(i,j,t)|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} > p(i,t) \tag{3.4}$$

$$Sell\ LSV(i,j,t) = LSV(i,j,t)|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} < p(i,t) \tag{3.5}$$

Furthermore, in order to compare the herding tendency of females versus male investors, we use Kim and Wei's (2002) method, constructing a daily LSV herding measurement across all stocks for each investor group i on a given day t:

$$LSV(i,t) = \frac{1}{n}\sum_{j=1}^{n} LSV(i,j,t) \tag{3.6}$$

$$Buy\ LSV(i,t) = \frac{1}{n}\sum_{j=1}^{n} Buy\ LSV(i,j,t) \tag{3.7}$$

$$Sell\ LSV(i,t) = \frac{1}{n}\sum_{j=1}^{n} Sell\ LSV(i,j,t) \tag{3.8}$$

3.4 Gender differences in herding tendency

[Insert Figure 3.1 about here]

We first investigate whether female or male investors are more prone to herd in same-sex groups. Figure 3.1 reports the stock–day level distribution of herding tendency for female and male investors. Compared to the distribution of males, the distribution of female investors has a relatively higher probability concentrated on a large herding tendency, given the fact of a fatter right tail than that of males. Besides, the median value of herding measures for both female and male investors is very similar to the mean, thus we cannot conclude that the high herding tendency of individual investors in the Chinese stock market is caused by a minority of stocks.

[Insert Table 3.2 about here]

To compare the herding tendency of females and males, we follow the study of Kim and Wei (2002), by aggregating herding measures at the daily average level. Table 3.2 reports the summary statistics of daily average herding measurement during both the whole sample period and the two sub-sample periods. Table 3.2 also shows a comparison of average herding tendencies between females and males as well as two sub-periods. Panel A presents the descriptive statistics of herding measurement across the whole period. Panel B and Panel C shows the results for bull-market and financial-crisis periods, respectively. Panel D reports herding tendencies of two investor groups sorted by market conditions.

The results from Table 3.2 can be summarized as follows: first, there is a strong herding tendency for both females and males on a daily basis. This result is consistent with Hsieh's (2013) and Zhou and Lai's (2009) findings in the Taiwan and Chinese stock markets.[10] This result is also in line with previous studies in psychology, which suggests that people who live in collectivistic countries tend to display a high level of conformity. Second, in three different periods, the sell-side herding tendency of females and males is higher than the buy-side herding tendency, confirming Wermers' (1999), Zhou and Lai's (2009) and Hsieh's (2013) findings, which they thought could be explained by loss-aversion: individual investors are more reluctant to lose money than make profits.

Third, in all three sample periods, both the average herding tendency and the buy-side (sell-side) herding tendency of female investors are higher than for males. For instance, during the bull-market period, the average female herding tendency is 1.44% higher than that for males, suggesting that if 10,000 investors in each group traded stock on a given day, then there would be 144 more female investors trade on the same side than male investors. The higher herding tendency of female investors is consistent with their correlated trading behaviour in other financial markets. It is also consistent with the overconfidence hypothesis. Female investors tend to be less overconfident during our sample period since, on average, they have a lower trading frequency and portfolio turnover. Consequently, females appear to be more engaged in herding in the stock market.

Last but not least, previous researchers, such as Goodfellow et al. (2009), suggest that herding will be more pronounced during periods with market stress in the Polish stock market, whereas

[10] Hsieh (2013) adopts an adjusted LSV measurement, as developed by Zhou and Lai (2009). Specifically, she uses trading frequency rather than trading volume to derive the LSV herding measurement.

the results from studies in the Taiwan and Chinese stock market have been mixed (Chang et al., 2000; Lao and Singh, 2011; Hsieh, 2013). Given these contradictory results in different stock markets, this study also examines whether market conditions could affect both female and male investors' herding tendencies.

Panel D of Table 3.2 shows the herding tendencies of two investor groups sorted by market conditions. Compared with the financial-crisis period, the average herding tendency, the buy-side and sell-side herding tendencies of females are more profound during the bull-market period. A similarly correlated trading pattern can be found in the male investor group, in that both their average herding tendency and buy-side herding tendency are also higher during the bull-market period. Furthermore, the result shows an increase in average herding tendencies for both male and female investors, which is primarily noticeable on the buy side. These results reveal that during a bull market, individual investors tend to participate in buying by following the crowd. The higher herding tendency during the bull-market period may indicate that individual investors engage in behavioural-driven herding. However, this has to be verified by examining the relationship between herding and stock returns.

3.5 Herding and stock characteristics

Apart from market conditions, stock characteristics also have an impact on herding tendency. For instance, Shyu and Sun (2010), who report that institutional investors have a higher herding tendency on small-cap stocks, argue that the herding of these investors could be induced by information cascades, since lower market-cap stocks are mostly accompanied by a combination of poor information quality and more private information. Individual investors also tend to be attracted by extremely high trading volume stocks; consequently, they concentrate on the same side of stocks with better market liquidity (Barber and Odean, 2008; Hsieh, 2013). Moreover, Wermers (1999) reveals that the herding tendency could relate to the past performance of stocks, in that institutional investors are more prone to behave as momentum traders when they crowd on one side of the market. The volatility of stocks is also related to herding behaviour. Venezia et al. (2011) use Falkenstein's (1996) theory and insist that investors tend to exhibit herding behaviour on stocks with less risk. Likewise, Kremer and Nautz (2013) use the standard deviation of stocks as an independent variable of buy-side and sell-side herding tendency, respectively. They find that stock volatility has a different impact on buy-side and sell-side herding.

Consequent upon these findings, in this part of the study a panel data regression is used, firstly to analyse whether stock characteristics have an impact on the individual herding tendency, and secondly, to examine whether they affect the herding behaviour of female and male investors in different ways. We include both time and stock fixed effects and double-clustered standard errors.

[Insert Table 3.3 about here]

Table 3.3 reports the results of the regression model. LSV is the stock–day level herding tendency of females and males without distinguishing the direction of trades. *Buy LSV* and *Sell LSV* is the herding measurement on the buy side and sell side, respectively. *MarketCap* is calculated as the logarithm of the closing market value for stock i at day t. *Turnover* is measured by the trading volume at day t divided by the outstanding shares on the same day. *Return* is the lag return of stock i at day t-1.[11] Lastly, we add the *Std_250* as a proxy for stock risk, which is calculated as the standard deviation of the past 250 daily stock returns. Indeed, the results remain stable when using the standard deviation of the past 180 daily stock returns.

The outcomes from Specifications (1) – (6) show that the coefficient estimates on *MarketCap* and *Turnover* are both significantly positive for females and males, which means individual investors tend to crowd on the same side (either buy or sell) of stocks with higher market value and turnover. Stocks with higher turnover and market capitalization tend to have better information quality and market liquidity. Investors intensively crowd on those stocks, a tendency that could be driven by attention-grabbing bias, as documented in Barber and Odean's (2008) paper, which argues that individuals are more inclined towards securities with a particularly high trading volume.

The absolute value of one-day lag return influences males and females differently: the significantly negative coefficient on the absolute return at day t-1 for female investors indicates that they are less likely to crowd on stocks with extreme past one-day returns. The impact of returns on herding measures is more pronounced among the female group as well. In particular, we find that for both female and male investors, the sell-side herding tendency increases with past returns, while the buy-side herding tendency is a decreased function of past returns for the

[11] We also use cumulative abnormal returns from five days before to one day before the herding day as a proxy for the past performance; the results are consistent with the current ones. Given the fact that the Chinese stock market is highly liquid and herding measures themselves are on a daily basis, it is better to use one-day lag returns instead of five-day cumulative returns.

female group only. This shows that individual investors in the Chinese stock market, especially females, tend to crowd on the buy-side of stocks with lower past returns and the sell-side of those with higher past returns. This result is consistent with current evidence (Kaniel et al., 2008; Hsieh, 2013).

The coefficient estimates for the standard deviation of returns suggest that it is not a determinant of the herding tendency for both females and males. To investigate whether the volatility of returns influences buy-side and sell-side herding similarly, we also add the *Std_250* to Specifications (2) – (3), as well as Specifications (5) – (6). The evidence from Table 3.3 shows that the volatility of stock returns affects the sell-side herding tendency of females and males in a similar way, while it has a different impact on the buy-side herding of female and male investors. More specifically, both female and male investors herd less intensively on the sell side of stocks with high volatility, while only the volatility of stocks is significantly and positively correlated with the buying intensity of females. The different signs of the coefficient estimate on *Std_250* for the buy-side and sell-side herding measurements of female investors indicate that females as a group tend to use similar risk management strategies when trading in the stock market (Daníelsson, 2008).

3.6 Stock returns around herding

3.6.1 Cumulative abnormal returns and herding intensity

In this section, the relationship between herding tendency and stock returns will be investigated. When a group of investors crowds on the same side of a given stock, they could propel the stock price into a particular direction. Hirshleifer et al. (1994) argue that if herding behaviour is caused by fundamental information, then a price continuity should be observed. However, if herding behaviour occurs either for emotional or impulsive reasons, then price reversal is likely to happen.

In order to analyse the association between herding tendency and stock returns, we first construct buy- and sell-side portfolios, based on the stock-level LSV measurements. Thereafter, following Wermers' (1999) method, for each transaction day, the stock herding measurements are split into buy-side herding and sell-side herding groups. Subsequently, for each herding group, stocks are further classified into quintile portfolios based on the value of the herding measurements. Consequently, this method leads to the construction of ten portfolios, where portfolio B1 comprised stocks with the highest buy-side herding tendency, while portfolio S1 included stocks with the highest sell-side herding tendency. We use the method documented in Daniel et al. (1997) to adjust stock returns. Specifically, the abnormal return of each stock in buy-side (sell-side) quintile portfolios is adjusted by matching a value-weighted portfolio return of A-share stocks within the same size, book-to-market ratio, and momentum quintile at one day before the formation day.[12] Thereafter, for each buy-side (sell-side) portfolio, we calculated the equally weighted cumulative abnormal returns during the period, from five days before to twenty days after the formation day. This procedure is conducted separately for female and male groups.[13]

[Insert Table 3.4 about here]

Table 3.4 shows the benchmark adjusted cumulative abnormal returns concerned with investor herding. Standard errors are adjusted following Newey and West (1987) since the daily portfolio returns with overlapping days up to 20 days. Panel A (Panel B) of Table 3.4 reports the results for male (female) investors. In Panel C, the intense buying and intense selling portfolios of female investors are compared with those of male investors. From Panel A, we find that the cumulative abnormal returns of the portfolio B1 for the male group are significantly negative from the portfolio formation day to at least twenty days after it. Specifically, the cumulative abnormal returns one day after the portfolio formation date is -1.887%. This negative value enlarges to -3.928% twenty days after the portfolio formation date, and it is still significantly negative. Portfolios (B2–B5), which comprise stocks with comparatively lower buy-side herding tendencies, perform relatively better than the intense buying portfolio.

Contrarily, after male investors crowd on the sell side, the stocks they sell earn a significantly positive cumulative abnormal return from one day after the formation date to at least twenty days after it. In particular, this significantly positive cumulative abnormal return is more pronounced in portfolios with a higher sell tendency. The cumulative abnormal return of

[12] Stocks are first grouped into quintiles based on their market value one day before the formation day. Subsequently, for each size quintile, stocks are further sorted into quintiles based on their book-to-market-ratio. The book-to-market ratio is calculated by using the most closely available book value divided by market value and it is adjusted by the industry average book-to-market ratio. Lastly, stocks in size-BM portfolios are grouped into quintiles based on their prior-three-month returns. Overall, this procedure constructs 125 portfolios and the return of each stock is adjusted by a value-weighted portfolio return which contains stocks within the same size, book-to-market, and momentum quintiles.

[13] We also calculate the abnormal return for each portfolio as equally weighted portfolio returns minus the market index as well as a market-cap adjusted portfolio on the day they are constructed. The results are consistent with the benchmark adjusted CARs.

portfolio S1 on one day after the intense selling period is 2.446%, and it decreases to 1.529% (but still significant) until twenty days after. The evidence from the zero-investment portfolio tells a clear story: for males, the portfolio with the highest buy intensity underperforms the portfolio with the highest sell intensity by 4.333% one day after the intense herding period, which is a difference that rises to 5.458% twenty days after the portfolio formation date. Overall, males who herd intensively follow a negative feedback trading strategy: the stocks they purchase (B1) have a negative past return, while those they crowd to sell (S1) experience a positive past return.

Panel B of Table 3.4 shows the outcomes for females. Similar to the performance of the intense buying portfolio of males, these stocks that female investors intensively crowd to buy experience a significantly negative cumulative abnormal return until at least twenty days after its formation date. The cumulative abnormal return one day after the intense buying period is -2.092%, a loss that expands to -4.054% until twenty days later. On the contrary, after females crowd highly on the sell side (S1), those stocks they sell, on average, earn significantly positive cumulative abnormal returns from one day after the formation date to at least twenty days after it. Again, female investors lose money when they trade intensely, since their portfolio consists of stocks with the highest buy-side tendency (B1), underperforming the portfolio with the highest selling intensity (S1) by 5.174% one day after the formation date and this value increases to 6.045% twenty days after the portfolio formation date.

Barber et al. (2009) and Dorn et al. (2008) argue that retail investors could move the market, and it is possible that stocks with the highest buy tendency would experience positive returns and vice versa. However, different from the US stock market and other developed stock markets, small investors account for a huge proportion in the Chinese stock market. In consequence, those investors are hard to move the market even if they gather on the same side of a given stock.[14] Besides, small investors would find it is difficult to beat the market if institutional investors are on the opposite side. Similar results can be found in the study of

[14] In term of herding measurement, we use the number of individual investors, rather than the number of orders crowding on the same side as a proxy for the herding tendency of each investor group. Accordingly, the stock with the highest buy-side herding tendency only means that more investors crowded on the buy side of that stock, instead of more orders. Therefore, stock prices would drop if the number of shares sold by a small proportion of investors is more than shares bought by a majority of investors. For instance, if there were only 105 investors in the market, and 100 individual investors buy 500 shares each while 5 investors sell 20,000 shares each, then the stock is in the face of high sell pressure and the share price might decrease a lot, even though most of the investors are crowded on the buy side.

Chen et al. (2015), which verified that stocks that are highly crowded by small investors on the buy side experienced a significantly negative return on the portfolio formation day.

In Panel C, the intense buying (selling) portfolio, together with the zero-investment portfolio of females, are compared with those of males. From the first row of Panel C, we find the portfolio that female investors intensively crowd to buy underperforms the intense buying portfolio of males, and this return difference persists until twenty days after the portfolio formation date. By contrast, the stocks that females sell intensively (S1), outperform the intense selling portfolio of males twenty days after the formation day. The last row of Panel C reveals that the magnitudes of return differences between the intense buying portfolio and the intense selling portfolio for female investors are higher than those of male investors. This means that, to some extent, females lose more because of their intensive herding behaviour.

[Insert Figure 3.2 about here]

In Figure 3.2, we report the benchmark adjusted cumulative abnormal returns of Portfolio B1 and Portfolio S1 for female and male investors, from one day after the formation day to ninety days after the formation day. Figure 3.2 suggests that the intense buying portfolios (B1) for both females and males experience negative cumulative abnormal returns until at least 90 days, while the positive cumulative abnormal return of intense selling portfolios turns negative after around 50 days after herding. In other words, the intensively sell-side herding of females and males tends to be driven by behavioural factors since a price reversal can be detected after herding.

3.6.2 Stock returns around herding in different market conditions

Previous studies have shown that the herding tendency of individual investors could have been influenced by market conditions (Goodfellow et al., 2009; Lao and Singh, 2011; Lee et al., 2013). Table 3.2 of this study also verifies that the buy-side and sell-side herding tendencies of both females and males are higher during the bull-market period, suggesting that herding tendency is more likely to be driven by behavioural factors since it is more intensive during a volatile period (Hirshleifer et al., 1994; Shyu and Sun, 2010). Therefore, in this section, we investigate the stock returns around herding during the bull-market and financial-crisis periods. Using the procedure described in Section 3.6.1, we analyse whether the herding of individual investors continuously destabilizes the market during two sub-periods.

[Insert Table 3.5 about here]

Table 3.5 summarizes the cumulative abnormal returns around herding during two sub-periods. Panel A (Panel B) of this table reports the results for males (females). Panel C presents a comparison of females' and males' portfolio. The upper and lower parts of each panel show the results during the bull-market period and financial-crisis periods, respectively. The evidence from Panel A documents that males make a loss in the two sub-periods. During the bull-market period, the cumulative abnormal return one day after the intense buying period is -1.994% and this negative value persists for at least twenty days. By contrast, after male investors intensively crowd on the sell side (S1), the stocks they sell on average earn a significantly positive cumulative abnormal return twenty days after the intense selling period. In fact, similar results can be observed during the crisis period. Furthermore, the results from the zero-investment portfolio indicate that males lose more in the bull market. The portfolio with the highest buy-tendency stocks underperforms the intense selling portfolio by 6.664% twenty days after the portfolio formation date during the bullish period, while this loss decreases to 4.901% during the financial-crisis period. A similar pattern can be found in the portfolios of female investors. Panel B shows that females' portfolios experience more loss in the bull market. During this period, the portfolio with the highest buy intensity underperforms the intense selling portfolio by 7.407%, twenty days after intense trading.

Finally, in Panel C, we compare the intense buying and selling portfolios of female investors with those of males during the bull-market and financial-crisis periods. Three conclusions can be drawn from this panel. First, the portfolio female investors intensively crowd to buy underperforms that of males during both the bull-market and financial-crisis markets. Second, regarding the portfolio that females intensively sell, this contrarily outperforms the intense selling portfolio of males. Finally, during both sub-periods, females lose more than males; however, the magnitude is larger in the bull-market period. Overall, the evidence from Table 3.4 and Table 3.5 indicates that the herding of both females and males, especially the sell-side herding, destabilized the market.

3.7 Individual herding measurement

3.7.1 The robustness of gender differences in herding

The difference in the herding tendency between women and men could be driven by other confounding factors (e.g., age and investment experience). In order to verify whether female investors herd more after controlling for these factors, this study constructs an individual-level herding measurement and matches it with investors' characteristics including their gender, age, investment experience, turnover, and portfolio value. One drawback of using the LSV method is that to compare the herding tendency of females to males, it is necessary to separate them into gender categories at the beginning. However, this procedure may lead to selection bias. Therefore, Merli and Roger's (2013) procedure is followed in order to build an individual-level herding tendency for each investor. We first use the LSV method to compute the herding tendency for all individual investors in our sample, in other words, we do not separate investors into female and male groups in advance. Then, on each month t,[15] the signed LSV measurement equals to LSV measurement if the proportion of buyers of stock j is higher than the average proportion of buyers across all stocks, otherwise, it equals to a negative LSV measurement:[16]

$$SLSV(j,t) = \begin{cases} LSV(j,t) | \frac{B(j,t)}{B(j,t)+S(j,t)} > p(t) \\ -LSV(j,t) | \frac{B(j,t)}{B(j,t)+S(j,t)} < p(t) \end{cases} \tag{3.9}$$

Accordingly, for each transaction, there are six possible circumstances. For instance, if an investor purchases a buy-side herding stock, then she is on the herding side of that stock on a given month. By contrast, if an investor sells a buy-side herding stock, then she is on the anti-herding side of that stock. Subsequently, for an investor i who trades several times on a given month t, the individual-level herding tendency $IHM(i,t)$, will be given as follows:

$$IHM_{i,t} = \frac{\sum_{j=1}^{J} n_{i,j,t} P_{j,t} SLSV_{j,t}}{\sum_{j=1}^{J} |n_{i,j,t}| P_{j,t}} \tag{3.10}$$

$$IHM_t^{female} = \frac{1}{n} \sum_{i=1}^{n} IHM_{i,t} \, | i = female \tag{3.11}$$

$$IHM_t^{male} = \frac{1}{n} \sum_{i=1}^{n} IHM_{i,t} \, | i = male \tag{3.12}$$

Where $n_{i,j,t}$ is the number of shares of security j traded by investor i at month t. $P_{j,t}$ is the average share price of stock j from the beginning of month t to the end of month t. The

[15] To match investors' turnover ratio, we use the monthly herding tendency instead.

[16] Where $LSV(j,t)$ is the herding tendency for all individual investors of stock j at month t. $B(j,t)$ is the number of net buyers of stock j at month t, while $S(j,t)$ defines the net sellers of stock j at month t. $p(t)$ is the average proportion of net buyers across all securities.

individual-level herding measurement accounts for investors who actually trade a stock during a specific month and is adjusted by the transaction value of each trade. In particular, the positive value of the individual-level herding measurement suggests that the investor i is on the 'herding side' at month t, while the negative value means that she is on the 'anti-herding side'. To demonstrate the validity of the individual measure and compare it with LSV measures, this study first conducts a correlation test. Specifically, LSV measures are aggregated into a monthly horizon by using Equation (3.6), (3.7), and (3.8). The evidence from an unreported table shows that both Spearman and Person correlation tests report a positive and significant correlation between individual-level herding measures and monthly LSV measures.[17]

Thereafter, we divide the sample of investors into groups by *Age*Experience*Turnover* to compare the female and male investors in each group. Specifically, the age is investors' age at a given month. The trading experience is proxied by trading years, which is measured as the number of years since the account is opened until each month. The method of Barber and Odean (2001) is followed to construct the monthly portfolio turnover, by using the average value of the monthly sell turnover and the monthly buy turnover. To be more specific, the sell turnover is calculated as the market value of shares sold at the beginning of month t divided by the market value of the portfolio hold by that investor.[18] Similarly, the buy turnover is measured as the market value of shares bought scaled by the market value of the portfolio at the beginning of month $t+1$.[19] Both sell turnover and buy turnover are updated on the monthly basis.

[Insert Table 3.6 about here]

[17] In Merli and Roger's (2013) study, individual investors are divided into two equal groups based on the value of individual herding measurements (*ihm*). Additionally, for each investor group, they construct an LSV herding measurement. The comparison of LSV herding measures between high and low *ihm* groups shows that investors in the high *ihm* group also have a higher LSV measure than their counterparts.

[18] For a given month, the first thing is to identify the A-share stocks an individual investor holds at the month's beginning. The 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 the month t divided by the whole market value of an individual's portfolio. S_{it} is the total amount of shares in stock i sold during month t, while N_{it} is the number of shares of stock i held at the beginning of month t.

[19] To obtain the monthly buy turnover, these stocks purchased during month t are matched and the 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 amount of shares in security i purchased in month t, while $\rho_{i,t+1}$ and $N_{i,t+1}$ are the same as previously. 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, tax-motivated selling can be ignored.

We sorted investors by their age, trading experience, and monthly turnover ratio separately. For each month, investors are divided into two equal groups based on their age, investment experience, and turnover, respectively. Consequently, we have 8 combinations and a robust comparison between female and male investors can be used within each group. Table 3.6 shows the outcomes of individual herding tendencies between females and males within the same *Age*Experience*Turnover* group. The results are consistent with our findings in Table 3.2 since female investors herd significantly more than males in all combinations. In particular, we find that gender differences in herding are more pronounced in high experience groups after considering the effect of confounding factors. In other words, other factors also have an impact on the herding difference between two genders, even if females have obtained experience from trading.

Apart from the investment experience, turnover also plays a crucial role in the gender difference in herding. The difference of individual-level herding measures between female and male investors is nearly doubled in the two *Low Experience*Low Turnover* combinations, compared with that in the *Low Experience*High Turnover* group. However, to examine to what extent the overconfidence theory and trading experience can interpret the higher herding intensity of females, comparisons of the overconfidence level and trading experience are necessary.

3.7.2 The mechanism behind herding

To further explore the mechanism behind herding, this study uses a panel regression to analyse the relationship between herding and personal characteristics. According to the summary statistics from Table 3.1, either the monthly trading frequency or the portfolio turnover of female investors are lower than that of males on average. Compared with U.S. investors, Chinese individual investors seemingly have a higher turnover: the monthly turnover is 73% for males and 68% for females.[20] Chen et al. (2007) argue that as the emerging stock market lacks alternative investment vehicles, Chinese individual investors exhibit more active self-managing behaviour. As for another measurement of trading frequency, on average male investors exercise 17.36 trades per month, while females trade 16.44 times. This result is slightly higher than Feng and Seasholes' finding (2003), in which on average Chinese individual investors trade 6.1 times (2.9 purchase trades and 3.2 sell trades) per month between

[20] Barber and Odean (2001) report that both male and female individual investors in the US have annual turnovers lower than 1. Similarly, Grinblatt and Keloharju (2009) show the annual turnover for their US sample is 22.8%.

1999 and 2000. The relatively higher trading frequency in the current data perhaps relates to the emergence of online trading (Barber and Odean, 2002; Choi et al., 2002; Zhang and Zhang, 2015).

[Insert Table 3.7 about here]

To obtain a deeper insight into the difference in turnover and experience between females and males, for each month investors are grouped into two equal parts based on their age and investment experience, respectively. Thereafter, four combinations are generated to compare the overconfidence level between females and males. By using the same procedure, we create four comparisons of trading experience between the two genders. Table 3.7 Panel A presents the results of turnover comparisons after controlling investors' age and trading experience, while Table 3.7 Panel B reports the results of experience comparisons.

Overall, the portfolio turnover of females is lower than that of males for all combinations. Specifically, the portfolio turnover of younger females with more trading experience is 6.13% lower monthly, while the portfolio turnover of females with more experience and allocated in the older group is 5.90% lower than their male counterparts. If using the turnover as a proxy for overconfidence (see Barber and Odean, 2001), then our results indicate that females are less overconfident than their male counterparts for all circumstances. Similarly, Panel B implies that, on average, females opened their stock account later than male investors. This result is more pronounced in the comparison of the higher age group, regardless of investors' portfolio turnover.

[Insert Table 3.8 about here]

The evidence from Table 3.6 and Table 3.7 is in line with both overconfidence theory and the findings in Merli and Roger (2013), that is, females engage in herding either because they are lacking in trading experience, or because they are less overconfident. To investigate the main channel of the gender effect on herding, we use a panel data regression that includes time fixed effects and double-clustered standard errors at the individual and time level. Table 3.8 shows the outcomes of the regression model. The dependent variable *ihm* is the monthly individual herding measurement. *Age*, *Experience* and *Turnover* have been defined in Section 3.7.1. Apart from the age, experience, and turnover channels, the account value of each investor may also affect herding behaviour. In fact, Merli and Roger (2013) have explored whether the wealth allocated in the stock market may have an impact on the herding behaviour of individual investors. Although, the results in their study are mixed over different quarters, the differences in individual herding measurements between different wealth groups are most significant. Besides, Chen et al. (2015) point out that wealthier investors are more informed than the small ones, and that the correlated trading of them can positively predict future returns. To control for the wealth effect on wealth, we add the monthly *portfolio value* of individual investors as a proxy for the wealth allocated in the stock market for all regressions.

Both independent and dependent variables are standardized in our four regressions. We include a dummy variable *Female* in Specifications (1) – (4), which equals to 1 if an investor is a female, otherwise equals to 0. To analyse whether overconfidence or trading experience dominates the gender effect on herding, we add the *Female*Low Turnover* and *Female*Low Experience* dummy variables in Specification (2) and (3), respectively.[21] The dummy variable *Female*Low Turnover*Low Experience* is included in Specification (4), which equals to 1 if an investor is a female and allocated in the low turnover and low experience groups, otherwise equals to 0.

The results of Specification (1) confirm our previous findings: females exhibit a higher herding tendency after considering investors' characteristics. In particular, the significantly negative coefficients on *Turnover* and *Experience* reveal that investors with higher portfolio turnover (or more overconfidence) and more trading experience herd less in the stock market. A one-standard deviation increases in the portfolio turnover of an investor is accompanied by a 0.20% decline in herding tendency if other variables remain the same.[22] In addition, we detect a negative correlation between portfolio value and individual herding measures from Specifications (1) – (4). Three channels may induce a lower herding intensity of wealthier investors. Firstly, Merli and Roger (2013) suggest that wealthier investors are more sophisticated (they use trading frequency as a proxy for the level of sophistication) and have higher trading experience; accordingly, those investors are less likely to herd. Secondly, Chen et al. (2015) show that the trading behaviour of large investors is similar to that of institutional investors, who are more likely to act as the competitors of individuals; lastly. Lastly, Li et al.

[21] *Female* Low Turnover* equals to 1 if an investor is a female in the low turnover group, otherwise equals to 0. *Female* Low Experience* equals to 1 if an investor is a female in the low experience group, otherwise equals to 0. Turnover and experience groups are defined in the same way as in Section 3.7.1.

[22] The mean and the standard deviation of ihm is 1.95 and 6.85%, respectively.

(2017b) find that wealthier investors in the Chinese stock market have an information advantage; as a result, they have less incentive to follow the crowds.

In Specification (2) and Specification (3), we add an interaction term to examine whether portfolio turnover and trading experience is one of the channels behind the higher herding intensity of females. The positive coefficient of *Female* Low Turnover* in Specification (2) suggests that female investors with lower portfolio turnover herd significantly more intensively than those who have a higher turnover. More interestingly, the coefficient estimation on *Female* turns out to be insignificant, indicating that females in the high turnover group do not significantly herd more than their male counterparts after considering confounding factors. In other words, when females come to be overconfident, they do not exhibit a higher herding tendency than males.

On the contrary, from Specification (3) we find that females with less experience do not show a higher herding tendency than females with more experience. The significantly positive coefficient estimation on the female dummy in Specification (3) implies that other factors may play a crucial role in herding except for experience since females in the high experience group also herd more than their male counterparts. Meanwhile, in Specification (4), the negative (but not significant) coefficient estimate on *Female* Low Turnover*Low Experience* indicates that the inexperienced females in the low turnover group do not herd more intensively than experienced females in the similar turnover group. Combining the outcomes from these regression models, we could conclude that both turnover and trading experience have an impact on individual herding behaviour. However, it is overconfidence, rather than the herding experience, that drives the gender differences in herding.

3.8 Robustness check

To verify the robustness of our results, following Wermers' (1999) procedure, we also use the buy-sell imbalance as a proxy for the correlated trading behaviour of individual investors. One drawback of the LSV measurement is that it ignores the trading volume of each transaction. For instance, if ten individual investors buy 200 shares each and two investors sell 1000 shares each. One could detect that the buy-side herding tendency of herding is defined as the proportion of buyers. However, herding does not exist if it is calculated as the transaction value. Therefore, we use the buy-sell imbalance to analyse whether females tend to have a higher correlated-trading tendency than males. Also, the abnormal stock returns around correlated trading are used to examine whether individual investors lose money. For each stock, the buy-sell imbalance is updated daily; hence, on each day, the buy-sell imbalance for each investor group is computed as the transaction value bought, minus the transaction value sold, divided by the total transaction value for that stock:

$$IMB_{i,j,t} = \frac{Buy_{i,j,t} - Sell_{i,j,t}}{Buy_{i,j,t} + Sell_{i,j,t}} \tag{3.13}$$

Where $Buy_{i,j,t}$ is the transaction value of buy trades exercised by investor group i on stock j at day t, while $Sell_{i,j,t}$ is the transaction value of sell trades made by investor group i on stock j at day t. To investigate the relation between stock returns and correlated trading, within each investor category i, we first construct quintile buying portfolios and quintile selling portfolios at day t based on the value of the buy-sell imbalance measurement. Again, stock returns are adjusted by using the same procedure documented in Section 3.6. Each portfolio is then calculated to obtain the benchmark adjusted cumulative abnormal returns during the period, from five days before to twenty days after their formation day:

$$Buy_{side}IMB_{i,j,t} = IMB_{i,j,t} | IMB_{i,j,t} > 0 \tag{3.14}$$

$$Sell_{side}IMB_{i,j,t} = -IMB_{i,j,t} | IMB_{i,j,t} < 0 \tag{3.15}$$

To compare the buy-sell imbalance between females and males, we calculate the average buy-sell imbalance for investors in group i, on day t:

$$IMB(i,t) = \frac{1}{n} \sum_{j=1}^{n} |IMB(i,j,t)| \tag{3.16}$$

$$Buy_{side}IMB(i,t) = \frac{1}{n} \sum_{j=1}^{n} Buy_{side}IMB(i,j,t) \tag{3.17}$$

$$Sell_{side}IMB(i,t) = \frac{1}{n} \sum_{j=1}^{n} |Sell_{side}IMB(i,j,t)| \tag{3.18}$$

[Insert Table 3.9 about here]

Panel A of Table 3.9 presents the summary statistics of the buy-sell imbalance sorted by gender. In general, the result of the buy-sell imbalance is consistent with the LSV measurement. All three correlated-trading tendencies of female investors are higher than those of males. Indeed, we also employ Spearman correlation tests to analyse the cross-correlation between LSV herding measures and buy-sell imbalance. The evidence from the unreported table shows that for both female and male investors, the buy-side (sell-side) herding measure is positively related to the buy-side (sell-side) IMB. Panel B (Panel C) of Table 3.9 shows the outcomes for males (females). In Panel D, we compare the buying and selling portfolios of female investors with those of male ones.

Although the intense buying portfolios of females and males perform better after taking trading volume into account, however, the intense buying portfolios of females and males still significantly underperform their intense selling portfolios, at least until twenty days after their portfolio formation date. Again, Panel D shows that female investors lose more than males, with the magnitude of return differences between the intense buying portfolio and the intense selling portfolio for females being higher than for males.

Since the impact of herding measures on stock returns is relatively more remarkable than that of the buy-sell imbalance, we employ a dependent double sort of herding measures and buy-sell imbalance to analyse whether the marginal effect of herding measures exists on the stock returns besides that of the buy-sell imbalance.[23] The outcomes from the dependent double sort suggest that the marginal effect of herding measures causes more losses for both females and males and is more pronounced in the group with the highest buy-sell imbalance. We also find that the marginal contribution of herding measures has a more considerable impact on female investors than males. Overall, although the magnitude of return differences between the intense buying portfolio and the intense sell portfolio dropped after using the number of orders to measure herding tendency, these results are consistent with our previous findings, as shown in Table 3.4.

3.9 Conclusion

This study has analysed the herding behaviour of individual investors in the Chinese stock market by using a unique dataset that includes investors' trading records during the period from 1st January 2007 to 31st July 2009. To investigate whether females or males are more inclined to follow the behaviour of their same-sex investors, the LSV method is used to ascertain the

[23] We first use LSV measures to identify buy-side and sell-side stocks. Accordingly, for each investor group, buy-side (sell-side) stocks are divided into quintiles based on the value of the buy-sell imbalance. Subsequently, for each buy-sell imbalance quintile, stocks are further sorted into five groups based on the herding measures. Thereafter, buy-side stocks in group i are matched with sell-side stocks in group i. Consequently, we create ten equally weighted portfolios for stocks within the same buy-sell imbalance quintile by using this procedure (five buy-side IMB portfolios and five sell-side IMB stocks). The zero-investment portfolio for each buy-sell imbalance quintile is constructed by holding stocks with the highest buy-side tendency (herding measures) and shorting stocks with the highest sell-side herding intensity. In other words, the stratagem of Portfolio 5 is holding stocks with the highest buy-side LSV measures in the highest buying IMB group and shorting stocks with the highest sell-side LSV measures in the highest selling IMB group.

daily herding tendency. The strong herding tendency of both females and males in the Chinese stock market is verified. In particular, females exhibit a somewhat higher degree of herding than males during our sample period. Similar outcomes are observed during bull-market and financial-crisis sub-periods. These findings have been shown to be robust to an individual-level herding measurement.

The panel data regression is adopted to identify whether females and males crowd on a similar set of stocks. If herding behaviour is shown to be driven by either information cascades or information asymmetry, intensively herding around stocks with lower market capitalization and weaker liquidity would be more likely to be observed. However, we find both females and males crowd more intensively on stocks with higher market value and better market liquidity. Also, both female and male investors herd to sell stocks which have higher past returns and lower volatility, while only females significantly herd more on the buy side of stocks with lower past returns and high volatility. This result indicates that the herding behaviour of investors, especially females, might be induced by attention-grabbing and individuals engaging in negative feedback trading. Besides, female investors are less inclined than males to crowd on the same side of stocks with extreme past returns.

Furthermore, either similar information sets, or behavioural factors could lead investors to crowd on the same side of stocks. Therefore, in this study, we also investigate the relationship between stock returns and herding behaviour. The results demonstrate that the sell-side herding of investors tends to destabilize the market. Also, stocks that female and male investors intensively crowd to buy experience a negative cumulative abnormal return immediately after the intensive purchases, while stocks that female and male investors crowd on the sell side earn a significantly positive cumulative abnormal return for at least twenty days. Meanwhile, the more intensively investors of both genders herd, the more money they lose. However, it is found that females lose more than males because of their more intensive herding behaviour. Such outcomes are ascertained by using the buy-sell imbalance as a proxy for correlated trading behaviour.[24]

[24] One thing we have to mention is that the underperformance of stocks bought compared to stocks sold only indicates that portfolio performance is better when such trades are not made. In other words, female investors may perform better if they do not herd intensively, but it does not conclude that the performance of females should be worse than that of males. In an unreported table, we use the method documented in Barber and Odean (2001) to construct monthly own-benchmark abnormal net (gross) return for each investor. The evidence shows that female investors have a lower portfolio turnover after controlling personal characteristics, and their own-benchmark abnormal net (gross) returns are significantly higher than males. Besides, in another unreported table, we develop

Finally, to be able to recognize the mechanism behind herding behaviour, we develop an individual-level herding measurement and match it with investors' characteristics. The evidence from regression models demonstrates that portfolio turnover, trading experience, and portfolio value is a decreasing function of individual-level herding measures, while the herding tendency increases with investors' age. Besides, female investors, especially those with lower portfolio turnover, significantly herd more in the stock market. The herding difference between genders disappears when females come to be overconfident in the stock market. By contrast, females who have less trading experience do not exhibit a higher herding tendency than their female counterparts. However, females herd more than males, even if they obtain experiences in the stock market. Combining these findings, we conclude that female investors herd more intensively than males, and their lower portfolio turnover drives the gender differences in herding.

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transaction-based calendar-time portfolios of stock bought and sold for investors in four groups by double sorting the individual-level herding measures and the portfolio turnover. Thereafter, the zero-investment portfolio for each group is constructed by holding stocks on the buy side and shorting stocks on the sell side. We then compare the average monthly returns of four zero-investment portfolios and the results suggest that herding has a greater negative impact on the trading than the effect of overconfidence. Overall, these two unreported tables eliminate the possible contradiction between our study and Barber and Odean (2001).

Tables of results

Table 3.1 Summary statistics

This table provides a summary of stocks and individual investors. The dataset chosen for this study is collected from a large anonymous Chinese brokerage firm containing more than 2 million individual investor accounts. After the 'clean-up' process (described in Panel B), the remaining dataset amount to 1,612,324 individual investors. The sample includes 1,604 A-share stocks traded between 1st January 2007 and 31st July 2009. Panel A comprises the summary statistics of stocks shown as averages across the period, (i) *Average Market Cap* ─ the daily market value, (ii) *Average price* ─ the daily closing stock price, (iii) *Average turnover* ─ the daily turnover calculated as the number of shares traded over the number of outstanding shares, and (iv) *Average volume* – the daily trading value. Panel B shows the characteristics of individual investors in the sample. To ensure the study's dataset compliance, the following accounts are deleted, those (i) that only hold security investment funds, index funds or B-share stocks, (ii) where ages and gender are not recorded, (iii) where stock holdings or balances showed negative values, (iv) where investors had not traded at least once during the sample period. Investors' age is calculated based on their birthday and the end of the sample period. The trading experience is measured as the average trading year, based on the difference between the account opening date and the 31st July 2009. Average trading frequency is the average number of transactions investors made over the sample period. Turnover is the average value of the monthly buy and sell turnover ratio.

	Average market cap (In million CNY)	Average price (In CNY)	Average turnover (In percent)	Average volume (In million CNY)
Panel A. Descriptive statistics of stocks in the sample				
Mean	4,304	13.18	3.847	112.86
Median	1,610	9.61	2.780	47.88
SD	12,657	12.38	3.724	262.82
Min	61	1.07	0.014	0.001
Max	839,305	294.17	93.26	68,028.08
	Female investors		**Male investors**	
Panel B. Descriptive statistics of female and male investors				
Number (percent)	751,674 (46.62%)		860,650 (53.38%)	
Age	39.33		38.11	
Trading experience (in Year)	4.82		4.91	
Trading frequency	16.44		17.36	
Turnover	0.68		0.73	

Table 3.2 Herding behaviour under different market conditions

This table shows the comparison of herding tendencies between females and males in different market conditions. The sample period is from 1st January 2007 and 31st July 2009. Only those who held A-share stocks at a large brokerage firm, and whose age and gender can be identified, are recorded. Herding behaviour in each group is measured on the daily average level by using the methodology of Lakonishok et al. (1992). Panel A represents the summary statistics of herding tendency in the overall sample period. Panel B shows the comparison in the bull-market condition during the sub-period between 1st January 2007 and 16th October 2007, when the Chinese stock market hit its highest point in the 21st century. Panel C summarizes the statistics of herding tendencies during the financial-crisis period between 17th October 2007 and 28th October 2008 when the market index dropped from 6,124 points to 1,664 points. Panel D reports the comparison of herding tendencies for female and male investors in two sub-periods. The t-values are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

	Female (1)	Male (2)	Diff (1)-(2)
Panel A. Overall period (2007/01/01–2009/07/31)			
LSV	0.0486 (0.0105)	0.0381 (0.0065)	0.0106*** (21.51)
Buy LSV	0.0433 (0.0132)	0.0336 (0.0090)	0.0097*** (15.20)
Sell LSV	0.0530 (0.0141)	0.0412 (0.0090)	0.0118*** (17.75)
Panel B. Sub-period 1 (2007/01/01–2007/10/16)			
LSV	0.0539 (0.0090)	0.0395 (0.0059)	0.0144*** (18.34)
Buy LSV	0.0488 (0.0103)	0.0355 (0.0077)	0.0133*** (14.23)
Sell LSV	0.0587 (0.0124)	0.0429 (0.0081)	0.0158*** (14.63)
Panel C. Sub-period 2 (2007/10/17–2008/10/28)			
LSV	0.0444 (0.0100)	0.0371 (0.0070)	0.0073*** (9.54)
Buy LSV	0.0362 (0.0114)	0.0303 (0.0088)	0.0059*** (6.47)
Sell LSV	0.0509 (0.0157)	0.0416 (0.0107)	0.0092*** (7.75)
Panel D. Herding differences between two sub-periods			
Diff = LSV Sub-period 1 – Sub-period 2	0.0095*** (10.35)	0.0025*** (3.96)	
Diff = Buy LSV Sub-period 1 – Sub-period 2	0.0126*** (11.95)	0.0052*** (6.43)	
Diff = Sell LSV Sub-period 1 – Sub-period 2	0.0078*** (5.64)	0.0012 (1.31)	

Table 3.3 Herding and stock characteristics

This table shows the results of a fixed-effects panel regression. The sample period of this dataset is from 1st January 2007 to 31st July 2009. We only consider investors who hold A-share stocks at a large brokerage firm and whose gender and age can be identified. The dependent variable, herding tendency for each stock is calculated by using Lakonishok et al.'s (1992) method. The following definitions pertain: (i) *Marketcap* – the market value for each stock transaction day, (ii) *Turnover* – the number of shares traded over the number of outstanding shares, (iii) *Return* – the one-day lag return of stocks, (iv) *Std_250* – the standard deviation of stock returns in the past 250 transaction days. We include both time and stock fixed effects and double-clustered standard errors. The t-values are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

	Male investors			Female investors		
	Specification (1)	Specification (2)	Specification (3)	Specification (4)	Specification (5)	Specification (6)
	LSV	*Buy LSV*	*Sell LSV*	*LSV*	*Buy LSV*	*Sell LSV*
Marketcap	0.0122***	0.0119***	0.0119***	0.0184***	0.0178***	0.0186***
	(18.52)	(13.53)	(13.83)	(25.49)	(19.62)	(18.45)
Turnover	0.3154***	0.3476***	0.2819***	0.4193***	0.3060***	0.4883***
	(38.68)	(30.33)	(28.23)	(39.61)	(24.33)	(37.18)
| *Return* |	-0.0000			-0.0225***		
	(-0.00)			(-3.21)		
Return		-0.0070	0.0153**		-0.0365***	0.0204***
		(-1.16)	(2.48)		(-3.26)	(3.33)
Std_250	-0.0026	0.0002	-0.0068*	-0.0036	0.0075***	-0.0210***
	(-0.82)	(0.05)	(-1.70)	(-1.46)	(2.87)	(-3.98)
R^2	0.0618	0.0869	0.0631	0.0715	0.0863	0.0822
Stock fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N of observations	896,578	422,109	474,463	895,501	449,354	446,140

Table 3.4 Benchmark adjusted CARs before and after investors' herding

This table shows the benchmark adjusted cumulative abnormal returns (CARs) for the portfolios of stocks held sorted by herding tendencies of each investor group. The outcomes of male (female) investors are presented in Panel A (Panel B). Panel C presents a comparison of females' and males' portfolios. The sample period is from 1st January 2007 to 31st July 2009. Only individuals who held A-share stocks at a large brokerage firm, and whose age and gender can be identified, are included. The portfolios are constructed by using daily herding measurements. Stocks are grouped into buying (selling) quintiles based on the magnitude of buy-side (sell-side) herding tendency. Portfolio B1 includes stocks that experienced the highest buy-side pressure, and portfolio S1 includes stocks with the highest sell intensity. Equal-weighted portfolios are constructed on the formation day (herding day), and benchmark adjusted abnormal returns are aggregated from 5 days before and 20 days after their formation day. The t-statistics reported in parentheses are based on Newey-West standard errors. ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

Portfolios	T-5	T-3	Formation day	T+1	T+2	T+3	T+5	T+10	T+15	T+20
Panel A. Average male investors herding – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)										
Portfolio B1	-0.582***	-0.336***	-1.459***	-1.887***	-2.094***	-2.262***	-2.522***	-3.066***	-3.526***	-3.928***
(Highest buy tendency)	(-7.86)	(-6.02)	(-71.98)	(-65.80)	(-57.65)	(-51.22)	(-41.90)	(-34.09)	(-27.72)	(-24.03)
Portfolio B2	-0.273***	-0.121***	-1.089***	-1.370***	-1.481***	-1.622***	-1.816***	-2.312***	-2.742***	-3.143***
	(-4.50)	(-2.96)	(-65.61)	(-50.76)	(-41.42)	(-35.30)	(-30.69)	(-24.39)	(-20.34)	(-18.14)
Portfolio B3	-0.231***	-0.116***	-0.843***	-1.071***	-1.179***	-1.274***	-1.452***	-1.901***	-2.325***	-2.687***
	(-4.91)	(-3.56)	(-54.72)	(-41.45)	(-33.89)	(-30.53)	(-25.64)	(-19.44)	(-16.88)	(-15.51)
Portfolio B4	-0.330***	-0.206***	-0.607***	-0.787***	-0.876***	-0.958***	-1.108***	-1.538***	-1.968***	-2.309***
	(-7.37)	(-7.05)	(-42.36)	(-35.46)	(-29.18)	(-26.52)	(-22.55)	(-18.66)	(-17.26)	(-15.89)
Portfolio B5	-1.007***	-0.716***	-0.520***	-0.606***	-0.643***	-0.679***	-0.772***	-1.118***	-1.465***	-1.820***
	(-34.35)	(-31.76)	(-41.45)	(-30.03)	(-24.86)	(-21.45)	(-18.02)	(-14.46)	(-12.88)	(-12.05)
Portfolio S5	-0.861***	-0.604***	-0.278***	-0.315***	-0.340***	-0.356***	-0.440***	-0.752***	-1.080***	-1.408***
	(-28.53)	(-29.36)	(-23.26)	(-16.90)	(-14.62)	(-12.70)	(-11.51)	(-11.33)	(-10.96)	(-10.18)
Portfolio S4	-0.264***	-0.158***	0.071***	-0.014	-0.083***	-0.156***	-0.300***	-0.627***	-0.980***	-1.331***
	(-6.68)	(-5.90)	(5.85)	(-0.86)	(-3.79)	(-5.80)	(-7.96)	(-9.57)	(-10.24)	(-10.64)
Portfolio S3	-0.139***	-0.076**	0.507***	0.487***	0.399***	0.334***	0.209***	-0.098	-0.448***	-0.817***
	(-3.10)	(-2.43)	(39.79)	(28.61)	(17.80)	(12.13)	(5.28)	(-1.52)	(-5.14)	(-7.52)
Portfolio S2	-0.124**	-0.065*	1.063***	1.143***	1.081***	1.029***	0.880***	0.592***	0.269***	-0.091
	(-2.33)	(-1.74)	(59.76)	(46.67)	(38.49)	(32.99)	(21.83)	(10.03)	(3.35)	(-0.89)
Portfolio S1	0.160***	0.200***	1.990***	2.446***	2.496***	2.473***	2.372***	2.157***	1.875***	1.529***
(Highest sell tendency)	(2.77)	(5.13)	(73.29)	(59.20)	(51.28)	(44.46)	(35.75)	(26.52)	(19.55)	(12.87)
B1-S1	-0.742***	-0.536***	-3.450***	-4.333***	-4.590***	-4.735***	-4.894***	-5.224***	-5.401***	-5.458***

	(-6.49)	(-6.48)	(-86.37)	(-71.54)	(-62.65)	(-54.76)	(-44.99)	(-35.80)	(-29.65)	(-24.86)

Panel B. Average female investors herding – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)

Portfolio B1	-0.617***	-0.533***	-1.734***	-2.092***	-2.249***	-2.397***	-2.585***	-3.160***	-3.656***	-4.054***
(Highest buy tendency)	(-8.10)	(-10.02)	(-88.96)	(-73.12)	(-59.47)	(-51.38)	(-40.44)	(-32.27)	(-27.13)	(-23.31)
Portfolio B2	-0.241***	-0.213***	-1.373***	-1.613***	-1.716***	-1.827***	-1.993***	-2.443***	-2.913***	-3.298***
	(-4.00)	(-5.07)	(-76.34)	(-58.21)	(-47.68)	(-41.23)	(-34.24)	(-26.06)	(-21.04)	(-18.70)
Portfolio B3	-0.140**	-0.113***	-1.034***	-1.244***	-1.327***	-1.417***	-1.563***	-2.052***	-2.460***	-2.795***
	(-2.59)	(-3.15)	(-61.79)	(-48.31)	(-40.08)	(-34.41)	(-27.22)	(-20.72)	(-17.29)	(-15.31)
Portfolio B4	-0.287***	-0.199***	-0.716***	-0.903***	-0.984***	-1.071***	-1.212***	-1.600***	-1.980***	-2.379***
	(-6.63)	(-6.53)	(-46.29)	(-36.49)	(-30.31)	(-27.36)	(-23.61)	(-19.18)	(-17.03)	(-16.03)
Portfolio B5	-0.953***	-0.662***	-0.564***	-0.637***	-0.654***	-0.695***	-0.777***	-1.113***	-1.471***	-1.814***
	(-29.08)	(-28.26)	(-43.90)	(-32.74)	(-27.49)	(-23.71)	(-19.51)	(-15.16)	(-13.24)	(-12.53)
Portfolio S5	-0.865***	-0.590***	-0.272***	-0.318***	-0.320***	-0.357***	-0.443***	-0.756***	-1.073***	-1.402***
	(-25.68)	(-27.60)	(-23.66)	(-17.52)	(-13.93)	(-12.79)	(-11.55)	(-11.74)	(-11.51)	(-10.44)
Portfolio S4	-0.231***	-0.108***	0.178***	0.108***	0.041*	-0.034	-0.194***	-0.541***	-0.890***	-1.193***
	(-5.34)	(-3.64)	(13.05)	(5.50)	(1.72)	(-1.15)	(-4.71)	(-7.79)	(-9.49)	(-10.36)
Portfolio S3	-0.208***	-0.044	0.738***	0.718***	0.629***	0.566***	0.400***	0.102*	-0.228***	-0.597***
	(-4.32)	(-1.28)	(45.93)	(36.28)	(27.32)	(21.01)	(11.21)	(1.79)	(-2.76)	(-5.52)
Portfolio S2	-0.154**	0.046	1.483***	1.543***	1.423***	1.346***	1.173***	0.916***	0.606***	0.229**
	(-2.50)	(1.07)	(66.12)	(55.35)	(45.72)	(41.15)	(30.65)	(17.71)	(8.73)	(2.52)
Portfolio S1	0.231***	0.359***	2.646***	3.081***	3.070***	3.061***	2.891***	2.675***	2.375***	1.991***
(Highest sell tendency)	(3.29)	(7.33)	(72.35)	(58.76)	(52.48)	(48.11)	(38.40)	(28.35)	(22.56)	(15.75)
B1-S1	-0.848***	-0.892***	-4.380***	-5.174***	-5.318***	-5.458***	-5.476***	-5.835***	-6.031***	-6.045***
	(-6.62)	(-9.98)	(-88.85)	(-71.68)	(-63.23)	(-56.31)	(-45.13)	(-35.68)	(-31.19)	(-26.36)

Panel C. Average female investors herding vs. average male investors herding – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)

B1 (female)-B1 (male)	-0.035	-0.197***	-0.275***	-0.206***	-0.155***	-0.135***	-0.063**	-0.093**	-0.130**	-0.126**
	(-1.04)	(-8.31)	(-21.74)	(-11.98)	(-7.60)	(-5.92)	(-2.17)	(-2.18)	(-2.40)	(-2.16)
S1 (female)-S1 (male)	0.071**	0.159***	0.656***	0.635***	0.574***	0.588***	0.519***	0.518***	0.500***	0.462***
	(2.29)	(6.41)	(41.09)	(31.72)	(25.61)	(24.02)	(18.08)	(14.38)	(12.48)	(10.02)
B1-S1 (female) vs.	-0.106**	-0.356***	-0.931***	-0.841***	-0.729***	-0.723***	-0.582***	-0.611***	-0.629***	-0.587***
B1-S1 (male)	(-2.06)	(-9.57)	(-42.75)	(-30.01)	(-23.43)	(-21.50)	(-13.72)	(-10.09)	(-9.41)	(-7.62)

Table 3.5 Benchmark adjusted CARs before and after investors herd during bull-market and financial-crisis periods

This table reports the benchmark adjusted cumulative abnormal returns (CARs) for the portfolios of stocks held sorted by herding tendencies of each investor group in the two sub-periods – 1st January 2007 to 16th October 2007 and 17th October 2007 to 28th October 2008. The outcomes of male (female) investors are presented in Panel A (Panel B). Panel C presents a comparison of females' and males' portfolio. The sample period is from 1st January 2007 to 31st July 2009. The first sub-period is the bull-market period, while the second sub-period is the financial-crisis period. Stocks with buy (sell) side herding are grouped into quintiles based on the herding tendency. Portfolio B1 consists of stocks that have the highest buy-side pressure, while portfolio S1 consists of stocks with the highest sell intensity. The equally weighted portfolios are constructed on the formation day (herding day), and benchmark adjusted abnormal returns are aggregated from 5 days before and 20 days after their formation day. The t-statistics reported in parentheses are based on Newey-West standard errors. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

Portfolios	T-5	T-3	Formation day	T+1	T+2	T+3	T+5	T+10	T+15	T+20
Panel A. Average male investors herding – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)										
Bull-market Period (1st Jan 2007 – 16th Oct 2007)										
Portfolio B1	-0.459***	-0.240**	-1.527***	-1.994***	-2.239***	-2.491***	-2.901***	-3.770***	-4.540***	-5.127***
(Highest buy tendency)	(-2.96)	(-2.02)	(-36.37)	(-33.95)	(-32.96)	(-29.82)	(-26.26)	(-25.87)	(-21.58)	(-19.94)
Portfolio B5	-1.049***	-0.787***	-0.676***	-0.838***	-0.928***	-1.006***	-1.181***	-1.739***	-2.262***	-2.816***
	(-16.91)	(-15.28)	(-26.52)	(-19.18)	(-16.81)	(-14.47)	(-12.42)	(-10.77)	(-9.44)	(-8.92)
Portfolio S5	-0.932***	-0.637***	-0.371***	-0.501***	-0.565***	-0.612***	-0.758***	-1.236***	-1.713***	-2.174***
	(-13.53)	(-13.45)	(-13.67)	(-12.29)	(-11.22)	(-10.57)	(-9.20)	(-8.49)	(-7.76)	(-6.84)
Portfolio S1	-0.015	0.152*	2.285***	2.843***	2.909***	2.887***	2.777***	2.493***	2.027***	1.537***
(Highest sell tendency)	(-0.12)	(1.86)	(42.95)	(34.42)	(29.43)	(25.23)	(20.49)	(15.96)	(10.53)	(5.56)
B1-S1	-0.444*	-0.392**	-3.812***	-4.837***	-5.148***	-5.377***	-5.678***	-6.263***	-6.567***	-6.664***
	(-1.94)	(-2.27)	(-46.93)	(-39.74)	(-36.03)	(-31.49)	(-27.51)	(-24.89)	(-20.36)	(-15.68)
Financial crisis period (17th Oct 2007 and 28th Oct 2008)										
Portfolio B1	-0.737***	-0.457***	-1.390***	-1.845***	-2.061***	-2.198***	-2.426***	-2.825***	-3.167***	-3.557***
(Highest buy tendency)	(-7.91)	(-6.35)	(-40.98)	(-39.42)	(-33.13)	(-30.07)	(-25.52)	(-22.49)	(-21.99)	(-21.50)
Portfolio B5	-1.005***	-0.678***	-0.423***	-0.477***	-0.502***	-0.518***	-0.572***	-0.845***	-1.120***	-1.395***
	(-21.84)	(-20.82)	(-24.02)	(-18.77)	(-15.56)	(-14.16)	(-13.11)	(-11.34)	(-11.17)	(-12.17)
Portfolio S5	-0.776***	-0.535***	-0.222***	-0.236***	-0.253***	-0.245***	-0.284***	-0.519***	-0.790***	-1.077***
	(-17.54)	(-18.06)	(-14.30)	(-9.64)	(-9.06)	(-7.01)	(-6.06)	(-6.67)	(-7.43)	(-7.83)
Portfolio S1	0.300***	0.265***	1.693***	2.115***	2.183***	2.163***	2.057***	1.846***	1.640***	1.344***
(Highest sell tendency)	(3.31)	(4.18)	(46.91)	(39.42)	(35.39)	(30.68)	(25.23)	(19.32)	(13.48)	(10.20)
B1-S1	-1.037***	-0.723***	-3.083***	-3.959***	-4.244***	-4.361***	-4.484***	-4.671***	-4.807***	-4.901***
	(-6.61)	(-6.19)	(-53.10)	(-45.77)	(-39.62)	(-35.15)	(-29.63)	(-25.64)	(-22.14)	(-21.10)
Panel B. Average female investors herding – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)										

Bull-market Period (1st Jan 2007 – 16th Oct 2007)										
Portfolio B1	-0.371**	-0.424***	-1.916***	-2.345***	-2.534***	-2.748***	-3.087***	-3.974***	-4.740***	-5.362***
(Highest buy tendency)	(-2.14)	(-3.45)	(-47.91)	(-41.44)	(-36.04)	(-31.72)	(-25.92)	(-23.07)	(-20.85)	(-20.30)
Portfolio B5	-1.023***	-0.687***	-0.711***	-0.865***	-0.912***	-0.990***	-1.137***	-1.707***	-2.259***	-2.772***
	(-13.18)	(-12.68)	(-26.80)	(-20.35)	(-17.85)	(-16.27)	(-14.27)	(-11.58)	(-10.32)	(-10.16)
Portfolio S5	-1.028***	-0.691***	-0.336***	-0.462***	-0.500***	-0.575***	-0.735***	-1.193***	-1.657***	-2.170***
	(-12.48)	(-13.97)	(-14.86)	(-13.89)	(-11.64)	(-10.19)	(-9.06)	(-8.22)	(-8.30)	(-7.23)
Portfolio S1	-0.097	0.170	3.010***	3.591***	3.558***	3.569***	3.412***	3.105***	2.580***	2.045***
(Highest sell tendency)	(-0.69)	(1.64)	(41.31)	(32.60)	(28.87)	(26.61)	(21.20)	(15.56)	(11.00)	(6.69)
B1-S1	-0.273	-0.594***	-4.926***	-5.936***	-6.092***	-6.317***	-6.500***	-7.078***	-7.320***	-7.407***
	(-1.04)	(-3.00)	(-49.48)	(-39.68)	(-36.05)	(-32.58)	(-27.51)	(-24.26)	(-21.61)	(-17.92)
Financial crisis period (17th Oct 2007 and 28th Oct 2008)										
Portfolio B1	-0.791***	-0.596***	-1.619***	-2.005***	-2.194***	-2.317***	-2.479***	-2.909***	-3.299***	-3.642***
(Highest buy tendency)	(-8.76)	(-9.01)	(-53.23)	(-46.62)	(-36.89)	(-32.46)	(-27.40)	(-25.22)	(-23.77)	(-22.25)
Portfolio B5	-0.960***	-0.662***	-0.478***	-0.528***	-0.544***	-0.571***	-0.626***	-0.873***	-1.120***	-1.450***
	(-21.31)	(-20.40)	(-26.12)	(-22.75)	(-19.31)	(-16.27)	(-12.39)	(-12.01)	(-9.96)	(-10.54)
Portfolio S5	-0.756***	-0.545***	-0.241***	-0.246***	-0.243***	-0.258***	-0.306***	-0.557***	-0.828***	-1.100***
	(-18.75)	(-18.24)	(-14.39)	(-8.92)	(-7.17)	(-6.53)	(-6.13)	(-7.76)	(-8.20)	(-8.50)
Portfolio S1	0.524***	0.536***	2.298***	2.684***	2.700***	2.686***	2.513***	2.323***	2.112***	1.764***
(Highest sell tendency)	(4.86)	(7.00)	(46.01)	(39.76)	(35.63)	(33.75)	(28.13)	(21.26)	(16.24)	(12.21)
B1-S1	-1.315***	-1.132***	-3.917***	-4.689***	-4.894***	-5.003***	-4.991***	-5.231***	-5.411***	-5.407***
	(-7.41)	(-9.09)	(-57.03)	(-48.80)	(-41.29)	(-37.39)	(-31.38)	(-27.12)	(-24.11)	(-22.26)

Panel C. Average female investors herding vs. average male investors herding – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)

Bull-market Period (1st Jan 2007 – 16th Oct 2007)										
B1 (female)-B1 (male)	0.089	-0.184***	-0.389***	-0.352***	-0.295***	-0.257***	-0.186***	-0.204**	-0.200	-0.235*
	(1.16)	(-3.69)	(-14.82)	(-10.35)	(-7.26)	(-5.53)	(-2.94)	(-2.11)	(-1.51)	(-1.69)
S1 (female)-S1 (male)	-0.082	0.018	0.725***	0.748***	0.648***	0.682***	0.636***	0.611***	0.553***	0.508***
	(-1.23)	(0.34)	(23.71)	(17.07)	(13.27)	(12.70)	(10.61)	(7.13)	(5.82)	(5.02)
B1-S1 (female) vs.	0.171	-0.203**	-1.114***	-1.099***	-0.944***	-0.939***	-0.822***	-0.815***	-0.752***	-0.743***
B1-S1 (male)	(1.48)	(-2.45)	(-25.52)	(-18.64)	(-14.46)	(-13.23)	(-9.11)	(-5.88)	(-4.86)	(-4.39)
Financial crisis period (17th Oct 2007 and 28th Oct 2008)										
B1 (female)-B1 (male)	-0.054	-0.139***	-0.229***	-0.161***	-0.133***	-0.120***	-0.052	-0.084	-0.132*	-0.086
	(-1.23)	(-4.12)	(-11.27)	(-5.77)	(-4.10)	(-3.38)	(-1.26)	(-1.32)	(-1.76)	(-1.02)
S1 (female)-S1 (male)	0.224***	0.271***	0.605***	0.569***	0.517***	0.523***	0.456***	0.476***	0.473***	0.420***
	(5.38)	(8.15)	(24.51)	(20.05)	(15.79)	(15.29)	(11.54)	(10.60)	(9.58)	(6.86)
B1-S1 (female) vs.	-0.278***	-0.410***	-0.834***	-0.730***	-0.650***	-0.643***	-0.508***	-0.560***	-0.604***	-0.506***
B1-S1 (male)	(-4.27)	(-8.20)	(-24.74)	(-17.24)	(-13.71)	(-12.96)	(-8.75)	(-6.65)	(-6.34)	(-4.52)

Table 3.6 Individual-level herding tendencies sorted by personal characteristics

This table presents the results of univariate tests of individual-level herding tendency after controlling for investors' age, experience, and portfolio turnover. The sample period of this dataset is from 1st January 2007 to 31st July 2009. We only consider investors who hold A-share stocks at a large brokerage firm and whose gender and age can be identified. Specifically, the age is investors' age at a given month. The trading experience is proxied by trading years, which is measured as the number of years since the account is opened until each month. Turnover is the average value of monthly buy turnover and sell turnover ratio. For each month, investors are divided into two equal groups based on their age, investment experience, and portfolio turnover, respectively. The herding measurement for each stock is calculated by using the method of Lakonishok et al. (1992). Thereafter, the monthly individual-level herding measurement (ihm) is calculated as the sum of the transaction-size adjusted herding measurement divided by the sum of the transaction value at a given month. The t-values are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

ihm Diff=Female-Male	*Low Turnover*	*High Turnover*
*Low Age * Low Experience*	0.00051***	0.00027***
	(6.74)	(3.11)
*Low Age * High Experience*	0.00268***	0.00284***
	(28.80)	(23.06)
*High Age * Low Experience*	0.00053***	0.00023*
	(5.73)	(1.92)
*High Age * High Experience*	0.00227***	0.00232***
	(35.59)	(24.48)

Table 3.7 Gender differences in trading experience and portfolio turnover

This table reports the comparison of trading experience and portfolio turnover between female and male investors in different groups. The sample period is from 1st January 2007 to 31st July 2009. We only consider investors who hold A-share stocks at a large brokerage firm and whose gender and age can be identified. Investors' age, trading experience, and portfolio turnover are defined in the same way as in Table 3.6. For each month, investors are divided into two equal groups based on their age, investment experience, and portfolio turnover, respectively. Panel A shows the gender differences in portfolio turnover after controlling for investors' age and experience. In each month, investors are grouped into two equal parts based on their age and investment experience, respectively. Four combinations are generated to compare the turnover between females and males. Panel B reports the comparison of trading experience between two genders by using the same procedure. The t-values are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

Panel A. Gender differences in portfolio turnover sorted by age and trading experience

Turnover Diff=Female-Male	*Low Experience*	*High Experience*
Low Age	-0.0443***	-0.0613***
	(-130.00)	(-130.00)
High Age	-0.0390***	-0.0590***
	(-88.04)	(-170.00)

Panel B. Gender differences in trading experience sorted by age and portfolio turnover

Experience Diff=Female-Male	*Low Turnover*	*High Turnover*
Low Age	-0.2468***	-0.3010***
	(-70.74)	(-95.74)
High Age	-0.3346***	-0.5445***
	(-85.50)	(-130.00)

Table 3.8 Herding and personal characteristics

This table presents the relationship between individual-level herding tendency and personal characteristics, including gender, age, trading experience, turnover, and portfolio value. The sample period is from 1st January 2007 to 31st July 2009. We only consider investors who hold A-share stocks at a large brokerage firm and whose gender and age can be identified. For each trading month, we calculate investors' age, investment experience, portfolio turnover, portfolio value, and matches these variables with their monthly herding tendency. *Female* is a dummy variable which equals to 1 if an investor is a female, otherwise equals to 0. Investors are further divided into two equal groups based on their investment experience and portfolio turnover, respectively. *Low Turnover* (*Low Experience*) is a dummy variable that equals to 1 if an investor is in the low turnover (experience) group, otherwise equals to 0. Independent and dependent variables are standardized in four regressions. We include the time fixed effects and double-clustered standard errors at the individual and time level. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

	Specification (1)	Specification (2)	Specification (3)	Specification (4)
	ihm	ihm	ihm	ihm
Female	0.0141***	-0.0016	0.0138***	-0.0015
	(4.37)	(-0.47)	(3.88)	(-0.46)
*Female*Low Turnover*		0.0192***		0.0176***
		(5.36)		(4.92)
*Female*Low Experience*			0.0008	
			(0.23)	
*Female*Low Turnover**				0.0032
Low Experience				(0.90)
Turnover	-0.0299***	-0.0285***	-0.0299***	-0.0285***
	(-5.99)	(-5.84)	(-5.97)	(-5.83)
Experience	-0.0288***	-0.0289***	-0.0287***	-0.0284***
	(-8.12)	(-8.14)	(-8.90)	(-8.57)
Age	0.0059**	0.0059**	0.0059**	0.0059**
	(2.55)	(2.55)	(2.56)	(2.56)
Portfolio Value	-0.0131***	-0.0131***	-0.0131***	-0.131***
	(-10.67)	(-10.67)	(-10.68)	(-10.68)
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R-square	0.01	0.01	0.01	0.01
N of observations	11,153,261	11,153,261	11,153,261	11,153,261

Table 3.9 Buy-sell imbalance summary statistics and cumulative abnormal returns for female and male investors

This table reports summary statistics of buy-sell imbalance and cumulative abnormal returns (CARs) for the portfolios of stocks hold sorted by the buy-sell imbalance of each investor group. Panel A represents the summary statistics of the buy-sell imbalance sorted by investors' gender. Raw IMB is the raw value of buy-sell imbalance measurement. The buy-sell imbalances for each stock are grouped daily into buy-side and sell-side based on the sign of the raw IMB. The outcomes of male (female) investors are presented in Panel B (Panel C). Panel D presents a comparison of females' and males' portfolios. The sample period is from 1st January 2007 to 31st July 2009. For each day, the portfolios are constructed by using IMB measurement. Stocks are grouped into buying (selling) quintiles based on their magnitude of buy-side (sell-side) intensity. Portfolio B1 comprises stocks that have the highest buy-side pressure, while portfolio S1 comprises stocks with the highest sell intensity. The equally weighted portfolios are constructed on the formation day (herding day), and benchmark adjusted abnormal returns are aggregated from 5 days before and 20 days after their formation day. The t-statistics reported in parentheses are based on Newey-West standard errors. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

Panel A. Summary statistics of buy-sell imbalance										
			Two sample t-test				**Wilcoxon rank-sum test**[25]			
Diff=Female - Male	Mean		Std Err	t Value	Pr > |t|		z-score	Pr > |Z|		
Raw IMB	0.0114***		0.00	8.17	0.0000		8.737	0.0000		
Buy-side IMB	0.0093***		0.00	7..37	0.0000		7.045	0.0000		
Sell-side IMB	0.0061***		0.00	4.79	0.0000		3.826	0.0001		
Portfolios	T-5	T-3	Formation day	T+1	T+2	T+3	T+5	T+10	T+15	T+20
Panel B. Average male investors buy-sell imbalance – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)										
Portfolio B1	-0.948***	-0.629***	-0.404***	-0.517***	-0.595***	-0.695***	-0.837***	-1.190***	-1.566***	-1.909***
(Highest buy tendency)	(-24.30)	(-23.54)	(-29.83)	(-22.93)	(-19.38)	(-18.31)	(-15.02)	(-12.77)	(-11.92)	(-11.91)
Portfolio B2	-0.598***	-0.375***	-0.236***	-0.386***	-0.492***	-0.587***	-0.759***	-1.199***	-1.546***	-1.908***
	(-21.26)	(-18.83)	(-22.16)	(-23.78)	(-24.48)	(-23.21)	(-22.35)	(-21.07)	(-19.24)	(-17.48)
Portfolio S2	-0.395***	-0.252***	0.095***	0.111***	0.083***	0.035	-0.066**	-0.358***	-0.698***	-1.022***
	(-13.45)	(-11.66)	(8.11)	(6.56)	(3.74)	(1.32)	(-1.97)	(-7.11)	(-9.36)	(-9.74)
Portfolio S1	-0.282***	-0.149***	0.296***	0.491***	0.569***	0.576***	0.556***	0.346***	0.065	-0.287**
(Highest sell tendency)	(-6.07)	(-5.04)	(22.89)	(23.77)	(19.67)	(15.93)	(11.77)	(4.30)	(0.60)	(-1.97)
B1-S1	-0.666***	-0.480***	-0.700***	-1.008***	-1.165***	-1.271***	-1.393***	-1.536***	-1.631***	-1.623***
	(-14.33)	(-13.98)	(-39.03)	(-34.50)	(-30.28)	(-27.81)	(-22.88)	(-18.37)	(-18.02)	(-16.66)

[25] Tests for differences in medians are based on the Wilcoxon rank-sum tests.

Panel C. Average female investors buy-sell imbalance – sorted benchmark adjusted equal-weighted portfolio excess returns (daily, in percent)

Portfolio B1	-0.889***	-0.644***	-0.692***	-0.780***	-0.845***	-0.923***	-1.054***	-1.419***	-1.796***	-2.134***
(Highest buy tendency)	(-18.88)	(-20.44)	(-48.42)	(-35.66)	(-27.74)	(-24.87)	(-19.64)	(-14.73)	(-13.12)	(-12.50)
Portfolio B2	-0.491***	-0.336***	-0.512***	-0.633***	-0.718***	-0.809***	-0.960***	-1.373***	-1.785***	-2.155***
	(-18.68)	(-17.42)	(-46.86)	(-38.10)	(-32.57)	(-29.87)	(-27.16)	(-23.98)	(-21.21)	(-20.19)
Portfolio S2	-0.443***	-0.243***	0.365***	0.374***	0.327***	0.283***	0.165***	-0.133***	-0.460***	-0.796***
	(-13.92)	(-11.05)	(32.23)	(23.30)	(16.11)	(11.14)	(4.89)	(-2.96)	(-7.19)	(-9.67)
Portfolio S1	-0.335***	-0.150***	0.573***	0.774***	0.819***	0.835***	0.796***	0.600***	0.276**	-0.052
(Highest sell tendency)	(-8.28)	(-5.39)	(36.07)	(30.20)	(23.62)	(19.55)	(14.42)	(6.68)	(2.31)	(-0.34)
B1-S1	-0.554***	-0.494***	-1.264***	-1.554***	-1.665***	-1.758***	-1.851***	-2.019***	-2.071***	-2.082***
	(-11.00)	(-13.94)	(-59.23)	(-45.23)	(-36.43)	(-31.54)	(-25.00)	(-19.25)	(-17.49)	(-15.78)

Panel D. Average female investors buy-sell imbalance vs. average male investors buy-sell imbalance – sorted benchmark adjusted equal-weighted portfolio excess returns
, in percent)

B1 (female)-B1 (male)	0.059*	-0.015	-0.288***	-0.263***	-0.250***	-0.228***	-0.218***	-0.229***	-0.229***	-0.225***
	(1.91)	(-0.66)	(-21.23)	(-12.93)	(-10.07)	(-7.96)	(-6.09)	(-4.45)	(-3.93)	(-3.62)
S1 (female)-S1 (male)	-0.053*	-0.000	0.276***	0.282***	0.250***	0.259***	0.240***	0.254***	0.211***	0.234***
	(-1.74)	(-0.02)	(18.96)	(12.50)	(9.26)	(8.41)	(6.79)	(5.37)	(3.95)	(3.84)
B1-S1 (female) vs.	0.112**	-0.015	-0.564***	-0.545***	-0.500***	-0.487***	-0.458***	-0.483***	-0.440***	-0.459***
B1-S1 (male)	(2.57)	(-0.44)	(-24.25)	(-15.04)	(-11.57)	(-10.00)	(-7.83)	(-5.87)	(-4.74)	(-4.57)

Figure 3.1 *LSV* distribution

This figure shows histograms of stock-day-level herding measures for female and male investors, respectively. The sample period is from 1st January 2007 to 31st July 2009. Only those who held A-share stocks at a large brokerage firm, and whose age and gender can be identified, are recorded. Stock-day level herding measures in each group are calculated by using the methodology of Lakonishok et al. (1992). Specifically, for a given investor group who traded at the transaction day t, the herding measure equals to

$$LSV(i,j,t) = \left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right| - E\left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right|.$$

Where $B(i,j,t)$ is the number of individual investors in group i who are net buyers of stock j at day t. $S(i,j,t)$ is the number of net sellers in group i on stock j at day t. $p(i,t)$ is the average proportion of net buyers in group i across all securities. The second term of the equation is an adjustment factor that captures the proportion of net buyers in group i on stock j at day t under the null hypothesis of no herding.

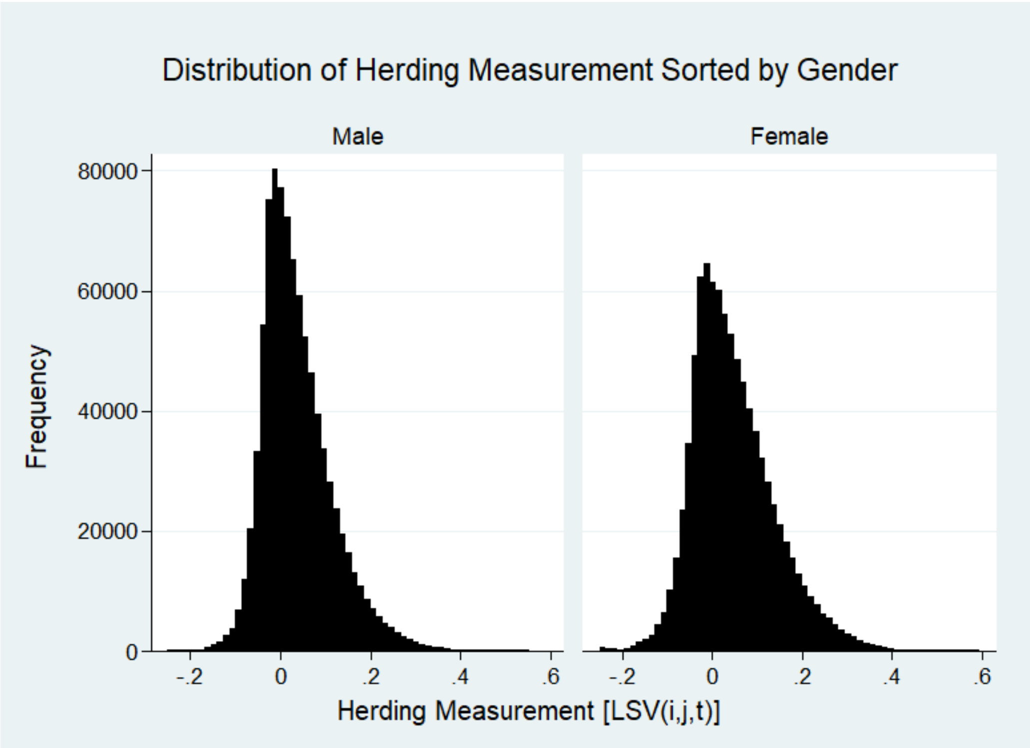
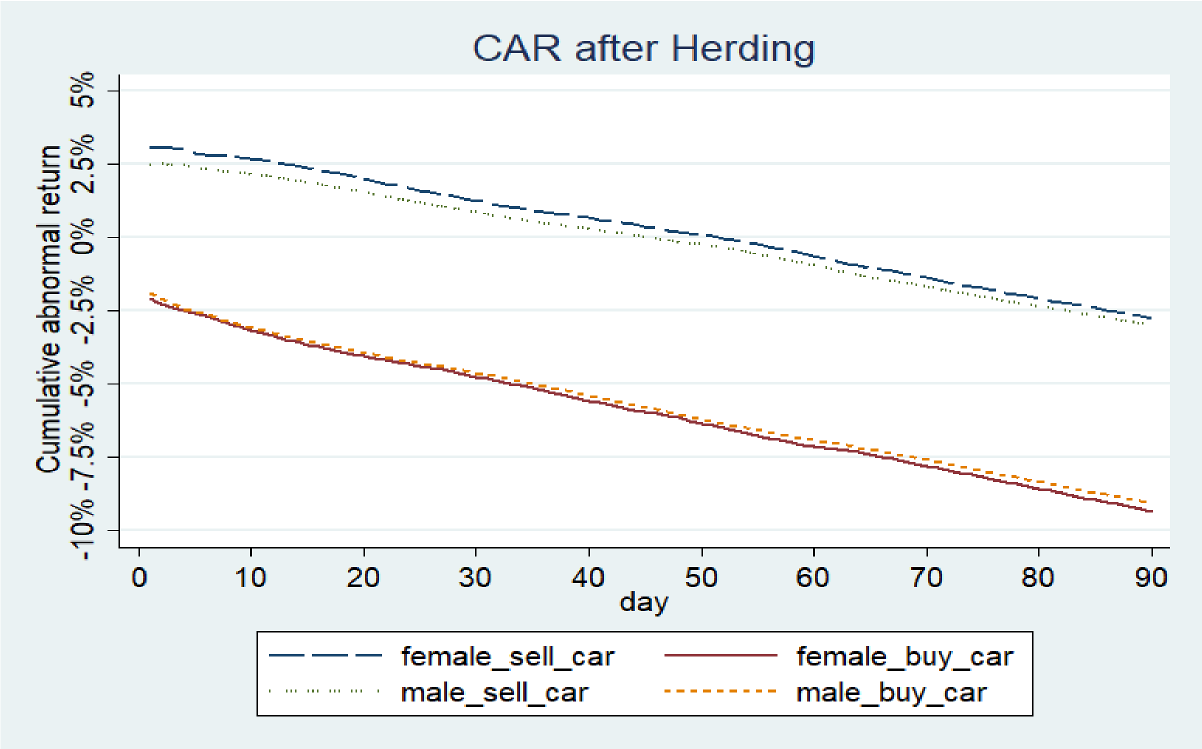


Figure 3.2 CARs after herding

This figure shows the benchmark adjusted cumulative abnormal returns (CARs) of portfolios with the highest buying and selling herding intensity for female and male investors. The sample period is from 1st January 2007 to 31st July 2009. Only those who held A-share stocks at a large brokerage firm, and whose age and gender can be identified, are recorded. Stocks are grouped into buying (selling) quintiles based on the magnitude of buy-side (sell-side) herding tendency on each transaction day. Equally weighted portfolios are constructed on the formation day (herding day), and benchmark adjusted abnormal returns are aggregated until 90 days after their formation day. This figure describes the cumulated abnormal returns of portfolios with the highest buy-side and sell-side intensity in two gender groups.



Chapter Four: What Drives Individual Investors In The Bear Market?

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 tend to provide liquidity by acting as net buyers. Particularly, males 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 superior stock-picking ability or a higher tendency to gamble during the market downswing.

4.1 Introduction

How do individuals react to the stock market turmoil? Anecdotal experience suggests that investors lose faith in the equity market, and many of them sell out their positions when a market crashes.[26] 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 et al., 2000; Hsieh, 2013).

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 either avoid buying or leave the market upon perceiving imminent market risk. However, recent findings in the French stock market suggest that, in general, individual investors provide liquidity when the market crashes (Barrot et al., 2016). Dorn and Weber (2013) also show that the holding position of investors in a large German retail bank is quite stable during a financial crisis. Hoffmann et al. (2013) find that although the return perception of investors is significantly volatile, their tolerance and perception of risk is stable and that individual investors act as net buyers when institutional investors withdraw liquidity. All these studies imply that individual investors engage in trading and are reluctant to reduce their risk-taking during financial crisis market periods.

Hoopes et al. (2016) argue that those who absorb liquidity demands during a financial crisis period must have an incentive to do so by requiring greater compensation, such as a higher risk premium. Individual investors, especially those who believe in mean-reversion, tend to use the depreciation of share prices as an opportunity to enter the market (Hoffmann et al., 2013). Meanwhile, 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, underreact to the public and private information, or have higher risk tolerances. However, due to a lack of data, the literature is not clear regarding which investors are more inclined to buy stocks in the face of a market in turmoil.

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[26] The *Wall Street Journal* (2008) suggests that individual investors withdrew their liquidity ($72 billion) from equity funds in October 2008. Additionally, reports from Deutsche Bank Research and Deloitte and Touche show that the trading activities of retail investors and the growth rate of online accounts are dramatically declined due to the turmoil in 2001.

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. The Chinese stock market experienced its darkest time between late 2007 and late 2008, somewhat earlier than the global financial turmoil that started in mid-2008. The Shanghai Stock Exchange Composite Index (SSEC) dropped from 6,124 to 1,664 between mid-October 2007 and late-October 2008. Consequently, the trading behaviour of individual investors in a bear market can be clearly observed.

Accordingly, this study investigates four research questions. 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 an aggregate 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 period of the bear market from the beginning of November 2007 to the end of October 2008. To ensure its validity, only active investors' data is used.[27] Also, we only include A-share stocks trade or hold by individual investors and listed on the SSE and SZSE. In total, the whole dataset 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 elder investors. A relatively higher inclination for buying during a market downswing by males, or

[27] Investors who have at least one transaction record or hold one stock are regarded as active investors.

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 (Hilary and Menzly, 2006; Glaser and Weber, 2009) and that the positive past portfolio performance in the crisis period amplifies a buying inclination and enhances investors' confidence to invest.

Additionally, we find 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. Finally, we prove the high intensity to buy in a bear market cannot be explained by either a better stock-picking ability or gambling behaviour.

To sum up, our study contributes to the existing literature in three ways: Firstly, it investigates individual investors' trading behaviour in a bear market. Although existing studies show that individual investors tend to provide liquidity and act as net buyers during a market downswing, however, these findings are primarily based on the individual investors' behaviour in an aggregated term (Hoffmann et al., 2013; Barrot et al., 2016). In contrast, this study takes advantage of the unique dataset with comprehensive transaction records by using the individual level net trading measurement and connecting the trading behaviour with investors' characteristics. Secondly, we explore the possible linkage between individuals' past performances and their buying intensities. In particular, our study differs from all previous research by adopting an individual-level analysis, which uncovers that only a positive past performance during a bear market amplifies buying inclinations. Besides, this result is also a crucial complement for the experimental findings of Duxbury (2012), since investors in our sample experienced the prior outcomes for real. Thirdly, we extend the literature on the individual investors' gambling behaviour and establish a connection with buying intensity during a market downswing (Barberis and Huang, 2008; Kumar, 2009). Previous studies show that investors with several specific characteristics are more likely to engage in trading lottery-type stocks; however, our results indicate that gambling cannot explain the intense buying in a bear market.

The remainder of this chapter is arranged as follows: Section 4.2 reviews previous studies of investors' trading behaviour, the impact of a market crash on stock market investment, and the dynamic relationship between past returns and trading. Section 4.3 reports hypothesis development. Section 4.4 provides the methodology and describes the data. Section 4.5 offers empirical analyses. Section 4.6 gives alternative explanations of the results, and Section 4.7 concludes the paper.

4.2 Literature review

Investors are living in a world where financial crises continue to happen, their investment style has a biological basis, although it can be affected by hedging demand, behavioural bias, and investors' personal life experiences (Boin, 2004; Cronqvist et al., 2015). In line with this argument, previous literature documents the impact of personal characteristics on trading. For instance, several studies show that male investors are more likely to be overconfident, which leads to more active trading (Benos, 1998; Barber and Odean, 2001; Hirshleifer and Luo, 2001).

Apart from different investment styles, trading intensity may also be influenced by risk perception, especially in a volatile market (Hoffmann et al., 2013). In particular, psychological studies suggest that gender plays an important role in trading intensity as females tend to trade less than males because they are more sensitive to perceived risk (Diener et al., 1985; Larsen and Diener, 1987). Likewise, Arch (1993) indicates that males and females interpret risk in different ways: males consider risks to be challenges they would like to face, while females see them as threats they must avoid.

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 elder investors are more likely to follow investment advice and more sensitive to risk (Korniotis and Kumar, 2011; Chai et al., 2011; Benjamin et al., 2013; Hoopes et al. 2016). 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 both decision making and market timing (Arrow, 1962; Grossman et al., 1977; Nicolosi et al., 2009; Seru et al., 2010; Feng and Seasholes, 2005; Dhar and Zhu, 2006) and Greenwood and Nagel (2009) suggest that inexperienced investors tend to be more optimistic during a market downturn. However, other studies show that some investors tend to overestimate their investment experience by making irrational decisions (Madrian and Shea, 2001; Kaustia and Knüpfer, 2008; Chiang et al., 2011).

This research also aligns with studies that analyse how individual investors react in a bear market. By matching survey data with transaction records, Hoffmann et al. (2013) find that individual investors during a bear market trade actively, however, they do not take fewer risks since they do not shift from risky stocks to cash. In fact, they show that individual investors regard a bear market as an opportunity to enter the market. Similarly, Dorn and Weber (2013) document that the risk-taking by retail traders in the German stock market does not decline during the financial crisis period, suggesting that their equity holdings are quite stable. Recent studies of the French stock market also suggest that individual investors provide liquidity during a financial crisis, although they are not compensated by doing so (Barrot et al., 2016). On the contrary, however, Weber et al. (2013) conduct surveys on risk-taking in the UK and find that it fluctuates during the financial crisis. Hoopes et al. (2016) examine the selling behaviour of individual investors, show that both older and wealthier investors are more sensitive to market volatility. Besides, Andersen et al. (2019) reveal that personal experience of losses during a financial crisis induces investors to shy away from risk-taking. Our study differs from previous studies by investigating individual-level net investments during a bear market period and comparing the outcomes with net investments during a market upswing period.

Our findings concur with studies that examine the dynamic correlations between stock characteristics, past returns, and individual trading. For instance, Kaniel et al. (2008), by adopting net individual trading in their investigation of the relationship between investors' trading and short-term stock returns, find that individual investors provide liquidity to meet the demands of institutional investors and engage in negative feedback trading. Ng and Wu (2007), who document similar outcomes by employing Chinese stock market data, find that investors with lower capital are less likely to buy stocks with better short-term performances. Barrot et al. (2016) find that individual investors in the French stock market also act as liquidity providers in the face of a price drop during the bear market. In the Indian stock market, Campbell et al. (2014) discover that investors with better past performances trade more aggressively in the short term, while Glaser and Weber (2009) find that investors who experienced high portfolio returns in the previous month tend to buy high-risk stocks while reducing the number of stocks in their portfolios during the following month. Our study extends the literature by using individual-level data to investigate how investors react to the changes in share prices when the market collapsed; it also examines the impact of past market and portfolio returns on net investments.

4.3 Hypothesis development

The possible impacts of investors' personal characteristics on trading behaviour have been widely analysed. However, only a small number of studies focus on the behaviour during turmoil periods (Barber and Odean, 2001; Croson and Gneezy, 2009; Bucciol and Miniaci, 2011; Korniotis and Kumar, 2011; Dohmen et al., 2011). The investment style of investors has a biological basis, and it can be affected by hedging demand, behavioural bias, and investors' personal life experiences (Boin, 2004; Cronqvist et al., 2015). Hoopes et al. (2016), who employ the population tax return data from the US market during the financial crisis of 2008 to 2009 in order to investigate individual sales, find 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; also that they are more likely to sell following an increase in the lagged value of VIX. The investment style of investors has a biological basis, and it can be affected by hedging demand, behavioural bias, and investors' personal life experiences (Boin, 2004; Cronqvist et al., 2015). Therefore, we expect that:

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

Investors' past performance in the stock market may also influence their future buying behaviour. Malmendier and Nagel (2011) suggest that investors' experiences of economic fluctuation could shape their willingness to take additional risks. Additionally, Campbell et al. (2014) find relatively better past trading performance contributes to more aggressive investment. Similarly, Glaser and Weber (2009) note that the past performance of the market index, or individual portfolios, have a significantly positive effect on the trading intensity in the following month. 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 who outperform markets might over-extrapolate the influence of their stock-picking ability thus exhibiting a self-attribution bias, which leads successful investors to become overconfident and, consequently, to take more risks (Daniel et al., 1998; Gervais and Odean, 2001; Statman et al., 2006; Hilary and Menzly, 2006). Hence, for our study, we hypothesize that:

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

In addition, stocks with specific characteristics potentially have higher buying intensities. Yu and Hsieh (2010) find that individual investors tend to be attracted by stocks with extreme intraday returns. Investors may act as net buyers of stocks that have lost large 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 certain 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 engage in buying 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 intensive buying 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 period. Furthermore, a bear market also provides excellent opportunities for investors to buy stocks at the bottom. Accordingly, investors may also be gambling by choosing to buy heavily during this period. We expect that:

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.

4.4 Data and methodology

4.4.1 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. More details of the dataset used in this thesis can be found in the introduction. Between 6 June 2005 and 16 October 2007, China's stock market experienced a two-year bull market, the Shanghai Stock Exchange Composite (SSEC) index increased from 998 points to 6,124 points. This was followed by a year-long bear market in China between 17 October 2007 and 28 October 2008, when the SSEC Index dropped 72.8% from 6,124 points to 1,664 points. Since then, the A-share 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. Panel A of Figure 4.1 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.

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 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 were 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. Apart from the above primary dataset, stock market data is collected from the *China Stock Market and Accounting Research* (*CSMAR*).[28] Finally, a cross-check is conducted with the stock data in the *RESSET Financial Research Database* (*RESSET/DB*), which is another professional financial data vendor in China.

4.4.2 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 et al. (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

[28] 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.

transaction, to construct an individual-level *NIT*.[29] 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:

$$NIT_{i,t} = \frac{\sum_{j=1}^{n}(Buy\_Value_{i,j,t} - Sell\_Value_{i,j,t})}{\sum_{j=1}^{n}(Buy\_Value_{i,j,t} + Sell\_Value_{i,j,t})} \tag{4.1}$$

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.

The portfolio turnover is controlled when investigating the relationship between net individual trading and investors' characteristics. In particular, the turnover ratio 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 multiplies by the price at the beginning of the month and divided by the market value of the portfolio hold by that investor.[30] The monthly buy turnover is measured as the number of shares bought multiplies by the beginning-of-next-month price per share scaled by the total market value of the portfolio at the beginning of the next month.[31]

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:

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[29] 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.

[30] 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.

[31] 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.

$$R_{ht} = \sum_{i=1}^{S_{ht}} \rho_{it} R_{it} \tag{4.2}$$

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.

4.4.3 Summary statistics

[Insert Table 4.1 about here]

Table 4.1 reports the summary statistics of our data. *NIT* is the net individual trading which 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. Similarly, trading experience is calculated based on the difference between the account opening date and each trading month. The trading frequency is the number of transactions each investor made monthly, 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 B of Table 4.1 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 4.4.1, the remaining dataset contains 1,549,468 individual investors, including 1,233,684 investors who traded during the financial crisis period. 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.

[Insert Figure 4.1 about here]

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 Panel B and Panel C of Figure 4.1, we show the trading volume of investors as a percentage of the total volume alongside the investors' positions. These graphs suggest 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, on average, individual investors increase their portfolio holdings by continuing to trade actively, particularly when the market crashed.

[Insert Figure 4.2 about here]

To provide a clearer picture of the net individual trading ratio, Figure 4.2 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 recorded by Hoffmann et al. (2013) and Ben-David et al. (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.

[Insert Table 4.2 about here]

More detailed summary statistics of the financial crisis period are presented in Table 4.2 since we primarily focus on this subsample. When compared with females, male investors have relatively smaller portfolios and more trading experience, and they also trade more aggressively. Elder 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 Table 4.1 and Table 4.2, we find that most Chinese investors are small and inexperienced, but they trade extremely actively.[32]

[32] 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 et al., 2002; Barber and Odean, 2002; Zhang and Zhang, 2015).

4.5 Results

4.5.1 Who are net buyers during the financial crisis period?

[Insert Table 4.3 about here]

Table 4.3 presents the relationship between investors' characteristics and *NIT* by 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 level. 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. In Specifications (2) and (4), we add a dummy variable which equals 1 if an investor's age is lower than 60 at a given month, and 0 otherwise.

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[33], an explanation for 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 et al., 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.

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 accords with Hoffmann et al. (2013), suggesting that buy-sell imbalance decreases with

[33] 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 arbitrarily high in a logistic model.

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 and Seasholes, 2005; Nicolosi et al., 2009). Consequently, experienced investors tend not to buy or sell aggressively when the market index dropped or when their portfolios' profitability decreased 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 who have 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, while Hoopes et al. (2016) and Li et al. (2017b) find that wealthier investors are better informed and more sensitive towards the increased market risks, which makes them less likely to buy during a market downswing.

Given the coefficient on age and squared age, we find an inverted U-shaped relationship between age and *NIT*. The transition to retirement, therefore, might trigger greater sensitivity towards risk, a relationship which Riley and Chow (1992) suggest is not linear, in that risk aversion at first decreases with age and then increases after 65. Similarly, Lee et al. (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. Hoopes et al. (2016) also find that investors approaching retirement are more sensitive to increased risk since they are likely to have fewer earning opportunities in the future.

To further understand the relationship between buying behaviour and age, we add a *Young* dummy variable in Specifications (2) and (4), which equals 1 if an investor is younger than 60. The positive coefficient on this suggests that younger investors tend to have a higher *NIT* than older investors, either retired or approaching retirement. Hence, Table 4.3 shows that male and younger investors have a higher tendency to buy during the financial crisis period.

4.5.2 Market returns, portfolio performance and *NIT*

[Insert Table 4.4 about here]

In Table 4.4, 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 at month $t-1$. We ignore intra-month trading when evaluating portfolio performance. Barber and Odean (2000, 2001) 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, 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. For simplicity, we only report the coefficient estimates related to past portfolio returns and past market returns. 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 have a significant impact on net individual trading in the following month; an outcome that also holds in the bull market period. In contrast, lagged value of market index returns significantly affects net individual trading in two subsample periods. Specifically, *NIT* is an increasing function of market returns during both bull and crisis periods. Individuals invest more in the face of the short-term reversal of stock markets, probably because they 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 the crisis period, in Specifications (2) to (4), 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 $t-1$.

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 is in line with the overconfidence theory, in that investors with high past returns tend to become overconfident, hence they trade more aggressively (Daniel et al., 1998; Hilary and Menzly, 2006; Glaser and Weber, 2009). Second, we notice that investors would not invest more, even though they outperform the market in the previous month, indicating that investors do not directly use the market index return as a benchmark when making their buying decisions for the following month. Third, investors tend to buy more if their portfolios experience positive returns and outperform the market. By combining results from Specifications (2) to (4), we argue that, during the crisis period, investors who experienced positive returns in the previous month believe in their trading skills since they also engage in buying during the following month. This finding is consistent with Hoffmann and Post (2014) who report that, individual investors tend to show a self-attribution bias, using their past portfolio performances as indicators of their investment ability, consequently showing a more aggressive trading behaviour in the following month.

However, during the bull market period, we do not observe the same results: Specifications (5) to (8) show that investors do not invest significantly more the following month even though their portfolio returns have been positive, or higher than the market index. 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 propensity to re-invest between sunk costs and sunk benefits, given a good investment opportunity. Combing the results in Table 4.4, we argue that the positive past portfolio performance in the crisis period accelerates the buying tendency and enhances investors' confidence to invest.

4.5.3 Stock-level analysis

In this part, we use the Wermers (1999) method of constructing the stock-day level buy-sell imbalance to capture the buying and selling intensity of aggregate investors in different 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:

$$IMB_{i,t} = \frac{Buy_{i,t} - Sell_{i,t}}{Buy_{i,t} + Sell_{i,t}} \tag{4.3}$$

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 past performance and several characteristics of stocks. In particular, Ji et al. (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 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 tend to be attracted by extremely high trading volume stocks; consequently, they concentrate on the same side of stocks that have better market liquidity (Barber and Odean, 2008; Hsieh, 2013).

[Insert Table 4.5 about here]

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 4.5 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. The market capitalization and turnover of stocks are controlled in all regressions. *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 et al. (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.[34] The abnormal return of each stock is measured as the

[34] 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.

raw stock return minus a market index return.[35] 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 and Wu, 2007).[36] We include the time fixed effects in all regressions and standard errors are clustered at the stock level.[37]

In Specification (1), we find a significant negative correlation between past cumulative abnormal returns and buy intensity during the crisis period. The result is unaffected by using cumulative raw 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 and 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 et al., 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

[35] The results are reported by using the SSEC as a proxy for a market index. 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.

[36] In fact, we 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.

[37] 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. Overall, the results remain the same when we include the stock fixed effects and time fixed effects.

investors tend to have a higher buying intensity on stocks with better liquidity, higher market capitalization, and they believe in the mean-reversion strategy, given the negative correlation between buy-sell imbalance and past returns. Also, the higher buying intensity after the price decreases during the crisis period indicates that individual investors at an aggregate level tend to be exposed to the opposite position by the other competitors in the market.

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

One possible reason why 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 period. To verify this alternative explanation, we first divide stocks into buy and sell categories:

$$Buy_{side}IMB_{i,t} = IMB_{i,t}|IMB_{i,t} > 0 \tag{4.4}$$

$$Sell_{side}IMB_{i,t} = -IMB_{i,t}|IMB_{i,t} < 0 \tag{4.5}$$

[Insert Table 4.6 about here]

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 of Table 4.6, 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 on the day they are constructed. Also, for each portfolio, we calculate the cumulative abnormal returns during the period from five days before to twenty days after the trading day.

Table 4.6 shows the cumulative market-index adjusted abnormal returns concerned with buy-sell imbalance.[38] The first and second rows of each panel report cumulative abnormal returns

[38] 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

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 4.5.3, stocks allocated on the buy-side underperform those investors sold during the crisis period. 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 trading 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.[39] Barber et al. (2009) argue that retail investors could move the market, consequently, stocks with the highest 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 in 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 et al. (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.

return on the formation day. Indeed, the result is consistent in the short run when abnormal returns on the formation day are excluded.

[39] 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).

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 engage in buying during the crisis period due to their stock-picking abilities, since the stocks they purchased underperform those they sold.

4.6 Relative long-term performance and gambling behaviour

4.6.1 *IMB* and relatively long-run stock performance

In Section 4.5.4, we find that in the short run, stocks with the highest buying intensity underperform those with the highest sell-side intensity. 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:

$$\begin{aligned}&Return[1,\mathrm{y}]_{i,t} = \beta_0 + \beta_1 IMB[0]_{i,t} + \beta_2 Return(-1{,}0]_{i,t} + \\ &\beta_3 Return[-1,-5]_{i,t} + \beta_4 Return[-6,-27]_{i,t} + \\ &\beta_5 LogMarketCap_{i,t} + \beta_6 Turnover_{i,t} \qquad (4.6)\end{aligned}$$

and

$$\begin{aligned}&CAR[1,y]_{i,t} = \beta_0 + \beta_1 IMB[0]_{i,t} + \beta_2 CAR(-1{,}0]_{i,t} + \\ &\beta_3 CAR[-1,-5]_{i,t} + \beta_4 CAR[-6,-27]_{i,t} + \\ &\beta_5 LogMarketCap_{i,t} + \beta_6 Turnover_{i,t} \qquad (4.7)\end{aligned}$$

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 et al. (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.

[Insert Figure 4.3 about here]

At a first step, we estimate Equations (4.6) and (4.7) by using cumulative (abnormal) returns from day one to day y, where y takes values from one to eighty, as the dependent variable. In Figure 4.3, we report the eighty β_1 coefficients based on three different return measurements. The result is consistent with our findings in Table 4.6: 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 when we use 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.

4.6.2 Do net buyers gamble in the stock market?

Individual investors engage in buying during the crisis period probably because they tend to gamble. To explore the existence of a positive connection between net individual trading and the tendency to gamble, we first use Kumar's (2009) 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.[40] Here the idiosyncratic volatility of each stock is calculated by using a three-factor model: we first save the residuals of regression, then calculate their 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.[41] 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:

$$Lottery\ Preference_{i,t}^{(1)} = \frac{\sum_{j \in A_{t-1}} n_{i,j,t} P_{j,t}}{\sum_{j=1}^{N_{i,t}} n_{i,j,t} P_{j.t}} \tag{4.8}$$

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

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

[41] 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.

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 (2009) compares the real proportion of lottery-type stocks with an expected value, which is a condition of portfolio size:

$$Lottery\ Preference_{i,t}^{(2)} = \frac{NLW_{i,t} - ENLW_{i,t}}{ENLW_{i,t}} \tag{4.9}$$

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:

$$NLW_{i,t} = \frac{Lottery\ Preference_{i,t}^{(1)} - \min\left(Lottery\ Preference_{i,t}^{(1)}\right)}{\max\left(Lottery\ Preference_{i,t}^{(1)}\right) - \min\left(Lottery\ Preference_{i,t}^{(1)}\right)} \tag{4.10}$$

and

$$ENLW_{i,t} = \frac{Portfolio\ Size_{i,t}^{(1)} - \min\left(Portfolio\ Size_{i,t}^{(1)}\right)}{\max\left(Portfolio\ Size_{i,t}^{(1)}\right) - \min\left(Portfolio\ Size_{i,t}^{(1)}\right)} \tag{4.11}$$

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:

$$Lottery\ Preference_{i,t}^{(3)} = \frac{Lottery\ Preference_{i,t}^{(1)} - Lottery\ Preference_{t}^{market\ index}}{Lottery\ Preference_{t}^{market\ index}} \tag{4.12}$$

$Lottery\ Preference_t^{market\ index}$ captures the proportion of lottery-type stocks allocated to the market index.[42]

Lastly, we use another measurement to investigate whether individual investors actively seek lottery-type stocks. 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:

$$Lottery\ Preference_{i,t}^{(4)} = \frac{\sum_{j \in A_{t-1}} Buy\ Volume_{i,j,t}}{\sum_{j=1}^{n} Buy\ Volume_{i,j,t}} \tag{4.13}$$

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.

[Insert Table 4.7 about here]

Table 4.7 reports the outcomes of regression models. The sample period is from the beginning of November 2007 to the end of 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 net individual trading 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 at individual and month level for all specifications.

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 significantly negative correlation between *NIT* and portfolio-size adjusted lottery preference in Specification (2) suggests that the proportion of lottery-type stocks of intense buying investors is statistically lower than those who invest less. Investors with a higher *NIT* tend to be more active and might purchase lottery-type stocks deliberately rather than hold

[42] We use the CSI 300 index as a proxy for the market index in this section. The results are consistent as the CSI Small-cap 500 index, SSEC, and the CSI 800 index are used as proxies for the market index.

them passively. However, the significantly negative coefficient on *NIT* in Specification (4) reveals that the proportion of lottery-type stocks purchased by more intensive investors is significantly lower than their counterparts.

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 (2009) findings, in that males and younger investors show a higher propensity to gamble. Previous studies document individuals with less personal wealth are more likely to gamble in order to escape poverty (Brenner, 1986; Herring and Bledsoe, 1994; Kumar, 2009). Overall, the negative relationship between *NIT* and lottery preferences confirms that gambling behaviour cannot explain intense buying during the crisis period.

4.7 Conclusion

This study investigates the trading behaviour of individual investors in the Chinese stock market by using a unique dataset with daily transaction records during the period from 1st January 2007 to 31st July 2009. We use a dataset to focus on investors' net buying during the financial crisis period. To examine who tends to have a higher buying tendency, we employ an individual-level net investment measurement and match it with investors' characteristics. We find 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 may be because they have lower perceptions of risk and lower sensitivity towards risk increases.

Furthermore, we uncover that both market and portfolio returns have a significant impact on the tendency to buy the following month in different ways. During the crisis period, investors use the rise of index returns as proxies for market recovery and increase their investment in the following month. The past portfolio performance does not have a direct influence on net buying, whereas individuals are more likely to invest if they experienced positive portfolio returns in the previous month. We argue, therefore, that better performances during the financial crisis encourage investors to be overconfident, thus exhibiting self-attribution bias, since we do not find similar results in the bull-market subsample.

Finally, 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. We also 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 net investment during the crisis period, since net buyers do not have a higher proportion of lottery-type stocks in their portfolios, and they are less likely to deliberately seek lottery-type stocks.

Tables of results

Table 4.1 Summary statistics

This table presents the summary of statistics for individual investors. The study's dataset comes from a large anonymous Chinese brokerage firm comprising of more than two million individual accounts, which after 'clean-up' amount to 1,549,468. 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. 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 not recorded, (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. 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. The number of transactions is the average number of buys and sells made by investors over the sample period (financial crisis subsample for Panel B). 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.

Variables	Mean	Standard Deviation	Median
Panel A. Whole period (Number of Accounts=1,549,468)			
NIT	0.063	0.54	0.002
Age	41.17	11.79	40
Trading experience	4.32	4.21	1.92
Number of transactions	12.53	30.88	6
Account size (in RMB)	142,699.7	41,081.68	716,562.5
Panel B. Financial Crisis period (Number of accounts=1,233,684)			
NIT	0.129	0.58	0.019
Age	40.54	11.69	39
Trading experience	3.83	4.17	1.17
Number of transactions	10.78	23.59	5
Account size (in RMB)	146,474.4	726,554	41,293.1

Table 4.2 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. Standard errors are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	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
Diff=Male – Female	-2,203.75***	0.50***	0.54***	0.05***	0.22***
	(425.75)	(0.01)	(0.03)	(0.00)	(0.00)
By age					
<=30	52,797.81	4.93	3.97	0.52	1.32
31-50	118,176.6	6.24	4.95	0.49	4.06
>50	142,396.7	6.33	5.19	0.44	5.79
Diff=Age high – low	89,598.9***	1.40***	1.22***	-0.08***	4.47***
	(635.51)	(0.02)	(0.02)	(0.00)	(0.00)
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
Diff= Experience high – low	64,658.66***	-0.27***	-0.12***	-0.07***	7.89***
	(435.70)	(0.01)	(0.01)	(0.00)	(0.00)
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
Diff=Size high – low	1,047,850***	8.99***	6.90***	-0.13***	2.67***
	(1,145.72)	(0.02)	(0.02)	(0.00)	(0.01)

Table 4.3 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 level. 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
N of observations	6,673,127	6,673,127	6,673,127	6,673,127

Table 4.4 *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. For each trading month, we calculate age, investment experience, portfolio turnover, account size, portfolio, and market index returns in the previous trading month, then matching those variables with their monthly *NIT*. *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. Investors' gender, age, experience, turnover, and account size are controlled in all specifications; for simplicity, we do not report them. 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.

	Financial crisis period				Bull market period			
	Specification (1)	Specification (2)	Specification (3)	Specification (4)	Specification (5)	Specification (6)	Specification (7)	Specification (8)
	NIT	*NIT*	*NIT*	*NIT*	*NIT*	*NIT*	*NIT*	*NIT*
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 & *Excess return Dummy*				0.0460**				0.0113
				(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
N of observations	5,773,347	5,773,347	5,773,347	5,773,347	3,196,955	3,196,955	3,196,955	3,196,955

Table 4.5 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. 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
R-square	0.01	0.02	0.01	0.02
Number of Observations	349,654	349,654	349,654	349,654

Table 4.6 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)										
Buying Portfolio (B)	0.549**	0.353*	0.132	-0.069	-0.070	0.050	0.195	0.642*	1.157**	1.592***
	(2.19)	(1.88)	(1.45)	(-0.73)	(-0.47)	(0.22)	(0.71)	(1.84)	(2.58)	(3.04)
Selling Portfolio (S)	0.670***	0.425**	0.184*	0.361***	0.561***	0.805***	0.979***	1.466***	1.983***	2.467***
	(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 4.7 *NIT* and gambling

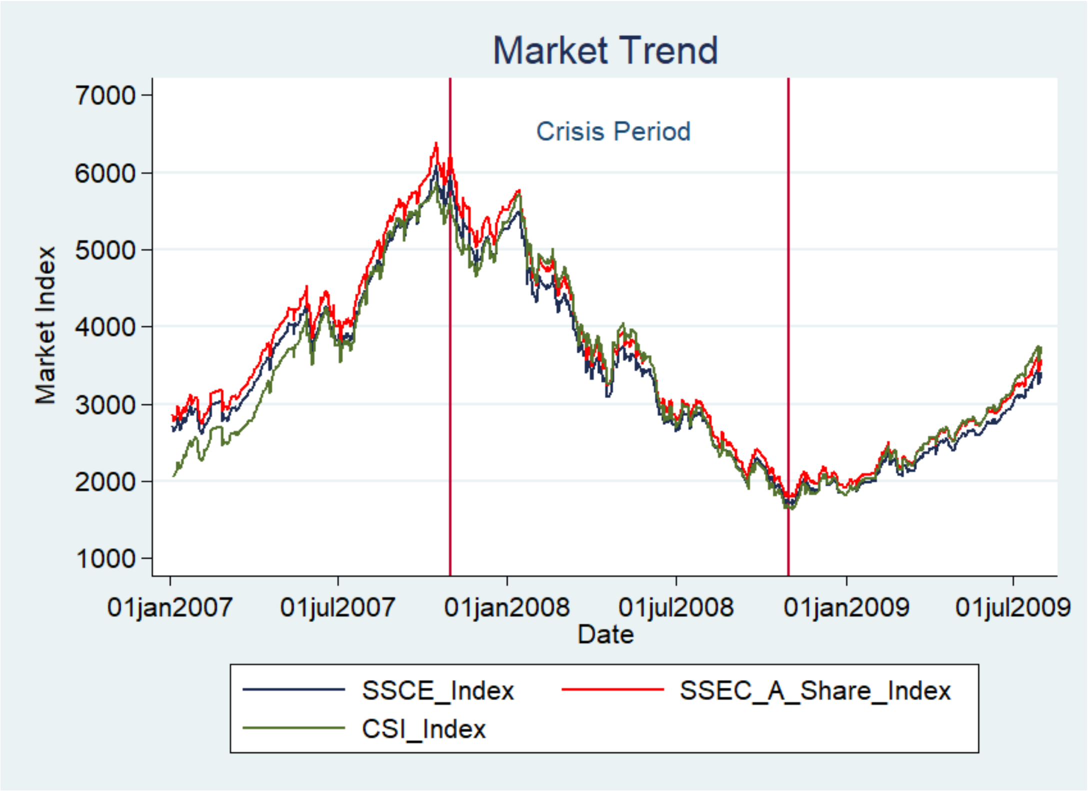
This table shows the relationship between *NIT* and investors' tendency to gamble after controlling personal characteristics. The subsample period of the financial crisis is from the beginning of November 2007 to the end of October 2008. We only consider investors who hold A-share stocks at a large brokerage 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 4.6.2. *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 level. 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
R-square	0.0044	0.0070	0.0057	0.0055	0.0044	0.0070	0.0057	0.0053
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

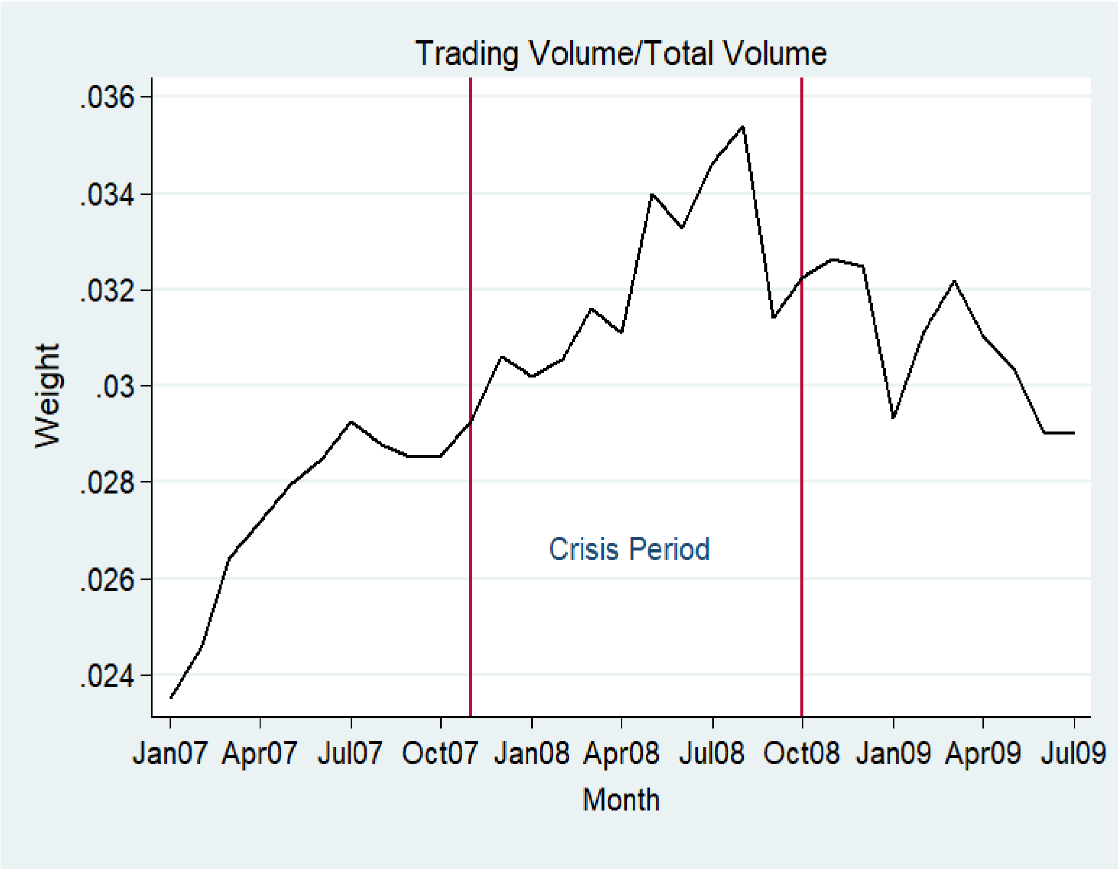
Figure 4.1 Market trend, proportion of trading volume, and investors' positions

This figure plots the performance of three market indices, the trading volume of investors as a percentage of total market-wide trading volume, and their monthly average positions. Panel A shows the performance of SSEC Index, SSCE A-share Index, and CSI 300 Index 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 decreased to 1,664 from 6,124 during this period. The proportion of trading volume is computed as the aggregate share of total market-wide volume traded (Panel B). 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 C). The sample includes individuals trading A-share stocks from the beginning of January 2007 to the end of July 2009.

Panel A. Performance of market indices



Panel B. Proportion of trading volume



Panel C. Investors' positions

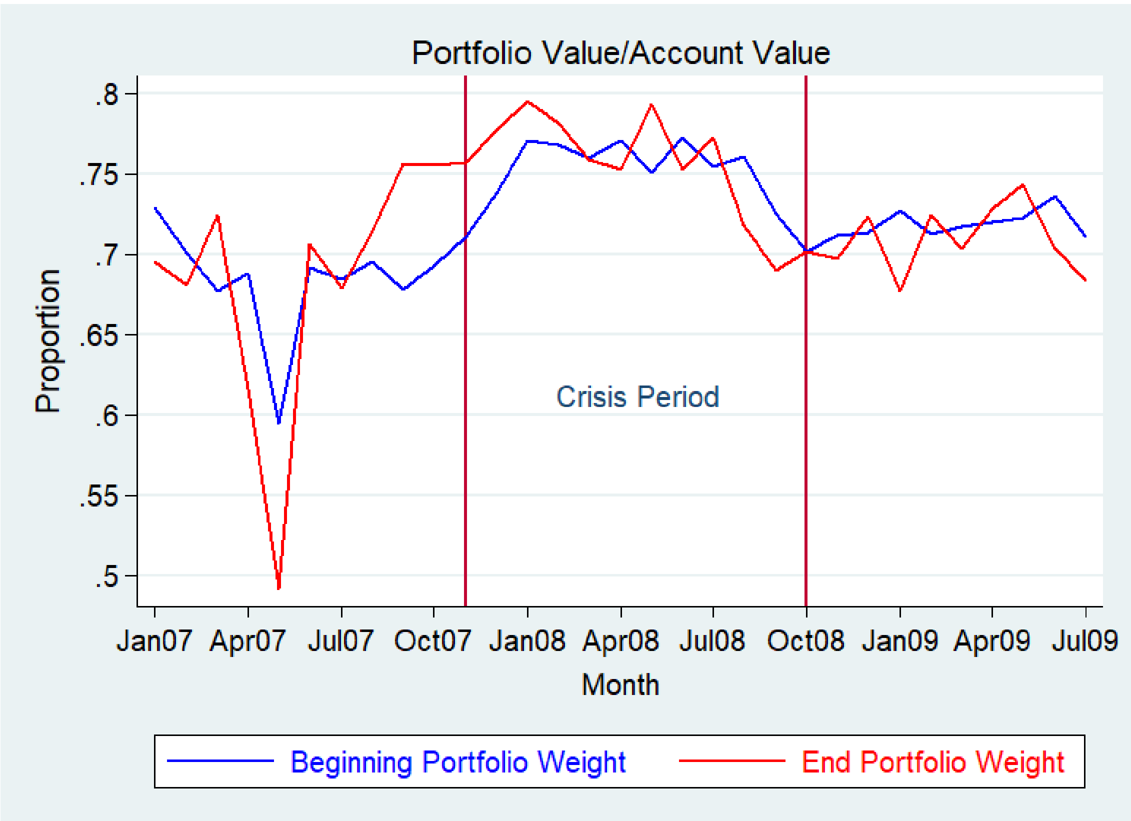


Figure 4.2 Investors' monthly *NIT* ratio

This figure 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.

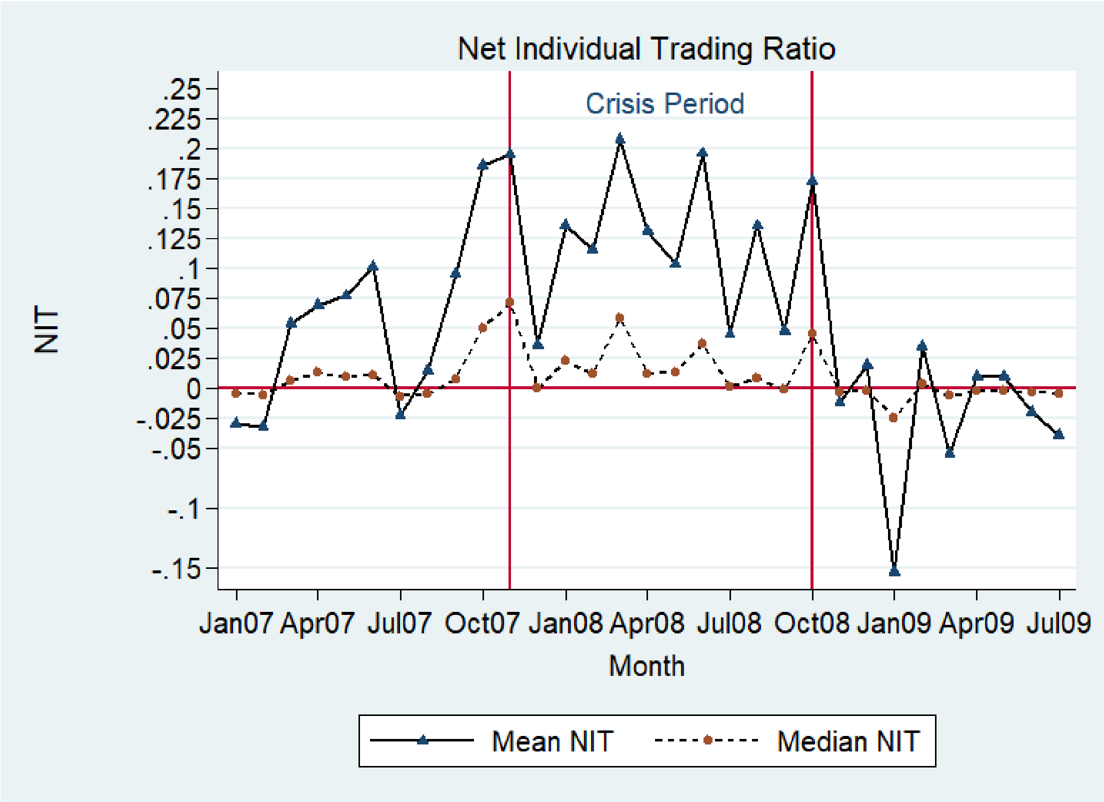
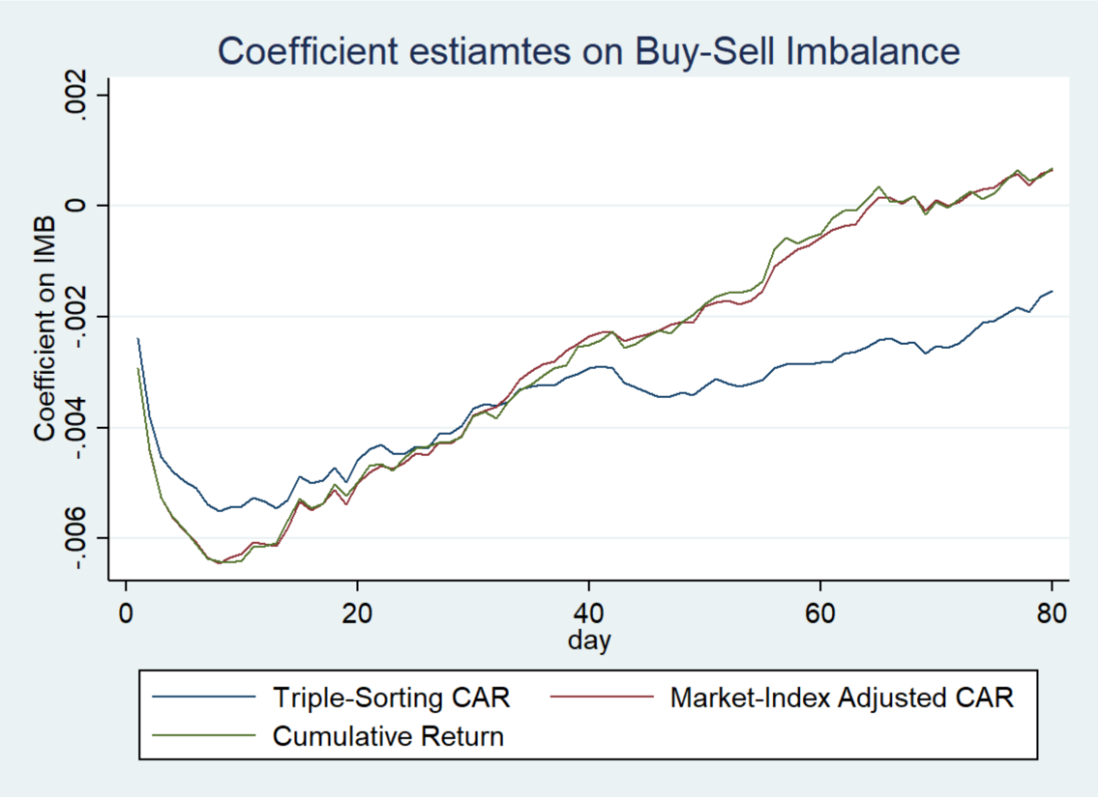


Figure 4.3 Stock returns and buy-sell imbalance

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.



Chapter Five: Investors' Reactions Under The Dynamic Relationship Between Media Tone And Earnings Surprises

This chapter investigates how individual investors react to earnings news and to what extent the media tone might influence investors' reactions. The empirical results show that, on average, individual investors increase (reduce) their holdings on stocks with positive (negative) earnings surprises. We develop firm-specific media tone measures and find that investors overreact to good earnings announcements for companies with positive media tone than for those with negative media tone, while they react more negatively to bad earnings news when the media tone is worse. The impact of media tone on investors' reactions to negative earnings surprises is more pronounced than for positive earnings surprises. Further evidence indicates that compared to wealthy and well-diversified investors, investors with lower wealth or poorly diversified portfolios are more likely to be influenced by media tone.

5.1 Introduction

The typical assumption of market efficiency is that security markets move in response to all known fundamental information and that arbitragers should counteract any noise-driven trading behaviour. However, a mounting body of evidence suggests that the aggregate trading behaviour of noise traders can be influenced by their limited attention, which leads to a failure of stock prices to reflect the prevailing market information adequately. For instance, Bernard and Thomas (1990) suggest that investors tend to underreact to earnings news, leading to a post-earnings announcement drift. According to the limited attention theory, investors may ignore useful firm-level information, and the stock price underreaction can be observed. Again, if investors ignore earnings announcements, they cannot immediately incorporate earnings news in share prices. Consequently, it is common to see a price drift in the same direction as earnings news after the announcements. Hou et al. (2009) find that post-earnings announcements drift should be more pronounced among stocks that receive less investor attention.

Apart from investors' limited attention, market sentiment can also influence their behaviour, which triggers the mispricing of share prices. For instance, Baker and Wurgler (2006) create a market sentiment measurement using principal components analysis on six commonly adopted sentiment measures. They demonstrate that the higher (lower) market sentiment early in the period is accompanied by relatively lower (higher) subsequent returns. They also show that the impact of market-wide sentiment is more pronounced among 'speculative' stocks. Besides, a growing literature has begun to analyse the impact of investor sentiment from an accounting perspective. Similarly, Schmeling (2009) uses consumer confidence as a proxy for the sentiment of individual investors and reveals that future stock returns tend to be lower when sentiment is high and vice versa. Hribar and McInnis (2012) uncover that analysts tend to report optimistic earnings forecasts when market sentiment is high. Mian and Sankaraguruswamy (2012) show that stock price is more likely to react to good earnings news when the market sentiment is higher, while it is more sensitive towards bad earnings news when the market sentiment is lower.

The studies mentioned above primarily employ survey data or use Baker and Wurgler's (2006) method to construct market-level investor sentiment and test its impact on the stock market. Nevertheless, firm-specific news also plays a crucial role in shifting investor sentiment. In particular, as a mediator of information dissemination, the media can invariably influence investors' expectations about the future of a listed firm by the way it is portrayed. Notably, the tone of the media may be a double-edged sword for individual investors. On the one hand, media news can intermediate corporate information to the public and mitigate possible information asymmetry between firms and investors (Aman, 2013). On the other hand, by attracting investors' attention and shaping their sentiment, the media may change or even mislead investors' trading behaviour. For instance, Tetlock (2007) demonstrates that the stock market experienced greater downward pressure when media pessimism is high, while Li et al. (2019) find that stocks with more positive media sentiment have a higher crash risk in the Chinese stock market.

Given the confounding outcomes regarding the relationship between investors reactions and earnings surprises (Lee, 1992; Hirshleifer et al., 2008; Vieru et al., 2006; Kaniel et al., 2012), and the possible impact of media tone on this relationship, this study constructs firm-specific media tone measures and empirically addresses the following research questions: how do investors react to earnings surprises? Will pre-announcement media tone influence investors' reaction to earnings surprise? Does the impact of media tone vary across investor groups?

To answer these research questions, we start by collecting individual investor trading data 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. The media and earnings data are collected from the *Genius Finance Database* and *CSMAR*, respectively. To match the individual trading data with media data and quarterly earnings information, we require firms to have been covered by articles in our sample at least once in 30 days preceding an earnings announcement. Also, firms are required to have at least one transaction record made by our sample of investors within 15 days of an earnings announcement. Our final sample consists of 202,580 articles released from 30 days before to 1 day before earnings announcements and 1,486,477 investors who traded within 15 days following the quarterly earnings announcements.

Our study constructs two measurements to identify the tone of media before earnings announcements. Additionally, the standardized holding change is used to capture the reactions of investors following earnings announcements. Empirical evidence demonstrates that, on average, individual investors act as net buyers (sellers) on stocks with positive (negative) earnings surprises. We also find that media tone has an asymmetric effect on firms with positive and negative earnings surprises. More precisely, our findings show that investors increase their holdings more following positive earnings surprises with high media tone than those with low media tone, while they react more negatively to bad earnings news for firms with negative media tone than for those with positive media tone. Also, consistent with Mian and Sankaraguruswamy (2012), we uncover that the effect of media tone is more salient for investors' reactions to negative earnings surprises than to positive earnings surprises.

This study also examines whether media tone affects reactions to earnings surprises in a similar manner across different investor groups. Our findings show that the effect of media tone predominates among investors in poorly diversified and low-wealth groups. The evidence suggests that these investors increase more holdings on positive earnings surprises for firms with positive media tone than those with negative media tone. In contrast, they sell more positions to bad earnings news when the media tone is more pessimistic. We do not observe similar results among wealthy and well-diversified investors. This outcome indicates that investors who are more likely to have private information sets or be distracted by information about other stocks in their hands are less likely to be influenced by the tone of the media. Additionally, the results of this study are found to be robust by employing a different set of media data, and we do not find evidence that media tone influences investors' reactions by predicting upcoming earnings surprises.

The contributions of this study are as follows. Firstly, it extends the literature on learning the individual investors' trading behaviour following earnings announcements. Existing studies on investors' reactions to earnings news have not reached a unified conclusion. For instance, Hirshleifer et al. (2008) and Lee (1992) suggest that investors tend to be involved in attention-grabbing events and act as net buyers after negative and positive extreme earnings surprises. In comparison, a series of studies uncover individual investors' contrarian trading behaviour, as they tend to sell stocks with extremely positive earnings surprises and buy stocks with negative earnings surprises after earnings announcements (Luo et al., 2020; Vieru et al., 2006; Kaniel et al., 2012). To our knowledge, this is the first study that investigates individual investors' reactions after earnings announcements in the Chinese stock market, and our findings show that, on average, individual investors increase (reduce) their holdings on stocks with positive (negative) earnings surprises.

Secondly, our study contributes to the literature by examining the effect of media tone on investors' reactions to earnings news (Mian and Sankaraguruswamy, 2012; Cahan et al., 2013;

Cahill et al., 2017; Seok et al., 2019). Although the media tone cannot predict earnings surprises, the findings show that it can influence investors' reactions to earnings surprises. Specifically, we find that investors increase (reduce) their holdings more following positive (negative) earnings surprises with high (low) media tone than those with low (high) media tone. Thirdly, previous studies document that more informed investors trade differently after announcements (Ekholm, 2006; Li et al., 2017b); we add to this line of literature by analysing how media tone affects different types of investors. Our research evidence suggests that investors who allocated more wealth or have well-diversified portfolios in the stock market are less likely to be influenced by media tone in their post-earnings announcement reactions.

The remaining of this chapter will continue as follows: Section 5.2 reviews a series of related studies that investigate investors' reactions following earnings news, considers the role of media, and then presents our hypotheses. Section 5.3 provides the methodology and describes the data. Section 5.4 presents empirical analyses. Section 5.5 and Section 5.6 contain the results of the robustness check and present the study's conclusions.

5.2 Literature review and hypothesis development

5.2.1 Investors' reactions to earnings surprises

Earnings announcements convey essential information about the price of an asset, and therefore have the potential to prevent or modify irrational price movements. In addition, price movements may be particularly susceptible to excessive fear or greed due to increased information asymmetry during the period approaching earnings announcements (Jansen and Nikiforov, 2016). Existing studies on investors' reactions to earnings surprises have not reached a unified conclusion. Dey and Radhakrishna (2007) show that individual investors react slowly after the earnings announcements compared to institutional investors, while they become overconfident and overreact to the news in the latter half of the announcement day and the next day. Luo et al. (2020) find that individual investors, especially those who pay more attention to their accounts, tend to sell stocks with positive earnings surprises and buy stocks with negative earnings surprises. However, Hirshleifer et al. (2008) find individuals are net buyers after both negative and positive extreme earnings surprises. Their results suggest that investors tend to be involved in attention-grabbing events and act as net buyers eventually. Similarly, by examining the relationship between the sign of earnings surprises and recent value-line earnings forecasts, Lee (1992) finds that small trades following positive and negative earnings surprises tended to be inferred-buying for more than two days.

Different types of investors may react differently to earnings surprises. The evidence documented in Ekholm (2006) shows that individual investors' holdings decrease with positive earnings surprises, while large investors increase their holdings of stocks with positive earnings surprises. Frieder (2008) finds that the net buying of small investors increases with the number of consecutive positive earnings surprises, while the high net buying of stocks with positive surprise is negatively correlated with returns throughout the following year. Another study by Bhattacharya et al. (2007) investigates how investors' trading behaviour related to pro forma earnings information. The outcomes show that less sophisticated investors' announcement-period abnormal trading is significantly positively associated with the magnitude and direction of the earnings surprises, while they do not find an association between sophisticated investors' trading and manager-reported pro forma information. Vieru et al. (2006) find that investors in the most active group show a contrarian trading behaviour, tending to sell stocks with good news after the earnings announcement.

Previous papers widely reported that the limited attention can, to some extent, explain investors' underreaction after earnings announcement and post-earnings announcement drift. Hirshleifer and Teoh (2003b) and Hirshleifer et al. (2011) argue that limited investor attention leads to an initial underreaction to earnings announcements and other accounting data followed by drift. Hou et al. (2009) argue that investors may ignore earnings announcements when they pay less attention to firm news. Consequently, price drift in the same direction of earnings news after the announcement should be observed since investors cannot incorporate earnings news immediately. In particular, post-earnings announcement drift should be more pronounced among stocks that receive less investor attention. Bernard and Thomas (1990) suggest that seasonal random walk quarterly earnings changes are positively serially correlated. Individual investors tend to be net buyers on stocks with negative earnings surprises and net sellers after positive earnings surprises if they cause the post-earnings announcement drift. As a result, their net selling, which generates under-pricing, should predict higher subsequent stock returns, while their net buying, which generates overpricing, should predict lower stock returns shortly.

5.2.2 The role of media

Kahneman (1973) develops the theory of limited attention, which is that an individual's attention tends to be affected by another thing since the attention of human beings is limited in overall capacity. Engelberg et al. (2012) suggests that, due to restrictions in investors' time and energy, they cannot effectively process all accessible information, which results in a lack of reaction to related information on stock fundamentals. Media news can directly link to the attention of investors by grabbing their eyes, and it plays a crucial role in intermediating corporate information to the public and mitigating possible information asymmetry between firms and investors (Tetlock, 2007; Tetlock et al., 2008; Aman, 2013). Apart from acting as an information intermediary and corporate monitor, Li et al. (2019) argue that media news may also shape investors' sentiment. Accordingly, the media may mislead investors since their evidence shows that stocks with more positive media sentiment have a higher crash risk in China.

It has been widely documented that the media can influence investors' sentiment, attention, and thus their trading behaviour in the stock market. For instance, through textual analysis of the content of the *Wall Street Journal*, Tetlock (2007) find that the stock market experiences downward pressure when the level of media pessimism is high. Also, the trading volume would be higher when media pessimism is extremely high or low. Wu and Lin (2017) reveal that the buy–sell imbalance of individual investors is negatively associated with the media tone. Besides, both positive and negative media tone are significantly and positively correlated with abnormal returns. Schmitz (2007) uses a unique dataset of corporate news and shows that the incorporation of information in share price is fast since price reaction primarily happens on the day of the arrival of the new information. However, when combining the news data and the transaction records of investors, he finds that stock investors react slowly to new information. The evidence of his study also shows that the post-news trading volume increases significantly for both positive and negative news, whereas the post-news drifts are more pronounced for negative news than positive news.

Dong and Gil-Bazo (2020) adopt the data of a social media platform to construct a stock-level media sentiment measurement. Their study demonstrates that positive sentiment predicts higher risk-adjusted stock returns in a short period followed by price reversals. Additionally, they imply that the relationship between sentiment and stock returns is primarily driven by positive sentiment and individual investors. Likewise, McGurk et al. (2020) employ Taddy's (2013) method and Twitter-based data to construct a stock-specific investor sentiment measurement. The results show that an increase in positive sentiment is associated with an increase in abnormal returns, while the connection between negative sentiment and abnormal returns is limited. Similarly, Renault (2017) uses messages posted on the microblogging platform to construct a novel investor sentiment measurement and combine it with the intraday market index ETF return data. The findings of his study reveal that the first half-hour change in investor sentiment predicts the last half-hour return, even after controlling for lagged market returns. Also, the short-term sentiment-driven price pressure is followed by a price reversal on the next trading day, which is consistent with the noise trading hypothesis.

5.2.3 Hypothesis development

Evidence from existing studies suggests that information asymmetry and dispersion of opinion may exist before the earnings announcement (Park et al., 2014; Sprenger and Welpe, 2011). At the same time, the quarterly financial reports of public firms contain a large amount of information about firms' operations and potential risks, which helps narrow information asymmetry between different investors. Therefore, the first hypothesis concerns the reaction of investors after earnings announcements. In Section 5.2.1, we review the studies that analyse how investors react to earnings surprises, while the evidence of previous literature is inconclusive. Individual investors would sell stocks with positive earnings surprises and buy stocks with negative earnings surprises if they are contrarians. Otherwise, we should detect a higher buying (selling) tendency among stocks with positive (negative) earnings surprises. In this case, we expect that:

H1a: Investors will react differently to stocks with positive and negative earnings surprises.

On the other hand, individual investors will be net buyers on stocks with both positive and negative earnings surprises if they are attracted by attention-grabbing events (Hirshleifer et al., 2008). Subsequently, we should observe that:

H1b: Investors will react similarly to stocks with positive and negative earnings surprises.

Widespread evidence in the literature shows that the reaction of individual investors could be different for stocks with negative and positive earnings surprises (Chan, 2003; Ekholm, 2006; Kaniel et al., 2012). Meanwhile, more recent findings prove the role of market-wide and firm-specific sentiment in shifting the movement of stock prices after earnings announcements (Mian and Sankaraguruswamy, 2012; Cahan et al., 2013; Cahill et al., 2017; Seok et al., 2019). Pinello (2008) finds that the extent to which investors are surprised at the time of an earnings announcement is determined by the comparison between the reported earnings and investors' earnings expectation. In this study, we argue that, to some degree, media tone can change investors' sentiment and their expectations of upcoming earnings news. For stocks with consistent media tone and earnings surprises – i.e., a positive pre-announcement media tone accompanied by a positive earnings surprise – investors tend to be more rational and confident before trading. Besides, the uncertainty of the stock would be relatively lower, and the opinion among investors would be more consistent. In comparison, stocks tend to have a higher level of uncertainty and greater dispersion of opinion when the pre-announcement media tone is not consistent with the direction of earnings surprises. Accordingly, we should observe that:

H2: Investors' reactions to earnings surprise will be influenced by pre-announcement media tone.

Furthermore, the impact of media tone may vary across different investor groups. Li et al. (2017b) find that super investors take advantage of private information and act as net buyers ahead of dividend announcements in the Chinese stock market. Wealthy investors are more likely to access private information and process public information rationally, while investors with well-diversified portfolios are more likely to be distracted by information about other stocks in their portfolios. As a result, their reactions to earnings surprises are less likely to be affected by media tone. Therefore, we expect that:

H3: The impact of media tone will differ among investor groups.

5.3 Data and methodology

5.3.1 Data source

5.3.1.1 Data of individual investors

The individual-level trading data used in this study is collected from a large anonymous Chinese brokerage firm.[43] The sample period is from the beginning of January 2007 to the end of July 2009. The original dataset contains more than two million individual investor accounts, though some of these are not fit for the research purpose of this study. To analyse the reactions of investors after the earnings announcements, we first need to delete accounts which only hold security investment funds, index funds or B-share stocks. Besides, we require that there are no missing values in the customer files, such as gender, date of birth, and account opening date. We also exclude from our sample investors younger than 18 years old at the time of account opening and who have outliers in their stock holdings or cash balances. Lastly, individual

[43] More details of the dataset used can be found in the introduction.

investors must have traded stocks in the sample during a specific period on and after the earnings announcement date.

5.3.1.2 Data of media and stock characteristics

The media data is collected from the *Genius Finance Database*, including articles from 16 newspapers. The complete database contains 2,034,796 articles published from 1st January 2002 to 31st December 2011. In these articles, keyword searches are performed in the full text of the articles and the headlines using company keywords (e.g., company name and its abbreviation, stock name, and stock symbol) or the names of company executives. This approach overcomes the limited scope of existing studies, such as the analysis of full-text content, thus avoiding omissions and ensuring the reliability and comprehensiveness of the results. We focus primarily on the articles published from 30 days before to 1 day before the earnings announcement released by firms in our sample. After the matching process, the media data includes 202,580 articles. We also collect data on stock characteristics (e.g., stock prices, returns, market value, quarterly earnings per share, and trading volume) from the *China Stock Market and Accounting Research* (*CSMAR*). A cross-check is conducted with the stock data in the *Wind Database*, which is another professional platform for Chinese financial markets.

5.3.2 Methodology

5.3.2.1 Earnings surprises

Contemporary studies investigating earnings surprises generally follow one of two paths – firstly, hypothesizing that earnings are based on a seasonal random walk and hence using time series model to estimating earnings (Ball and Brown, 1968; Foster, 1977; Chan et al., 1999; Hou et al., 2009; Shanthikumar, 2012), and secondly, finding the differences between realistic earnings and the analysts' forecast earnings when they are available (Brown et al., 1987; Chan et al., 1996; Pinello, 2008; Dellavigna and Pollet, 2009). Since analysts' forecast earnings data are only available in annual estimates during our sample period, in this study we use standardized unexpected earnings (SUE), by subtracting earnings four quarters ago from the most recent quarter and dividing it by the standard deviation of earnings changes over the last eight quarters:

$$SUE_{i,t} = (e_{i,t} - e_{i,t-4})/\sigma_{i,t} \tag{5.1}$$

Where $e_{i,t}$ is the quarterly earnings of stock i and $e_{i,t-4}$ is the quarterly earnings of stock i in the same quarter of the prior year. $\sigma_{i,t}$ is the standard deviation of unexpected earnings $e_{i,t-1} - e_{i,t-5}$, for the previous eight quarters.

5.3.2.2 Media tone and coverage

Since Dyck and Zingales (2003) pioneered the idea that the positive and negative media tone have different impacts on investor sentiment and asset prices to varying degrees, the study of media tone has generated considerable academic discussion. Antweiler and Frank (2004) constructs a bullishness index based on user messages from two platforms and forecast the yield for the next trading day; however, they do not find direct evidence that media tone can affect market returns and trading volume. Goetzmann et al. (2016) find a positive correlation between the previous day's market returns and the number of positive and negative words in the financial media. This effect seems to be asymmetric and is more significant for extreme negative returns. Tetlock (2007) uses a quantitative approach to portray media tone and predict stock price movements, thus taking the study of media tone and asset prices to a new level. Loughran and McDonald (2011) improve the list of words used to measure media sentiment and find that the new list of words improves the prediction of stock price movements.[44]

Unlike English, the basic elements of Chinese statements are Chinese characters rather than words. Therefore, we first use the most commonly used Chinese word separation software in China – NLPIR Chinese Word Separation System to split each news report into a collection of phrases.[45] Subsequently, the following three thesauri are used as standards to construct a financial thesaurus applicable to the financial press in China: 1) The Contemporary Chinese Dictionary, 5th edition; 2) The Latest Chinese-English Handbook of Commonly Used Economic and Financial Terms, 1st edition; and 3) Chinese translation of the wordlist used in Loughran and McDonald (2011). Finally, the positive and negative words provided by HowNet – Chinese Information Structure Database (2007 version) are matched and modified by the

[44] Loughran and McDonald (2011) argue that the lexical classification principles of the *Harvard Psychological Dictionary* used by Tetlock (2007) are not fully applicable to the financial sector and that the negative tone index calculated on this basis is highly biased in financial reports. Some adverse words in the *Harvard Psychological Dictionary* do not have negative connotations in financial media reports, such as liability, cost, and taxes.

[45] NLPIR Chinese word separation system, also known as NLPIR Natural Language Processing and Information Retrieval Sharing Platform. It is one of the most authoritative Chinese word separation systems, which can automatically discover new feature language in long text content based on information cross-entropy. Additionally, the NLPIR can adaptively test the language probability distribution model of the corpus to achieve adaptive word separation.

word frequencies of the articles. As a result, a lexicon of 3,863 negative words and 1,840 positive words is established for the financial media in China.[46]

This chapter uses two methods to measure media tone. In the first approach to measure media tone, we start by defining positive and negative news:

$$News_{tone\,j} = \frac{Number\ of\ good\ words_j - Number\ of\ bad\ words_j}{Number\ of\ total\ words_j} \tag{5.2}$$

$$News_j = Positive\ news\ if\ News_{tone\,j} > 0 \tag{5.3.1}$$

$$News_j = Negative\ news\ if\ News_{tone\,j} < 0 \tag{5.3.2}$$

Where $News\_tone_j$ is the media tone of news j, defined as the difference between the number of positive and negative words and divided by the total number of words in the article. Subsequently, if the number of good words in the articles is more than the number of negative words, news j is counted as positive news, otherwise, it is counted as negative news. Afterwards, similar to the study of Li et al. (2019), the pre-announcement media tone regarding firm i is defined as the difference between the number of positive and negative pieces of news and divided by the total amount of news during the period from 30 days before to 1 day before the announcement day t:

$$Media\ tone\ 1_{i,t} = \frac{\#\ of\ positive\ news_{i,t-1,t-30} - \#\ of\ negative\ news_{i,t-1,t-30}}{\#\ of\ total\ news_{i,t-1,t-30}} \tag{5.4}$$

In addition, following García's (2013) method, the second media tone measurement is constructed as the ratio of the difference between positive and negative words of all reports for firm i to the total number of words between 30 days before and 1 day before day t:

$$Media\ tone\ 2_{i,t} = \frac{\#\ of\ positive\ words_{i,t-1,t-30} - \#\ of\ negative\ wrods_{i,t-1,t-30}}{\#\ of\ total\ words_{i,t-1,t-30}} \tag{5.5}$$

We also calculate the media coverage for a given stock from 30 days before to 1 day before the announcement day t:

[46] HowNet is an electronic knowledge system in China, which is based on the concepts represented by Chinese words. It can reveal the relationship between different concepts and the attributes of the notion. It is the first electronic knowledge system in China and has a systematic classification of positive and negative words in Chinese vocabulary.

$$Media\ coverage_{i,t} = \sum_{n=1}^{30} News_{i,t-n} \tag{5.6}$$

Where $News_{i,t-n}$ is a dummy variable which equals one if firm i is mentioned in articles between day $t - 30$ and day $t - 1$.

5.3.2.3 Investors' reactions

This study constructs a variable to measure the changes in investors' holdings of stocks in the period following the earnings announcements by using the method of Ekholm (2006) to investigate their reactions to earnings news. Therefore, the first step is to identify which investors have traded the firm's shares since the quarterly announcement was released. Afterward, the reaction of investor i to stock j is calculated as:

$$Reaction_{i,j,t+n} = \left(H_{i,j,t+n} - H_{i,j,t-1}\right)/H_{i,j,t+n}\ if\ H_{i,j,t+n} - H_{i,j,t-1} > 0 \tag{5.7.1}$$

$$Reaction_{i,j,t+n} = \left(H_{i,j,t+n} - H_{i,j,t-1}\right)/H_{i,j,t-1}\ if\ H_{i,j,t+n} - H_{i,j,t-1} < 0 \tag{5.7.2}$$

$$Reaction_{i,j,t+n} = 0\ if\ H_{i,j,t+n} - H_{i,j,t-1} = 0 \tag{5.7.3}$$

Where $H_{i,j,t+n}$ is the shares of security j held by investor i n trading days after the earnings announcement date t. $H_{i,j,t-1}$ is the shares of security j held by investor i 1 day before the earnings announcement date t. The above equations can be described in the following way: First, if investor i increases his holdings in stock j n trading days after the earnings announcement, then the reaction on that stock is equal to the amount of the increase divided by the holdings at trading day n. Second, if investor i reduces his holdings in stock j n trading days after the earnings announcement, the reaction to stock j is equal to the reduction divided by the holdings 1 day before the announcement date. Lastly, the variable takes the value of 0 if investor i has traded stock j between day t and $t + n$, but has not had a change in the position. Furthermore, to compare the reactions between different stocks, we construct a quarterly reaction measurement across all investors for stock j in each quarter t:

$$Reaction_{j,t} = \frac{1}{m} \sum_{i=1}^{m} Reaction_{i,j,t+n} \tag{5.8}$$

In contrast to Ekholm (2006), who uses the holding positions for 6 calendar days after the earnings announcement as observations, this study adopts holding positions for 6 and 15 trading days after the announcement date as observations. In this way, we are able to identify whether there is a difference between investor's reactions in the short run and relatively long run.

5.3.2.4 Sample selection

To obtain the quarterly standardized unexpected earnings, we require no missing data on earnings per share for stocks in the most recent quarter and the same quarter of the prior year. Besides, stocks must have earnings per share data for the last 13 consecutive quarters since the standard deviation of the change in earnings over the last 8 quarters needs to be calculated. Stocks also have to be covered by articles in our sample at least once in the 30 days before an earnings announcement. Lastly, to match the individual trading data with media data and quarterly earnings information, stocks must have at least one transaction record made by our sample of investors within 15 days of an earnings announcement. Overall, our final sample consists of 1,486,477 investors who traded within 15 days following the quarterly earnings announcements and 202,580 articles that reported on stocks in our sample.

5.4 Empirical results

5.4.1 Summary statistics

[Insert Table 5.1 about here]

Table 5.1 reports the summary statistics of stock and media data. Our final sample contains 12,652 earnings announcements released by 1,452 firms between 1st January 2007 and 31st July 2009. The mean SUE is a positive value and significantly different from zero, indicating that firms' quarter earnings tend to be a positive surprise for investors.[47] *Media tone 1* (*tone 2*) and Media coverage are two variables mentioned in Section 5.3.2.2 to capture media attitudes and coverage in the period from 30 days before to 1 day before the earnings announcements. Overall, we find that, on average, firms have a positive pre-announcement media tone, and the result is found consistent by using two media tone measures. Besides, a high volume of news articles covers the stocks in our sample, and on average, each stock is mentioned twice a day.

[Insert Table 5.2 about here]

Table 5.2 shows the descriptive statistics of individual investors in our sample. Panel A of this table comprises the summary statistics of investors' characteristics. After matching four dataset

[47] The standard error of SUE is 0.039, thus, the mean has 0.076/0.039=1.97 standard deviations from zero.

files and applying the restrictions mentioned in Section 5.3.2.4, the final sample contains 1,486,477 investors who traded within 15 days following the quarterly earnings announcements. *Gender* is a dummy variable which equals one if an investor is a female, otherwise zero. In general, the proportion of females (46.6%) in the sample is slightly lower than that of males. *Age* (*Trading experience*) is the difference between the date of birth (account opening date) and the end of the sample period. The mean (median) trading experience of investors in our sample is 5.057 (2.333) years, indicating that most investors are inexperienced in the stock market. *The number of stocks* is the average number of stocks an investor holds one day before the earnings announcements. *Portfolio value* and *account size* are the market value of investors' portfolios and total wealth allocated in the stock market one day before an announcement date. Overall, we find that small investors hold the majority of accounts and that individual investors' portfolios are poorly diversified.

Panel B of Table 5.2 reports details of investors' reactions after earnings announcements. We define an investor as a buyer of stock *j* after an earnings announcement if she has a positive reaction; conversely, she is a seller. At the same time, investors are defined as non-responders if their reaction is equal to zero. Overall, although the percentage of buyers is higher than that of sellers after earnings announcements, most investors do not show reactions within 15 days. Additionally, the positive value of reaction suggests that, on average, individual investors in the Chinese stock market tend to buy stocks after earnings announcements.

5.4.2 Investors' reactions, earnings surprises, and media tone

5.4.2.1 Earnings surprises and investors' reactions

In this part, we examine how investors react to positive and negative earnings surprises, as well as stocks within different earnings surprises groups. To compare the reaction of stocks with different earnings surprises, for each investor we construct a quarterly variable by using Equations (5.7.1) – (5.7.3) to estimate their reaction to a given stock, which is then aggregated across all investors for each stock using Equation (5.8).

[Insert Table 5.3 about here]

Panel A of Table 5.3 compares investors' reactions in two different periods between stocks with positive and negative earnings surprises. We find that individual investors tend to increase their holdings in stocks with positive earnings surprises within 6 and 15 trading days following the announcement date. By contrast, investors react negatively to stocks with negative earnings surprises after 6 trading days, and their holdings consistently decrease until at least 15 trading days after the announcement date. Furthermore, the evidence from Panel A shows that the average reaction to stocks with positive earnings surprises is significantly higher than to stocks with negative earnings surprises. For instance, in the 6 trading days following the announcement date, investors' positions in positive *SUE* stocks have increased 1.54% more than those in negative *SUE* stocks. This number continuously increases over the 15 trading days after the announcement date.

In Panel B, stocks are grouped into quintiles each quarter based on the earnings surprise, with group 1 comprising stocks with the lowest (most negative) *SUE*, while group 5 contains stocks with the highest (most positive) *SUE*. The results from this panel suggest that investors' holdings increase with the magnitude of earnings surprise, since groups comprising stocks with higher *SUE* experience a higher reaction than those made up of stocks with lower *SUE*. Meanwhile, we find that investors reduce more holdings on stocks with the most negative earnings surprises, while holdings in stocks with the most positive earnings surprise (quintile 4 and 5) consistently increase until at least 15 trading days after the announcement date. In an unreported table, we also find that there are more buyers for stocks with positive earnings surprises, especially in the highest positive *SUE* group. Overall, the outcomes of Table 5.3 indicate that individual investors in the Chinese stock market tend to increase (reduce) their holdings after good (pessimistic) earnings news.

5.4.2.2 Can media tone affect investors' reactions to earnings surprises?

[Insert Table 5.4 about here]

Before analysing investors' reactions under the dynamic relationship between media tone and earnings surprises, this study explores whether the pre-announcement media tone is connected to their reactions after the announcement date. Table 5.4 illustrates the difference between investors' reactions to positive and negative media tone across two different periods after the announcement. In Panel A of Table 5.4, we employ *Media tone 1* to represent the attitude of articles towards stocks from 30 days before to 1 day before the earnings announcement date, which is replaced by *Media tone 2* in Panel B. The results in Panel A indicate that, on average, investors tend to increase their holdings after positive earnings surprises. Additionally, we find that the average reaction to stocks with a positive pre-announcement media tone is significantly higher than for stocks with a negative pre-announcement media tone. This result persists throughout two different reaction periods and remains stable when we change the media tone measurements.

[Insert Table 5.5 about here]

Given that the evidence from Table 5.4 show that investors' trading behaviour can be affected by media tone, in this section we investigate the extent to which the pre-announcement media tone could shift investors' reactions to earnings surprises. Table 5.5 reports investors' reactions to stocks with different pre-announcement media tone conditional on earnings surprise using univariate tests. We first separate stocks into two groups based on the positivity and negativity of earnings surprises. Stocks in each group are further divided into two groups based on the direction of media tone. This method results in four combinations, which makes it possible to explore the impact of media tone on the relationship between earnings surprises and investors' reactions.

The preliminary results in Table 5.5 show that investors' holdings increase most in stocks where both media tone and earnings surprises are positive. In contrast, their holdings have the highest reduction when media tone and earnings surprises are negative. To some extent, this result implies that positive media tone can exacerbate investors' buying behaviour on positive earnings surprises stocks, while negative media tone can amplify investors' selling on stocks with negative earnings surprises. More specifically, we find that for stocks with positive earnings surprises, individual investors tend to increase more holdings on stocks with positive pre-announcement media tone than those with negative pre-announcement media tone. Likewise, investors sell more intensively on stocks with negative media tone when the earnings news is terrible.

We then use regression models to further explore the sensitivity of investors' reaction to earnings surprises by media tone, following the method of Mian and Sankaraguruswamy (2012) and Cahan et al. (2013):

$$Reaction_{j,t}^{[0,x]} = \alpha + \beta_0 Down_{j,t} + \beta_1 UpSUE_{j,t} + \beta_2 DownSUE_{j,t} + \beta_3 UpSUE_{j,t} \times Media\ tone_{j,t} + \beta_4 DownSUE_{j,t} \times Media\ tone_{j,t} + \beta_5 UpSUE_{j,t} \times Media\ coverage_{j,t} + \beta_6 DownSUE_{j,t} \times Media\ coverage_{j,t} + \beta_7 NonlUp_{j,t} + \beta_8 NonlDown_{j,t} + \varepsilon_{j,t} \quad (5.9)$$

Where $Reaction_{j,t}^{[0,x]}$ is the average holding position changes of investors for firm j, during x days starting from the earnings announcement date t. *UpSUE* equals *SUE* if *SUE* is positive, and it equals 0 otherwise. Likewise, *DownSUE* equals *SUE* if *SUE* is negative, otherwise it equals 0. As a result, this model enables the coefficient on *SUE* to vary depending on the direction of the earnings surprise (Conrad et al., 2002; Seok et al., 2019). Besides, to compare the effect of negative and positive earnings surprises, the model contains a dummy variable, *Down*, which equals 1 if *SUE* is negative, and 0 otherwise. Furthermore, to estimate the impact of media tone on firms with different directions of earnings surprises, the regression model incorporates an interaction term in which the earnings surprises of firm *j* is multiplied by its pre-announcement media tone. More specifically, *UpSUE* × *Media tone* (*DownSUE* × *Media tone*) is used to identify whether investors' reactions to positive (negative) earnings surprises depend on pre-announcement media tone. Consequently, if investors tend to increase more holdings on stocks that have positive earnings surprises with higher media tone than those with lower media tone, we should observe a positive coefficient on β_3. Likewise, if investors tend to reduce more holdings on stocks with negative earnings surprises in the case of poorer media tone than in the case of better media tone, then a negative coefficient on β_4 should be detected.

To control the news effect on investors' attention, the model also includes the media coverage of firms from 30 days to 1 day prior to the announcement date, and it is interacted with *UpSUE* and *DownSUE* to test whether the attention has an asymmetrical effect on positive and negative earnings surprises (Qiu and Welch, 2006; Cahill et al., 2017). Lastly, given the possible nonlinear relationship between earnings surprises and investors' reactions, we add the square of *UpSUE*, i.e., *NonlUp*, and the square of *DownSUE* multiplied by negative one, i.e., *NonlDown*, to Equation (5.9) (Mian and Sankaraguruswamy, 2012).

[Insert Table 5.6 about here]

Table 5.6 shows the results of the regression model. For simplicity, the outcomes reported in this table are based on the first media tone measurement (*Media tone 1*), and the results remain consistent when using *Media tone 2* as the tone measurement. Columns (1) and (4) report the results for linear models, while Columns (2) – (3) and (5) – (6) show the results for nonlinear models. To ensure the robustness of the relationship between investors' reactions and earnings surprises, in Columns (1) – (2) and (4) – (5), we revisit the association between them, and media-related variables are not included in the model. In Columns (3) and (6), media tone and coverage are incorporated to analyse whether they could influence the relationship between investors' reactions and earnings surprises. The dependent variables in Columns (1) – (3) and (4) – (6) are the changes in standardized holdings 6 and 15 days after the earnings announcement, respectively.

Consistent with our findings in Table 5.4, the estimated coefficient on Down suggests that, compared with firms with positive earnings surprises, individual investors significantly reduce their holdings on stocks with negative earnings surprises in both the short run and a relatively long run. Besides, this relation remains stable when we add two nonlinearity variables *NonlUp* and *NonlDown*. The significantly negative coefficient on *NonlUp* in all columns indicates a concave buying-earnings association for good earnings news. Although individual investors tend to increase their holdings in when facing good earnings news, they show somewhat contrarian trading behaviour when the earnings are extremely large. Indeed, similar findings are documented in Seok et al. (2019) and Cahill et al. (2017), who argue that investors may engage in arbitrage when they believe the market has been driven too far by widespread good news.

On the contrary, we do not detect an S-shaped relation between investors' reactions and negative earnings surprises. Additionally, the estimated coefficient on *UpSUE* is significantly positive for both linear and nonlinear models. This result is also consistent in two reaction periods, implying that investors increase their holdings with the magnitude of positive earnings surprises. However, this is not the case when firms have negative earnings surprises. In Columns (1) – (3), the coefficient on *DownSUE* is insignificantly positive, while it is significantly positive in Columns (5) – (6), suggesting that investors react slowly to negative earnings surprises. Moreover, consistent with Conrad et al. (2002), who demonstrate that investors regard positive earnings surprise as more informative than negative earnings surprise, we find that investors react more strongly to positive earnings surprises since the coefficient on *UpSUE* is considerably greater than that on *DownSUE*.

In Table 5.6, we are primarily concerned with the coefficients on interaction terms, which measure the impact of the media on investors' reactions to earnings surprises in different directions. Firstly, we do not find that media coverage can significantly shift investors' reactions to positive and negative earnings surprises, given the estimates of *UpSUE* × *Media coverage* and *DownSUE* × *Media coverage*. Regarding the interaction variables of earnings surprises and media tone, the reported coefficients on *UpSUE* × *Media tone* are 0.0018 for

Reaction [0, 6] and 0.0038 for *Reaction [0, 15]*, respectively. These two significantly positive coefficient estimates reveal that investors react more strongly to positive earnings surprises with high media tone than those with low media tone. The coefficients of the interaction term *DownSUE* × *Media tone* are -0.0017 and -0.0015 for *Reaction [0, 6]* in Column (3) and *Reaction [0, 15]* in Column (6), indicating that investors react more negatively to negative earnings surprises for firms with negative media tone than for those with positive media tone. These results are consistent with our hypothesis, as investors' reactions to earnings surprise can be influenced by pre-announcement media tone.

To further explore the economic influence of these estimates, we use the method of Mian and Sankaraguruswamy (2012) by calculating the changes in *UpSUE* and *DownSUE* when holding the other variables constant, and there is one standard deviation increase or decrease in media tone.[48] One standard deviation shift in *Media tone* leads to a change of 0.0007 (*0.0018×0.365*) in *UpSUE* for *Reaction [0, 6]* and a change of 0.0014 (*0.0038×0.365*) in *UpSUE* for *Reaction [0, 15]*, respectively. Subsequently, for *Reaction [0, 6]*, the effect of *UpSUE* is 0.0057 (*0.0050+0.0007*) when the *Media tone* is one standard deviation higher than its mean, and when the media tone is one standard deviation below its mean, the effect of *UpSUE* is 0.0043 (*0.0050 − 0.0007*). Similarly, for *Reaction [0, 15]*, the effect of *UpSUE* is 0.0080 (*0.0066+0.0014*) when the media tone is one standard deviation higher than its mean, and when the media tone is one standard deviation below its mean, the effect of *UpSUE* is 0.0052 (*0.0066−0.0014*). Hence, the slope of *UpSUE* falls by 24.56% (*(0.0057−0.0043)/0.0057*) for *Reaction [0, 6]* and the slope of *UpSUE* decreases by 35.00% (*(0.0080−0.0052)/0.0080*) for *Reaction [0, 15]* when the media tone shifts from positive to negative.

As for the impact of media tone on stocks with negative earnings surprises, one standard deviation change in *Media tone* leads to a change of -0.0006 (*-0.0017×0.365*) and in *DownSUE* for *Reaction [0, 6]* and a change of -0.0005 (*-0.0015×0.365*) in *DownSUE* for *Reaction [0, 15]*, respectively. Accordingly, we use the same method to estimate the sensitivity of investors' reactions to negative earnings surprises and find that the slope of *DownSUE* falls by 170.00%

[48] The standard deviation of *Media tone 1* is 0.365, as reported in Table 5.1.

for *Reaction [0, 6]* and the slope of *DownSUE* drops by 71.43% for *Reaction [0, 15]* when the media tone shifts from highly negative to highly positive.[49]

Overall, the evidence from Table 5.6 implies that investors overreact to good earnings news for firms with positive media tone compared with those that have negative media tone, while they react more strongly to bad earnings news when the media tone is more negative. The impact of media tone on investors' reactions to negative earnings surprises also seems to be more pronounced than that for positive earnings surprises, given that the sensitivity of *DownSUE* varies more when the media tone changes. To some extent, this finding is consistent with Mian and Sankaraguruswamy (2012) as well as Cahan et al. (2013), who argue that, due to the higher uncertainty of bad earnings news, market-wide and media sentiment has a higher impact on the mispricing of negative earnings surprises than that of positive earnings surprises.

5.4.2.3 Does the impact of media tone vary across investor groups?

A series of studies demonstrate that investors may react differently given the same earnings news. Frieder (2008) suggests that compared to the large investors, the net buying of small investors increases with the number of consecutive positive earnings surprises. Ekholm (2006) finds that the overconfidence theory may play an important role in explaining the relationship between investors' trading and earnings surprise. He argues that when new public information is released, less overconfident investors tend to trade against more overconfident investors until a new balance is reached. In addition, the different reactions of investors to company news may stem from information asymmetry. Li et al. (2017b) find that super investors take advantage of private information and act as net buyers ahead of dividend announcements in the Chinese stock market.

This section investigates whether media tone has a similar impact on different investor groups' reactions to earnings surprises. To do so, we construct a quarterly reaction measurement across each investor group k for stock j in quarter t:

$$Reaction_{j,t}^{k} = \frac{1}{m}\sum_{i=1}^{m} Reaction_{i,j,t+n} \,|i \in k \qquad (5.10)$$

[49] The positive coefficient on *DownSUE* suggests that, for negative earnings surprises, investors increase their holdings as earnings surprises increase. However, when facing a more negative media tone, *Reaction [0, 6]* becomes negative, and thus we detect a reversal in slope (a change in slope of more than 100%).

We focus primarily on investors with varying wealth and numbers of stocks in the stock market. Wealthy investors are more likely to access private information and process public information rationally, while well-diversified investors have a greater likelihood of being influenced by other stocks in their portfolios. Thus, the reactions of those investors to earnings surprises are less likely to be affected by media tone than other investors.

[Insert Table 5.7 about here]

Table 5.7 shows the sensitivity of different investors' reactions to earnings surprises by employing Equation (5.9). The dependent variable in Columns (1) and (3) is standardized holding changes 6 days after the earnings announcement, and it is replaced with the changes of standardized holding 15 days after the earnings announcement in Columns (2) and (4). Panel A of this table shows the comparison between wealthy and poor investors. Individuals are deemed as *wealthy* investors if they have invested more than RMB 500,000 in the stock market, while all remaining investors are *poor* investors. Panel B shows the reactions of well-diversified and poorly diversified investors. *Well-diversified* investors are those who have more than 10 stocks in their portfolios, while the others are regarded as *poorly diversified* investors.

In Panel A of Table 5.7, we find the estimated coefficient on *Down* is significantly negative for wealthy and poor investors, indicating that investors in both groups significantly reduce their holdings on stocks with negative earnings surprises. However, the significantly negative coefficients of intercept term in Columns (1) and (2) show that wealthy investors also reduce holdings following positive earnings surprises, though the magnitude of reduction is somewhat less than that after negative earnings surprises. Besides, the estimated coefficient on *UpSUE* is significantly positive for wealthy and poor investors, implying that investors in two groups increase their holdings with the magnitude of positive earnings surprises. However, this is not the case when firms have negative earnings surprises, especially for wealthy investors. In terms of the interaction variables of earnings surprises and media tone, we find coefficients on *UpSUE* × *Media tone* and *DownSUE* × *Media tone* are insignificant for wealthy investors. This outcome suggests that media tone cannot shift wealthy investors' reactions to positive and negative earnings news. In contrast, the significantly positive (negative) coefficients on *UpSUE* × *Media tone* (*DownSUE* × *Media tone*) in Columns (3) and (4) demonstrate that poor investors overreact to good earnings news for firms with positive media tone compared with those with negative media tone, while they overreact to bad earnings news when the media tone is more pessimistic.

Panel B of Table 5.7 reports the comparison of reactions between well-diversified and poorly diversified investors. The estimated coefficients on *Down* and intercept term reveal that, although investors in these two groups significantly reduce their holdings on stocks with negative earnings surprises, well-diversified investors act as net sellers following positive earnings surprises. Furthermore, the significantly positive coefficients on *UpSUE* in Columns (1) – (4) indicate that investors in the two groups increase their holdings with the magnitude of positive earnings surprises, whereas this is not the case for firms with negative earnings surprises, especially for investors in the well-diversified group. The reported coefficients of interaction variables regarding earnings surprises and media tone are consistent with our hypothesis that, on the one hand, media tone fails to affect the reaction of diversified investors following positive or negative earnings news. On the other hand, investors in the poorly diversified group increase more holdings on good earnings news for firms with positive media tone than for those with negative media tone, while they sell more positions to bad earnings news when the media tone is more negative.

5.5 Robustness test

5.5.1 Another set of media data

In this section, we use another set of media data to ensure the robustness of our results. The media data in the *Genius Finance Database* comprises the news of 16 newspapers; however, investors may not have enough time and energy to process information from all the media due to limited attention. Solomon et al. (2014) argue that only news in four leading national newspapers can affect funds flows. Therefore, for the robustness check, we restrict the number of newspapers to 7 and only including the most well-known and authoritative media sources.[50]

[Insert Table 5.8 about here]

In the media mentioned above, we use the same method documented in Section 5.3 to match articles with listed companies and calculate media tone and coverage. Again, Equation (5.9) is adopted to analyse the sensitivity of investors' reactions to earnings surprises by media tone. Table 5.8 shows the results of the regression model. For simplicity, the outcomes in this table

[50] The eight most reputable publications in the Chinese security market are uniformly known as the Seven Newspapers and One Magazine, includes *Shanghai Security News*, *Securities Times*, *Financial News*, *Economic Daily*, *China Reform News*, *China Daily*, and *Capital Week*. The *Genius Finance Database* does not contain articles from *China Reform News* and *China Daily*. We added the *Security Daily*, a professional securities newspaper sponsored by Economic Daily Newspaper Group, in this alternative dataset. Also, it is an authorized publication that can disclose information on listed companies, insurance, trust, and property rights.

are based on the first media tone measurement (*Media tone 1*), and the results remain stable when using *Media tone 2* as the tone measurement. The dependent variables in Columns (1) and (2) are the changes in standardized holdings 6 and 15 days after the earnings announcement, respectively.

Overall, the results in Table 5.8 are consistent with those in Table 5.6. Firstly, individual investors significantly reduce their holdings on stocks with negative earnings surprises in both the short run and a relatively long run. Secondly, investors react more positively to positive earnings surprises with high media tone than those with low media tone, while they reduce more holdings to negative earnings surprises for firms with negative media tone than for those with positive media tone. Lastly, the impact of media tone on investors' reactions to negative earnings surprises is more pronounced than for positive earnings surprises.[51]

5.5.2 Can media tone predict earnings surprises?

[Insert Table 5.9 about here]

Apart from affecting investor sentiment and expectations, media tone may also influence investors' trading behaviour by successfully predicting the upcoming earnings news. Therefore, in this part, we investigate whether the pre-announcement media tone could predict firms' earnings surprises. Table 5.9 reports the relationship between pre-announcement media tone and standardized unexpected earnings. The dependent variable is standardized unexpected earnings. *Media coverage* is the number of articles mentioned from 30 days before to 1 day before the earnings announcement. *Media tone 1* and *Media tone 2* are the tone of media towards firms from 30 days before to 1 day before the earnings announcement. We control firms' specific characteristics in the regression models. *Momentum* is the prior six-month cumulative returns before the announcement date. *Ln(Size)* is the logarithm of stocks' closing market values one day before the announcement date. *B2M* is the book-to-market ratio, calculated using the most closely available book value divided by the market value one day prior to the announcement date. *ROA* is the return on assets at a given accounting quarter. *Turnover* is computed as the trading volume divided by the outstanding shares one day before

[51] For *Reaction [0. 15]*, the slope of *UpSUE* falls by 27.85% when the media tone shifts (one standard deviation) from positive to negative. By comparison, the slope of *DownSUE* falls by 53.33% when the media tone changes (one standard deviation) from negative to positive.

the announcement date. We include time fixed and industry effects in all regressions, and standard errors are double clustered at the stock and time level.

The evidence from Table 5.9 suggests that the pre-announcement media tone and coverage fail to predict firm's earnings surprises. To some extent, this is consistent with Trueman's (1997) and Lev and Penman's (1990) findings. They argue that firms with negative earnings surprises tend to release good news and delay the disclosure of bad news. Such information asymmetry makes it difficult for the media to predict firms' upcoming earnings. Interestingly, the coefficients on *Momentum* and *Turnover* show that *SUE* is (insignificantly) negatively correlated with the turnover ratio and it increases significantly with the cumulative returns before the announcements. This result is consistent with the findings of Park et al. (2014) and Sprenger and Welpe (2011), indicating that firms with greater earnings surprises are more likely to have information leakage, which leads to the increase of share prices. However, given the insignificant relationship between *Media coverage* and *SUE*, such information leakage may not be covered by media and only a few investors reflect the good news before the disclosure of forthcoming earnings. Li et al. (2017b) also find that only a small portion of super investors can take advantage of private information and act as net buyers ahead of dividend announcements in the Chinese stock market. In short, our findings suggest that while the media cannot predict earnings surprises, it has the potential to influence investors' reactions to earnings news by shifting their sentiment.

5.6 Conclusion

This study investigates how individual investors in the Chinese stock market react to earnings news, and the extent to which the tone of the media before earnings announcements affects investors' reactions to earnings surprises. By adopting a unique dataset with daily transaction records and holding positions from 1st January 2007 to 31st July 2009, we measure investors' reactions as changes in their stock holdings and match this to the pre-announcement media tone together with quarterly standardized unexpected earnings.

Our findings suggest that, on average, investors act as net buyers following earnings announcements, and their holding positions increase significantly with the magnitude of earnings surprises. Besides, although the pre-announcement media tone fails to predict earnings surprises, it plays a crucial role in shaping investors' reactions after earnings announcements. Specifically, we find that investors overreact to positive earnings surprises for firms with positive media tone than for those with negative media tone, while they react more negatively to bad earnings news when the media tone is worse. Meanwhile, the impact of media tone on investors' reactions to negative earnings surprises is more pronounced than that for positive earnings surprises.

This study further explores whether media tone has a similar impact on different investor groups' reactions to earnings surprises. Overall, the evidence shows that wealthy investors and those who have a well-diversified portfolio are less likely to be influenced by the tone of media. In particular, compared to wealthy and well-diversified investors, investors in the poorly diversified and low wealth groups increase more holdings to good earnings news for firms with positive media tone than for those with negative media tone, while they sell more positions to bad earnings news when the media tone is more pessimistic.

Tables of results

Table 5.1 Summary statistics: SUE and media

This table presents the summary of stocks and media data. The dataset of listed companies is collected from *CSMAR*, while the media data is obtained from the *Genius Finance Database*, including the articles of 16 newspapers. The sample period is from 1st January 2007 to 31st July 2009. To match the individual trading data, stocks are required to have at least one trade made by our sample of investors within 15 days of an earnings announcement. *SUE* is standardized unexpected earnings, calculated by subtracting the prior four quarters' earnings from the most recent quarter and dividing it by the standard deviation of earnings changes over the last eight quarters (Chan et al., 1999). *Media tone 1* (*tone 2*) is the media tone from 30 days before to 1 day before the earnings announcement, computed by using Equations (5.2) – (5.5), respectively. *Media coverage* is the average number of articles mention for a firm from 30 days to 1 day before the earnings announcement. *Size* is the market value of tradable shares one day before the earnings announcement. *B2M* is the book-to-market ratio, calculated by using the most closely available book value divided by the market value one day before the announcement date. *Momentum* is the cumulative prior six-month returns. *Turnover* is computed as the trading volume divided by the outstanding shares one day prior to the announcement date. *ROA* is the return on assets at the same accounting quarter of earnings announcements. The number of observations, means, standard deviations, and percentile statistics are reported.

	N of observations	Mean	SD	25%	Median	75%
SUE	12,652	0.074	4.444	-0.580	0.047	0.879
Media tone1	12,652	0.262	0.365	0.026	0.286	0.500
Media tone2	12,652	0.013	0.016	0.003	0.012	0.021
Media Coverage	12,652	66.868	315.026	11.00	21.000	46.000
Size (in million CNY)	12,652	4,167.041	11,520.760	931.664	1,719.440	3,557.058
B2M	12,652	0.349	0.305	0.187	0.298	0.450
Momentum	12,652	0.419	0.862	-0.281	0.317	0.944
Turnover	12,652	0.039	0.036	0.013	0.028	0.054
ROA	12,652	0.019	0.212	0.004	0.015	0.038

Table 5.2 Summary statistics: Individual investors and reactions

This table presents the summary of statistics for individual investors. The study's dataset comes from a large anonymous brokerage firm comprising more than two million individual investors who traded in the Chinese stock market from 1st January 2007 to 31st July 2009. 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, gender, and account opening date are not recorded, (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. After combining with stock and media data, the final sample of individual accounts contains 1,486,477 investors who traded during a specific period following earnings announcements. Panel A comprises the summary statistics of personal characteristics. Gender is a dummy variable which equals 1 if an investor is a female, 0 otherwise. Age is calculated based on their birthday and the end of the sample period. The trading experience is measured as the average trading year, based on the difference between the account opening date and 31st July 2009. The number of stocks is the average number of stocks investors hold one day prior to the earnings announcements. Portfolio value is the market value of investors' portfolio one day prior to the earnings announcements. Account size is the mean of wealth allocated in the stock market one day before the earnings announcements. The means, standard deviations, and percentile statistics are reported in Panel A. Panel B details the reactions of investors in two different periods after earnings announcements. Percentage of buyers (sellers and non-responders) describes percentage of three different trading behaviours based on number of accounts. Reaction is standardized holding changes after the earnings announcement.

Panel A. Descriptive of individual accounts (Number of Accounts=1,486,477)

Variables	Mean	SD	25%	Median	75%
Gender	0.466	0.499	0	0	1
Age	41.418	12.121	32	40	49
Trading experience	5.057	4.270	1.917	2.333	9
Number of stocks	3.008	2.908	1.5	2.318	3.700
Portfolio value (in RMB)	85,870.83	501,438	9,260.468	24,391.74	64,949.27
Account size (in RMB)	102,448	555,386.5	10,564.45	28,818.94	77,002.14

Panel B. Statistics of reaction after earnings announcements

	Percentage of Buyers	Percentage of Sellers	Percentage of Non-responders	Reaction
Period: [0, 6]	17.93%	16.54%	65.53%	0.0076
Period: [0, 15]	24.34%	23.18%	52.48%	0.0068

Table 5.3 SUE and investors' reactions

This table presents investors' reactions conditional on standardized unexpected earnings (SUE). The sample period is from 1st January 2007 to 31st July 2009. Stocks are required to have at least one trade made by our sample of investors within 15 days of an earnings announcement. Panel A of Table 5.3 shows the comparison of investors' reactions between stocks with positive and negative earnings surprises. SUE is standardized unexpected earnings calculated by using the method of Chan et al. (1999). Reaction is standardized holding changes after the earnings announcement. In panel B, stocks in our sample are sorted into quintiles each quarter based on the SUE, with group 1 (5) referring to the most negative (positive) SUE quintile. In both panels, we report the reaction of investors during two periods after the earnings announcement. The Student's t-test is used for statistical significance, and t-statistics are reported in brackets. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A. SUE and investors' reactions

Period: [0, 6]		N of Observations	Reaction	Diff= (1)-(2)
(1)	SUE>0	6,837	0.0147	0.0153***
(2)	SUE<0	5,579	-0.0006	(10.64)
Period: [0, 15]				
(1)	SUE>0	6,837	0.0178	0.0241***
(2)	SUE<0	5,579	-0.0063	(12.28)

Panel B. SUE group and reaction

Period: [0, 6]	SUE	Reaction
	1-negative	-0.0001
	2	0.0034
	3	0.0060
	4	0.0078
	5-Positive	0.0211
Period: [0, 15]	SUE	Reaction
	1-negative	-0.0070
	2	0.0004
	3	0.0045
	4	0.0092
	5-Positive	0.0267

Table 5.4 Media tone and investors' reactions

This table presents investors' reactions conditional on the pre-announcement media tone. The sample period is from 1st January 2007 to 31st July 2009. Stocks are required to have at least one trade made by our sample of investors within 15 days of an earnings announcement. Panel A (Panel B) of this table reports the comparison of investors' reactions in two different periods between stocks with positive and negative pre-announcement *Media tone 1* (*tone 2*). *Media tone 1* (*tone 2*) is the media tone of articles in our sample from 30 days before to 1 day before the earnings announcement. Reaction is standardized holding changes after the earnings announcement. The Student's t-test is used for statistical significance, and t-statistics are reported in brackets. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A. *Media tone 1* and reaction

Period: [0, 6]		Reaction	Diff= (1)-(2)
(1)	*Media tone 1* >0	0.0101	0.0113***
(2)	*Media tone 1* <0	-0.0012	(6.14)
Period: [0, 15]			
(1)	*Media tone 1* >0	0.0098	0.0151***
(2)	*Media tone 1* <0	-0.0053	(6.03)

Panel B. *Media tone 2* and reaction

Period: [0, 6]		*Reaction*	Diff= (1)-(2)
(1)	*Media tone 2* >0	0.0096	0.0101***
(2)	*Media tone 2* <0	-0.0004	(5.46)
Period: [0, 15]			
(1)	*Media tone 2* >0	0.0095	0.0136***
(2)	*Media tone 2* <0	-0.0041	(5.42)

Table 5.5 Media tone, SUE, and investors' reactions: Univariate test

This table shows investors' reactions to stocks with different pre-announcement media tones conditional on earnings surprises. The sample period is from 1st January 2007 to 31st July 2009. Stocks are required to have at least one trade made by our sample of investors within 15 days of an earnings announcement. Panel A (Panel B) of Table 5.5 compares investors' reactions in two different periods between stocks with positive and negative pre-announcement *Media tone 1* (*tone 2*) conditional on earnings surprises. *SUE* is standardized unexpected earnings calculated by using the method of Chan et al. (1999). *Media tone 1* (*tone 2*) is the media tone of articles in our sample from 30 days before to 1 day before the earnings announcement. Reaction is standardized holding changes after the earnings announcement. Stocks are first split into two groups based on the positivity or negativity of earnings surprises. Subsequently, stocks in each group are further divided into two groups based on the direction of media tone. This method results in four combinations, which allows exploring whether investors react differently to stocks with positive and negative media tone, given the same direction of earnings surprises. The Student's t-test is used for statistical significance, and t-statistics are reported in brackets. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A. *Media tone1* and reaction

Period: [0, 6]		Reaction	Diff= (1-2) & (3-4)
(1)	*SUE>0 & Media tone 1 >0*	0.0165	0.0114***
(2)	*SUE>0 & Media tone 1 <0*	0.0050	(4.01)
(3)	*SUE<0 & Media tone 1 >0*	0.0015	0.0076***
(4)	*SUE<0 & Media tone 1 <0*	-0.0060	(3.13)
Period: [0, 15]			
(1)	*SUE>0 & Media tone 1 >0*	0.0200	0.0147***
(2)	*SUE>0 & Media tone 1 <0*	0.0053	(3.75)
(3)	*SUE<0 & Media tone 1 >0*	-0.0040	0.0097***
(4)	*SUE<0 & Media tone 1 <0*	-0.0137	(3.01)

Panel B. *Media tone 2* and reaction

Period: [0, 6]		Reaction	Diff= (1-2) & (3-4)
(1)	*SUE>0 & Media tone 2 >0*	0.0162	0.0099***
(2)	*SUE>0 & Media tone 2 <0*	0.0063	(3.52)
(3)	*SUE<0 & Media tone 2 >0*	0.0011	0.0072***
(4)	*SUE<0 & Media tone 2 <0*	-0.0060	(2.97)
Period: [0, 15]			
(1)	*SUE>0 & Media tone 2 >0*	0.0198	0.0130***
(2)	*SUE>0 & Media tone 2 <0*	0.0067	(3.38)
(3)	*SUE<0 & Media tone 2 >0*	-0.0040	0.0091***
(4)	*SUE<0 & Media tone 2 <0*	-0.0130	(2.80)

Table 5.6 Sensitivity of investors' reactions to earnings surprises by media tone

This table presents the sensitivity of investors' reactions to earnings surprises by employing Equations (5.9). Columns (1) and (4) report the results for linear models, while Columns (2) – (3) and (5) – (6) show the results for nonlinear models. The results in Columns (1) – (2) and (4) – (5) do not include media-related variables. Columns (3) and (6), media tone and coverage, are incorporated to analyse the impact of media tone on the relationship between investors' reactions and earnings surprises. The dependent variable (*Reaction [0, x]*) in Columns (1) – (3) and Columns (4) – (6) is standardized holding changes 6 days and 15 days after the earnings announcement, respectively. *Down* is a dummy variable to estimate the effect of negative earnings surprises, which equals 1 if *SUE* is negative, and 0 otherwise. *UpSUE* equals *SUE* if *SUE* is positive, and it equals 0 otherwise. Likewise, *DownSUE* equals *SUE* if *SUE* is negative, otherwise it equals 0. *Media tone* and *Media coverage* are the tone of media and the number of news mentioned in articles from 30 days before to 1 day before the earnings announcement, respectively. *NonlUp* is the square of *UpSUE* and *NonlDown* is *DownSUE* squared multiplied by -1. T-statistics are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Reaction [0, 6]			*Reaction [0. 15]*		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Intercept	0.0102***	0.0083***	0.0083***	0.0116***	0.0086***	0.0086***
	(9.30)	(6.88)	(6.89)	(7.73)	(5.27)	(5.23)
Down	-0.0125***	-0.0109***	-0.0112***	-0.0196***	-0.0162***	-0.0164***
	(-7.46)	(-6.08)	(-6.25)	(-8.55)	(-6.63)	(-6.70)
$UpSUE$	0.0040***	0.0056***	0.0050***	0.0053***	0.0078***	0.0066***
	(11.59)	(10.36)	(7.85)	(11.17)	(10.46)	(7.54)
$DownSUE$	0.0003	0.0001	0.0001	0.0004	0.0009*	0.0009*
	(1.26)	(0.39)	(0.38)	(1.55)	(1.87)	(1.78)
$UpSUE \times Media\ tone$			0.0018*			0.0038**
			(1.67)			(2.59)
$DownSUE \times Media\ tone$			-0.0017***			-0.0015*
			(-2.73)			(-1.73)
$UpSUE$			0.0000			0.0000
$\times Media\ coverage$			(0.57)			(0.00)
$DownSUE$			0.0000			0.0000
$\times Media\ coverage$			(0.85)			(0.48)
$NonlUp$		-0.0000***	-0.0000***		-0.0001***	-0.0001***
		(-3.86)	(-4.17)		(-4.33)	(-4.87)
$NonlDown$		0.0000	0.0000		-0.0000	-0.0000
		(0.40)	(0.66)		(-1.19)	(-1.03)
Adjusted R^2 (%)	5.99	6.10	6.16	5.46	5.61	5.66
N of observations	12,652	12,652	12,652	12,652	12,652	12,652

Table 5.7 Reactions of different investors to earnings surprises and media tone

This table shows the sensitivity of different investors' reactions to earnings surprises by employing Equation (5.9). The dependent variable (*Reaction [0, 6]*) in Columns (1) and (3) is standardized holding changes 6 days after the earnings announcement. In Columns (2) and (4), the dependent variable is replaced with standardized holding changes 15 days after the earnings announcement. *Down* is a dummy variable to estimate the effect of negative earnings surprises, which equals 1 if *SUE* is negative, and 0 otherwise. *UpSUE* equals *SUE* if *SUE* is positive, and it equals 0 otherwise. Likewise, *DownSUE* equals *SUE* if *SUE* is negative, otherwise it equals 0. *Media tone* and *Media coverage* are the tone of media and the number of news mentioned in articles from 30 days before to 1 day before the earnings announcement, respectively. *NonlUp* is the square of *UpSUE* and *NonlDown* is *DownSUE* squared multiplied by -1. Panel A of this table shows the comparison between wealthy and poor investors. Individuals are deemed as *Wealthy* investors if they have allocated more than *RMB 500,000* in the stock market. Panel B shows the reactions of experienced and inexperienced investors. *Experienced* investors are those who have traded for more than 5 years in the stock market. T-statistics are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A. Wealthy vs. Poor

	Wealthy		Poor	
	Reaction [0, 6] (1)	Reaction [0, 15] (2)	Reaction [0, 6] (3)	Reaction [0, 15] (4)
Variables				
Intercept	-0.0068***	-0.0143***	0.0086***	0.0066***
	(-5.37)	(-8.89)	(6.84)	(3.86)
Down	-0.0090***	-0.0107***	-0.0115***	-0.0164***
	(-4.77)	(-4.47)	(-6.14)	(-6.46)
$UpSUE$	0.0034***	0.0054***	0.0053***	0.0069***
	(5.10)	(6.38)	(7.95)	(7.62)
$DownSUE$	-0.0003	-0.0006	0.0002	0.0010*
	(-0.78)	(-1.11)	(0.38)	(1.82)
$UpSUE \times Media\ tone$	-0.0008	-0.0013	0.0019*	0.0038**
	(-0.68)	(-0.91)	(1.71)	(2.51)
$DownSUE \times Media\ tone$	0.0000	0.0008	-0.0019***	-0.0016*
	(0.03)	(0.93)	(-2.82)	(-1.78)
$UpSUE \times Media\ coverage$	0.0000***	0.0000***	0.0000	-0.0000
	(4.03)	(2.65)	(0.11)	(-0.23)
$DownSUE$	0.0000	0.0000	0.0000	0.0000
$\times Media\ coverage$	(0.35)	(0.32)	(0.85)	(0.41)
$NonlUp$	-0.0000***	-0.0000***	-0.0000***	-0.00001***
	(-2.60)	(-2.76)	(-4.18)	(-4.83)
$NonlDown$	0.0000	0.0000	0.0000	-0.0000
	(1.10)	(0.81)	(0.65)	(-1.06)
Adjusted R^2 (%)	3.37	3.73	6.39	5.94
N of observations	12,652	12,652	12,652	12,652

Panel B. Well diversified vs. Poorly diversified

	Well diversified		Poorly diversified	
	Reaction [0, 6] (1)	Reaction [0, 15] (2)	Reaction [0, 6] (3)	Reaction [0, 15] (4)
Variables				
Intercept	-0.0196***	-0.0374***	0.0121***	0.0147***
	(-17.95)	(-25.95)	(9.58)	(8.51)
Down	-0.0076***	-0.0090***	-0.0116***	-0.0172**
	(-4.68)	(-4.20)	(-6.13)	(-6.71)
$UpSUE$	0.0059***	0.0081**	0.0049***	0.0064***
	(10.21)	(10.59)	(7.28)	(6.94)
$DownSUE$	-0.0001	0.0002	0.0017	0.0010*
	(-0.39)	(0.53)	(0.42)	(1.82)

$UpSUE \times Media\ tone$	-0.0012	-0.0017	0.0022*	0.0045***
	(-1.24)	(-1.28)	(1.92)	(2.94)
$DownSUE \times Media\ tone$	-0.0003	0.0001	-0.0019***	-0.0017*
	(-0.55)	(0.07)	(-2.87)	(-1.82)
$UpSUE \times Media\ coverage$	0.0000	0.0000	0.0000	-0.0000
	(0.84)	(0.63)	(0.55)	(-0.03)
$DownSUE$	0.0000	0.0000	0.0000	0.0000
$\times Media\ coverage$	(0.87)	(0.30)	(0.82)	(0.49)
$NonlUp$	-0.0000***	-0.0000***	-0.0000***	-0.0001***
	(-5.02)	(-4.81)	(-3.97)	(-4.71)
$NonlDown$	0.0000	0.0000	0.0000	-0.0000
	(1.28)	(0.03)	(0.57)	(-1.10)
Adjusted R^2 (%)	6.17	5.22	5.91	5.56
N of observations	12,652	12,652	12,652	12,652

Table 5.8 Robustness test

This table presents the sensitivity of investors' reactions to earnings surprises by employing Equation (5.9). The dependent variable (*Reaction [0, x]*) in Columns (1) and Columns (2) is standardized holding changes 6 days and 15 days after the earnings announcement, respectively. *Down* is a dummy variable to estimate the effect of negative earnings surprises, which equals 1 if *SUE* is negative, and 0 otherwise. *UpSUE* equals *SUE* if *SUE* is positive, and it equals 0 otherwise. Likewise, *DownSUE* equals *SUE* if *SUE* is negative, otherwise it equals 0. *Media tone* and *Media coverage* are the media tone and the number of articles mentioned in the seven most well-known and authoritative media, from 30 days before to 1 day before the earnings announcement, respectively. *NonlUp* is the square of *UpSUE* and *NonlDown* is *DownSUE* squared multiplied by -1. T-statistics are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Reaction [0, 6]	*Reaction [0. 15]*
	(1)	(2)
Variables		
Intercept	0.0082***	0.0086***
	(6.76)	(5.18)
Down	-0.0109***	-0.0162***
	(-6.03)	(-6.59)
$UpSUE$	0.0046***	0.0065***
	(7.12)	(7.44)
$DownSUE$	0.0003	0.0011**
	(0.83)	(2.04)
$UpSUE\ \times Media\ tone$	0.0033***	0.0040***
	(2.97)	(2.65)
$DownSUE\ \times Media\ tone$	-0.0019**	-0.0011*
	(-2.43)	(-1.68)
$UpSUE\ \times Media\ coverage$	0.0000	0.0000
	(0.95)	(0.58)
$DownSUE\ \times Media\ coverage$	0.0000	-0.0000
	(0.49)	(-0.03)
$NonlUp$	-0.0000***	-0.0001***
	(-4.72)	(-5.02)
$NonlDown$	0.0000	-0.0000
	(0.70)	(-1.13)
Adjusted R^2 (%)	6.19	5.63
N of observations	12,597	12,597

Table 5.9 SUE and media

This table shows the relationship between pre-announcement media tone and earnings surprises. The sample period of this dataset is from 1st January 2007 to 31st July 2009. Stocks are required to be reported by articles in our sample 30 days before earnings announcements and have at least one trade made by our sample of investors within 15 days of an earnings announcement. The dependent variable, *SUE* is standardized unexpected earnings, calculated by using the method of Chan et al. (1999). *Media coverage* is the number of articles mentioned for a firm from 30 days before to 1 day before the earnings announcement. *Media tone 1* and *Media tone 2* are the tone of media towards firms from 30 days before to 1 day before the earnings announcement. *Momentum* is the cumulative prior six-month returns before the announcement date. *Ln(Size)* is the logarithm of stocks' closing market values one day before the announcement date. *B2M* is the book-to-market ratio, calculated by using the most closely available book value divided by the market value one day before the announcement date. *ROA* is the return on assets at the same accounting quarter of earnings announcements. *Turnover* is computed as the trading volume divided by the outstanding shares one day prior to the announcement date. We include time fixed and industry effects in all regressions, and standard errors are double clustered at the stock and time level. T-statistics are reported in the brackets, ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	SUE	SUE
Variables		
Media coverage	-0.0010	-0.0010
	(-1.17)	(-1.18)
Media tone 1	0.2838	
	(1.81)	
Media tone 2		4.6613
		(1.66)
Momentum	0.4183**	0.4188**
	(3.06)	(3.08)
Ln(Size)	0.2165	0.2172
	(0.53)	(0.52)
B2M	-1.1104*	-1.1198*
	(-1.94)	(-1.96)
ROA	2.0677*	2.0684*
	(1.9)	(1.98)
Turnover	-2.2290	-2.2407
	(-1.77)	(-1.76)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2 (%)	7.46	7.44
N of observations	12,605	12,605

CHAPTER SIX: CONCLUSION

The main objective of this study is to identify behavioural biases of individual investors and explore the possible causes of such biases by investigating their trading behaviour in the stock market. Although contemporary studies have identified various behavioural biases, it remains unclear why some are more pronounced in certain types of investors. This thesis endeavours to contribute to this field by exploring the trading behaviour of individual investors and the factors that influence their decision-making process. To be more specific, Chapter 3 investigates gender differences in herding and the possible causes and consequences of an intensive herding tendency. Chapter 4 analyses trading behaviour, especially the purchasing of individual investors when the market crashes. Chapter 5 examines the reactions of individual investors to earnings surprises and whether their reactions could be influenced by media tone. Overall, this thesis offers a series of conclusive remarks and contributes to the relevant literature, which can be summarized as follows:

In Chapter 3, we detect a strong herding tendency of individual investors in the Chinese stock market, while females show a higher level of herding intensity than males. The higher herding tendency of females persists during both bull-market and financial-crisis subsamples. Our results show that both females and males herd more intensively during the bull-market period, and stock characteristics affect the herding tendency of females and males in similar ways. Furthermore, the outcomes of stock return around herding indicate that the herding behaviour of individual investors in China tends to be driven by behavioural factors, and female investors lose more due to their intensive herding. Finally, by using the individual-level herding measurement, we find that the lower portfolio turnover of females is the primary source of the gender difference in herding.

Chapter 3 complements those studies that have analysed the impact of gender differences in investment behaviour. Although this study uses the method of Merli and Roger (2013) to construct the individual-level herding measurement, the research purposes in this study are distinct: we investigate the sources and consequences of gender differences in herding. Additionally, our study extends the literature on herding behaviour in the Chinese stock market by focusing on the individual investors and using more complete data when highlighting the impact of market conditions and stock characteristics on herding.

Chapter 4 examines the buying behaviour of individual investors with an emphasis on the financial crisis period. Consistent with the findings in the French stock market (Barrot et al., 2016), our evidence shows that individual investors, on average, act as net buyers when the market crashed. In particular, male and younger investors invest more aggressively than their counterparts, which can be explained by their lower risk perceptions and sensitivity towards the increased market risk. Moreover, our findings suggest that the better past performance during the financial-crisis period leads to a more aggressive buying tendency, thus investors exhibit self-attribution bias and engage in buying. Besides, the stock-day level analysis reveals that investors show a negative feedback trading behaviour during the market downswing. Finally, we do not find evidence that a superb stock-picking ability or a higher propensity to gamble are able to explain the buying intensity during the financial crisis period. In summary, this chapter contributes to the literature that investigates how individual investors react to bear markets and what factors may influence their buying decisions during market downturns (Duxbury, 2012; Hoffmann et al., 2013; Barrot et al., 2016).

Chapter 5 aims to shed light on how individual investors react to public information and the extent to which outside information can disturb their reactions. The main evidence of this chapter shows that, on average, investors' holding positions increase (decrease) significantly after positive (negative) earnings surprises. Besides the earnings announcement itself, the tone of media before earnings announcements plays an essential role in influencing investors' sentiment. In particular, this chapter finds that investors overreact to positive earnings surprises when firms have a positive media tone ahead of their announcements, while they react more negatively to bad earnings news when the media tone is worse. Beyond this, we also find that investors with more wealth and well-diversified portfolios are less likely to be affected by media tone. This outcome indicates that the effect of media tone is limited when investors have a higher likelihood of accessing private information or being distracted by information about other stocks in their hands. Overall, Chapter 5 contributes to the literature that examines investors' reactions to corporate announcements (Ekholm, 2006; Hirshleifer et al., 2008; Vieru et al., 2006; Kaniel et al., 2012; Li et al., 2017b) and extends the body of studies on the role of media tone (Cahan et al., 2013; Cahill et al., 2017).

This thesis serves as an excellent cautionary tale for individual investors. For example, irrational herding often leads to impaired investment returns; short-term gains during financial crises can cause investors to overestimate their ability in the stock market, and media tones can affect investors' expectations of the future of a business. Investors need to be constantly reminded in the financial markets to avoid similar mistakes that can affect their profits.

In future research, trying to address the issue of how regulators guide individual investors will be one of the directions of research, as retail investors will continue to play an important role in the market. On the one hand, regulators need to guide investors and limit risky investments to the smallest investor accounts, such as derivatives trading and leveraged trading. On the other hand, regulators should provide guidance to individual investors to direct some of their investments into wealth products and pension plans to truly protect investors' returns and reduce downside risk, which regulation and many other researchers are working on.

Even though this thesis makes a substantial contribution to the behavioural finance literature, it also has some limitations that can be addressed in future research. Firstly, the sample period of individual investors’ data used in this thesis covers less than three years, which is not ideal for studying the long-term effects of behavioural biases on investors. Secondly, individual investors’ data do not include personal demographics, such as education, income, marital status, personal beliefs, etc. Therefore, this thesis cannot capture the impact of these factors. Finally, in measuring media tone, we cannot give different weights to the words by using the NLPIR Chinese Word Separation System. For example, although both ‘bad’ and ‘terrible’ are counted as negative words in the dictionary, they express different sentiments. By using the tools currently available, we cannot distinguish the difference. Therefore, developing a machine learning program to construct a new framework for media tone analysis for future research would be desirable.

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