Gender and Herding

Abstract

This study uses a unique dataset from a large anonymous brokerage firm to examine the herding behavior of Chinese individual investors. The empirical evidence reveals that females are more inclined to follow the behavior 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. By using individual-level herding measurements and examining the consequences of intensive herding, we show that the lower portfolio turnover of females is the main source of difference in herding between genders. However, females lose more due to their intensive herding tendency, as herding has a greater negative impact on trading than overconfidence in the Chinese stock market.

JEL Classification: G11; G14.

Keywords: Herding, Individual investors, Chinese stock markets, Gender

1. Introduction

Herding, which is deemed to be a type of correlative behavior, occurs when individuals ignore public or private information they have obtained and mimic the behavior of others (Avery and Zemsky, 1998; Hwang and Salmon, 2004). Contemporary studies analyzing herding behavior 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 behavior 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 behavior 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 source of gender differences in herding? What is the consequence of the higher herding tendency?

Although gender differences in investment behavior have been widely explored,[1] 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 fact, psychological studies suggest that females exhibit a higher degree of conformity than males (Cooper, 1979; Eagly, 1978; Eagly and Carli, 1981).[2] Hence, females are more likely to change their beliefs or behaviors 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

[1] 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 on the stock market.

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

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 behaviors.[3] In terms of the correlated trading behavior of female investors in other financial markets, it is worth examining whether female investors also show a higher level of conformity by way of herding in the stock market.

Goodfellow et al. (2009) also suggest that overconfident investors are less likely to follow others' behavior 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 behaviors 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.

Motivated by studies in psychology and behavioral finance, we investigate the herding behavior of Chinese investors. Four research questions are addressed in this study. First, we analyze whether the herding tendency of female investors is more intensive than that of males. In a psychological sense, females show a higher degree of conformity. Consequently, they are more likely to change their behavior 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' behavior. Therefore, we reckon that females are more prone to herd than 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. Besides, previous studies verify that the herding tendency could be

[3] Chinese DAMA refers to a group of middle-aged Chinese females. This word was first coined by the Wall Street Journal in 2013. In April 2013, a group of middle-aged Chinese female investors showed their purchase power on the global gold market over a short period. Subsequently, they displayed their influence in the innovative digital currency market after it was introduced via social media.

influenced by both market conditions and characteristics of stocks; however, their results have been mixed (Wermers, 1999; Shyu and Sun, 2010). For instance, in the Chinese stock market, contrary outcomes have been reported 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).

Third, we investigate the sources of gender differences in herding. Indeed, females and males differ along certain dimensions, and these differences may drive their different herding behaviors. 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.

Finally, this study examines the consequences of intensive herding. 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 behavioral 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 it could be assumed that similar outcomes may be reflected in the stock market.

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.[4] Also, only A-share stocks, traded or held by individual investors, listed on the Shanghai and Shenzhen Stock Exchanges (SSE and SZSE) have been included.[5] 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

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

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

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 behavior of female and male investors, but is more pronounced in the female groups, probably because females as a group tend to use similar risk management strategies.

To understand the mechanism behind herding, we construct an individual-level herding measurement by following the method of Merli and Roger (2013). The evidence reveals that females have a higher herding tendency after controlling for investors' characteristics, especially those who have a lower portfolio turnover. The relation of stock returns and herding indicates that herding by individuals tends to be caused by behavioral factors, and also that females lose more, especially in a bull market, because of their intensive herding. Females are less overconfident but loss more due to their intensive herding, which can be explained by the fact that in the Chinese stock market, herding has a greater negative impact on trading than overconfidence.

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 that the lower portfolio turnover of females is the main source of gender difference in herding. Besides, our investigation demonstrates that herding has a more significant impact on trading than overconfidence; thus, females experience larger losses than males in the Chinese stock market. 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 behavior 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 behavior 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) analyze 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 article will continue as follows: Section 2 reviews a series of related studies that analyze stock market herding behavior. Section 3 includes the methodology and describes the data. Section 4 compares the herding tendencies of female and male investors. Section 5 summarizes the relation between herding and market conditions, together with stock characteristics. Section 6 tries to pin down what drives gender differences in herding, and Section 7 presents the consequences of intensive herding. Section 8 and Section 9 contain the results of the robustness check and present the study’s conclusions.

2. Literature Review

The herding behavior of investors has been extensively analyzed 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, 2003; Lao and Singh, 2011). Chang et al. (2000) regard herding as irrational behavior if investors ignore their information sets and indiscreetly imitate the decisions of others.

Herding behavior 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 behavioral 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 behavior 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 behavior 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 behavioral-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 behavior 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. (2017) 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.

3. Data and Methodology

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. From 1st January 2007 to 16th October 2007, the Shanghai Composite Index hit its historically highest peak, rising from 2,675 points to 6,124 points. Then, between 17th October 2007 and 28th October 2008, it dropped dramatically to 1,664 points.

The original dataset contains more than 2 million individual investor accounts, however, not all of these are fit for purpose. To investigate the herding behavior of individual investors, we first delete those accounts that only have security investment funds, index funds or B-share stocks. This step leaves us 1,703,951 individual investors. Apart from that, 2,299 investors who have no information on age or gender, and whose age is lower than 18 years old when the account is opened are removed from our dataset. Also, 154 investors without data on account open date are eliminated from our sample. Then we delete 979 investors whose stock holdings, or cash balances, have a negative value. Finally, individual investors are required to have traded at least once during the sample period; accordingly, 88,195 individual accounts are excluded from the dataset. After filter steps, the final dataset leaves us with 1,612,324 individual investors.

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. In order to investigate the herding behavior 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), which is accessible through the Wharton Research Data Services (WRDS). 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.

The summaries of stock characteristics and customer information are reported in Table 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 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 in the stock market. The trading frequency is the average number of transactions each investor made in a

[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 6.

[7] Panel A 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/.

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.

3.2 Methodology

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

$$LSV(i,j,t) = \left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right| - E\left|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} - p(i,t)\right| \tag{1}$$

$$p(i,t) = \frac{\sum_{j=1}^{n} B(i,j,t)}{\sum_{j=1}^{n} B(i,j,t)+\sum_{j=1}^{n} S(i,j,t)} \tag{2}$$

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 (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:

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

$$= \sum_{k}^{n(i,j,t)} \binom{n(i,j,t)}{k} p(i,t)^{k}(1-p(i,t))^{n(i,j,t)-k} \left|\frac{k}{n(i,j,t)} - p(i,t)\right| \tag{3}$$

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 6.

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:

$$Buy\ \ LSV(i,j,t) = LSV(i,j,t)|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} > p(i,t) \tag{4}$$

$$Sell\ \ LSV(i,j,t) = LSV(i,j,t)|\frac{B(i,j,t)}{B(i,j,t)+S(i,j,t)} < p(i,t) \tag{5}$$

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:

$$LSV(i,t) = \frac{1}{n}\sum_{j=1}^{n} LSV(i,j,t) \tag{6}$$

$$Buy\ \ LSV(i,t) = \frac{1}{n}\sum_{j=1}^{n} Buy\ \ LSV(i,j,t) \tag{7}$$

$$Sell\ \ LSV(i,t) = \frac{1}{n}\sum_{j=1}^{n} Sell\ \ LSV(i,j,t) \tag{8}$$

4. Gender Differences in Herding Tendency

We first investigate whether female or male investors are more prone to herd in same-sex groups. Figure 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.

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 2 reports the summary statistics of daily average herding measurement during both the whole sample period and the two sub-sample periods. Table 2 also shows a comparison of average herding tendencies between females and males. 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.

The results from Table 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. Lastly, 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. During the bull-market period, the average female herding tendency is 1.44% higher than for males, suggesting that if 100 investors in each group traded a stock on a given day, 1.44 more female investors would have traded on the same side of this stock than male investors. The higher herding tendency of female investors is consistent with their correlated trading behavior 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.

5. Market Conditions, Stock Characteristics, and Herding

5.1 Herding and market conditions

[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.

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 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 will examine whether market conditions could affect both female and male investors' herding tendencies.

Table 3 shows the herding tendencies of two investor groups sorted by market conditions. Panel A (Panel B) presents the summary statistics of daily average herding tendencies for females (males) in the two sub-periods – i.e. the bull-market period, from 1st January 2007 to 16th October 2007, when the Shanghai Composite Index increased from 2,675 points to 6,124 points, and the financial-crisis period, from 17th October 2007 to 28th October 2008, when the market index declined from its historical highest to 1,664 points.

Panel A in Table 3 reports that, compared with the financial-crisis period, the average herding tendency, the buy-side and sell-side herding tendencies of females were 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 was 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 behavioral-driven herding. However, this has to be verified by examining the relationship between herding and stock returns.

5.2 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 behavior. Venezia et al. (2011) use Falkenstein's (1996) theory and insist that investors tend to exhibit herding behavior 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 analyze whether stock characteristics have an impact on the individual herding tendency, and secondly, to examine whether they affect the herding behavior of female and male investors in different ways. We include both time and stock fixed effects and double-clustered standard errors.

Table 4 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

[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.

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 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 4 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).

6. Individual Herding Measurement

6.1 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,[12] 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:[13]

$$SLSV(j,t) = \begin{cases} LSV(j,t) | \frac{B(j,t)}{B(j,t)+S(j,t)} > p(t) \\ -LSV(j,t) | \frac{B(j,t)}{B(j,t)+S(j,t)} < p(t) \end{cases} \quad (9)$$

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:

$$IHM_{i,t} = \frac{\sum_{j=1}^{J} n_{i,j,t} P_{j,t} SLSV_{j,t}}{\sum_{j=1}^{J} |n_{i,j,t}| P_{j,t}} \quad (10)$$

$$IHM_t^{female} = \frac{1}{n} \sum_{i=1}^{n} IHM_{i,t} \; | i = female \quad (11)$$

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

[13] 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.

$$IHM_t^{male} = \frac{1}{n}\sum_{i=1}^{n} IHM_{i,t} \,|i = male \quad (12)$$

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 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 (6), (7), and (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.[14]

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.[15] 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 $t+1$.[16] Both sell turnover and buy turnover are updated on the monthly basis.

[14] 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.

[15] 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.

[16] To obtain the monthly buy turnover, these stocks purchased during month t are matched and the buy turnover

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 5 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 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.

6.2 The mechanism behind herding

To further explore the mechanism behind herding, this study uses a panel regression to analyze the relationship between herding and personal characteristics. According to the summary statistics from Table 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

---

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.

and 68% for females.[17] Chen et al. (2007) argue that as the emerging stock market lacks alternative investment vehicles, Chinese individual investors exhibit more active self-managing behavior. 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 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).

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 6 Panel A presents the results of turnover comparisons after controlling investors' age and trading experience, while Table 6 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.

The evidence from Table 5 and Table 6 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

[17] 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%.

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 7 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 6.1. Apart from the age, experience, and turnover channels, the account value of each investor may also affect herding behavior. In fact, Merli and Roger (2013) have explored whether the wealth allocated in the stock market may have an impact on the herding behavior 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 herding, 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 analyze whether overconfidence or trading experience dominates the gender effect on herding, we add the *Female*Low Turnover* and *Female*Low Experience* dummy variables in Specifications (2) and (3), respectively.[18] 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

[18] *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 6.1.

a 0.20% decline in herding tendency if other variables remain the same.[19] 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 behavior 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. (2017) 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 tend to trust their own decision and 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

---

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

on individual herding behavior. However, females' lower portfolio turnover is the primary source of differences in herding between genders.

7. Stock Returns Around Herding

7.1 Cumulative abnormal returns and herding intensity

In this section, the consequences of intensive herding 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 behavior is caused by fundamental information, then a price continuity should be observed. However, if herding behavior occurs either for emotional or impulsive reasons, then price reversal is likely to happen.

In order to analyze 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.[20] Thereafter, for each buy-side (sell-side) portfolio, we calculated the equally weighted cumulative abnormal returns during the period, from five days

[20] 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.

before to twenty days after the formation day. This procedure is conducted separately for female and male groups.[21]

Table 8 shows the benchmark adjusted cumulative abnormal returns concerned with investor herding. Standard errors are adjusted following Newey-West (1987) since the daily portfolio returns with overlapping days up to 20 days. Panel A (Panel B) of Table 8 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 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 8 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

[21] 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.

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.[22] Besides, small investors will 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 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

[22] 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.

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 behavior.

In Figure 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 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 behavioral factors since a price reversal can be detected after herding.

Indeed, evidence from individual herding measurements and our findings in Table 8 and Figure 2 suggest that females' lower portfolio turnover is the primary source of gender differences in herding and that females lose more due to intensive herding. However, previous studies argue that overconfidence is also harmful to portfolio performance (Barber and Odean, 2000, 2001). One possible explanation is that herding has a higher impact on trading than overconfidence, hence, females with the highest herding intensity lose more than their male counterparts when trading in the stock market.

To examine this conjecture, we first divide investors into four groups by double sorting the individual-level herding measurement (ihm) and portfolio turnover. Thereafter, the monthly calendar-time portfolios of stocks bought and sold are constructed for investors in each group. Shi and Wang (2013) argue that this method avoids the issue of cross-sectional correlation among stock returns by aggregating the stock returns into returns of buy- and sell-side portfolios each month. For each calendar month, the return of each stock on the buy-side and sell-side is adjusted by matching a value-weighted portfolio return of A-share stocks within the same size, book-to-market ratio, and momentum quintile, following the method of Daniel et al. (1997). Afterward, the equally weighted cumulative abnormal returns for the buy-side and sell-side portfolios are calculated in the preceding one-, two-, and three-month portfolio formation period. We then construct a zero-investment portfolio for each group by holding buy-side stocks and shorting sell-side.

Panel A of Table 9 presents the mean returns of zero-investment portfolios in each group and their comparisons. Firstly, we find the average monthly return of the zero-investment portfolio for the high herding group is negative, while it is positive for investors in the low herding group, no matter which turnover groups they are allocated. This result persists over three different formation periods. Besides, we compare the return differences between investors within the same herding (turnover) group and different turnover (herding) groups. The results show that investors in a lower herding group significantly outperform those in the same turnover group but with a higher herding tendency, suggesting that herding tendency has a marginal contribution to the trading performance beyond turnover.

To ensure the results in Table 9 Panel A are not driven by the method of double sorting, we also conduct an independent sort of herding and turnover and compare the return of the zero-investment portfolio for investors in two herding and turnover groups, respectively. Panel B of Table 9 shows that the buy-sell portfolio of investors with lower herding tendency (portfolio turnover) experienced a higher return than their counterparts. Additionally, this difference is larger between the two herding groups. Overall, combining our findings in Tables 5 – 9 and Figure 2, we can conclude that the lower portfolio turnover is the main source of differences in herding between females and males, while herding has a greater negative impact on trading than overconfidence in the Chinese stock market; thus, females lose more due to their intensive herding tendency.

7.2 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 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 behavioral 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 Table 8, we analyze whether the herding of individual investors continuously destabilizes the market during two sub-periods.

Table 10 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 8 and Table 10 indicates that the herding of both females and males, especially the sell-side herding, destabilized the market.

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 behavior 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 analyze 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:

$$IMB_{i,j,t} = \frac{Buy_{i,j,t} - Sell_{i,j,t}}{Buy_{i,j,t} + Sell_{i,j,t}} \tag{13}$$

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 7. 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:

$$Buy_{side}IMB_{i,j,t} = IMB_{i,j,t} | IMB_{i,j,t} > 0 \tag{14}$$

$$Sell_{side}IMB_{i,j,t} = -IMB_{i,j,t} | IMB_{i,j,t} < 0 \tag{15}$$

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:

$$IMB(i,t) = \frac{1}{n}\sum_{j=1}^{n} |IMB(i,j,t)| \tag{16}$$

$$Buy_{side}IMB(i,t) = \frac{1}{n}\sum_{j=1}^{n} Buy_{side}IMB(i,j,t) \tag{17}$$

$$Sell_{side}IMB(i,t) = \frac{1}{n}\sum_{j=1}^{n} |Sell_{side}IMB(i,j,t)| \tag{18}$$

Panel A of Table 11 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 analyze 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 11 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 analyze 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

[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.

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 8.

9. Conclusion

This study has analyzed the herding behavior 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 behavior of their same-sex investors, the LSV method is used to ascertain the 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 behavior 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 behavior 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, to recognize the source of gender differences in herding, 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. Indeed, our findings suggest that the lower portfolio turnover of female investors is the primary source of the difference in herding between genders. When females come to be overconfident in the stock market, the gender difference in herding disappears. By contrast, females continuously herd more intensively than males, even after gaining experience in the stock market.

Finally, we investigate the consequences of herding effect. 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. Such outcomes are ascertained by using the buy-sell imbalance as a proxy for correlated trading behavior. However, it is found that even though females are less overconfident than males, they lose more due to their more intensive herding, as herding has a greater negative impact on trading than overconfidence in the Chinese stock market.

References

Avery, C., Zemsky, P., 1998. Multidimensional Uncertainty and Herd Behavior in Financial Markets. *American Economic Review*, 88(4), 724–748.

Barber, B., Odean, T., 2001. Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics*, 116(1), 261–292.

Barber, B., Odean, T., 2002. Online Investors: Do the Slow Die First?. *Review of Financial Studies*, 15(2), 455–488.

Barber, B., Odean, T., 2008. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies*, 21(2), 785–818.

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

Bikhchandani, S., Sharma, S., 2001. Herd Behavior in Financial Markets. *IMF Staff Papers*, 47(3), 279–310.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, 100(5), 992–1026.

Bond, R., Smith, P., 1996. Culture and Conformity: A Meta-analysis of Studies Using Asch's (1952b, 1956) Line Judgment Task. *Psychological Bulletin*, 119(1), 111–137.

Chang, E., Cheng, J., Khorana, A., 2000. An Examination of Herd Behavior in Equity Markets: An International Perspective. *Journal of Banking and Finance*, 24(10), 1651–1679.

Chen, G., Kim, K., Nofsinger, J., Rui, O., 2007. Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors. *Journal of Behavioral Decision Making*, 20(4), 425–451.

Chen, H., Chow, E., Shiu, C., 2015. The Informational Role of Individual Investors in Stock Pricing: Evidence from Large Individual and Small Retail Investors. *Pacific-Basin Finance Journal*, 31(C), 36–56.

Choe, H., Kho, B., Stulz, R., 1999. Do Foreign Investors Destabilize Stock Markets? The Korean Experience in 1997. *Journal of Financial Economics*, 54(2), 227–264.

Choi, J., Laibson D., Metrick A., 2002. How Does the Internet Affect Trading? Evidence from Investor Behavior in 401(k) Plans. *Journal of Financial Economics*, 64(3), 397–421.

Choi, S., 2016. Herding Among Local Individual Investors: Evidence from Online and Offline Trading. *Economics Letters*, 144(C), 4–6.

Christie, W., Huang, R., 1995. Following the Pied Piper: Do Individual Returns Herd Around the Market?. *Financial Analysts Journal*, 51(4), 31-37.

Cialdini, R., Goldstein, N., 2004. Social Influence: Compliance and Conformity. *Annual Review of Psychology*, 55(1), 591–621.

Cooper, H., 1979. Statistically Combining Independent Studies: A Meta-Analysis of Sex Differences in Conformity Research. *Journal of Personality and Social Psychology*, 37(1), 131–146.

Croson, R., Gneezy, U., 2009. Gender Differences in Preferences. *Journal of Economic Literature*, 47(2), 448–474.

Crutchfield, R., 1955. Conformity and Character. *American Psychologist*, 10(5), 191–198.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance*, 52(3), 1035-1058.

Daníelsson, J., 2008. Blame the Models. *Journal of Financial Stability*, 4(4), 321–328.

Demirer, R., Kutan, A., 2006. Does Herding Behavior Exist in Chinese Stock Markets?. *Journal of International Financial Markets, Institutions and Money*, 16(2), 123–142.

Devenow, A., Welch, I., 1996. Rational Herding in Financial Economics. *European Economic Review*, 40(3–5), 603–615.

Dorn, D., Huberman, G., Sengmueller, P., 2008. Correlated Trading and Returns. *Journal of Finance*, 63(2), 885–920.

Dow, J., 2004. Is Liquidity Self-Fulfilling?. *Journal of Business*, 77(4), 895–908.

Eagly, A., 1978. Sex Differences in Influenceability. *Psychological Bulletin*, 85(1), 86–116.

Eagly, A., Carli, L., 1981. Sex of Researchers and Sex-Typed Communications as Determinants of Sex Differences in Influenceability: A Meta-Analysis of Social Influence Studies. *Psychological Bulletin*, 90(1), 1–20.

Falkenstein, E., 1996. Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holding. *Journal of Finance*, 51(1), 111–135.

Feng, L., Seasholes, M., 2003. A Profile of Individual Investors in an Emerging Stock Market. *Working Paper*, University of California at Berkeley.

Goodfellow, C., Bohl, M., Gebka, B., 2009. Together We Invest? Individual and Institutional Investors' Trading Behaviour in Poland. *International Review of Financial* Analysis, 18(4), 212–221.

Grinblatt, M., Keloharju, M., 2009. Sensation Seeking, Overconfidence, and Trading Activity. *Journal of Finance*, 64(2), 549–578.

Hirshleifer, D., Hong Teoh, S., 2003. Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis. *European Financial Management*, 9(1), 25-66.

Hirshleifer, D., Subrahmanyam, A., Titman, S., 1994. Security Analysis and Trading Patterns when Some Investors Receive Information Before Others. *Journal of Finance*, 49(5), 1665–1698.

Hsieh, S., 2013. Individual and Institutional Herding and the Impact on Stock Returns: Evidence from Taiwan Stock Market. *International Review of Financial Analysis*, 29(C), 175–188.

Hsu, Y., Shiu, C., 2010. The Overconfidence of Investors in the Primary Market. *Pacific-Basin Finance Journal*, 18(2), 217–239.

Hwang, S., Salmon, M., 2004. Market Stress and Herding. *Journal of Empirical Finance*, 11(4), 585-616.

Kaniel, R., Saar, G., Titman, S., 2008. Individual Investor Trading and Stock Returns. *Journal of Finance*, 63(1), 273–310.

Kim, W., Wei, S., 2002. Foreign Portfolio Investors Before and During a Crisis. *Journal of International Economics*, 56(1), 77–96.

Kremer, S., Nautz, D., 2013. Causes and Consequences of Short-Term Institutional Herding. *Journal of Banking and Finance*, 37(5), 1676–1686.

Kumar, A., 2009. Who Gambles in the Stock Market?. *Journal of Finance*, 64(4), 1889–1933.

Lakonishok, J., Shleifer, A., Vishny, R., 1992. The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics*, 32(1), 23–43.

Lao, P., Singh, H., 2011. Herding Behaviour in the Chinese and Indian Stock Markets. *Journal of Asian Economics*, 22(6), 495–506.

Lee, C., Chen, M., Hsieh, K., 2013. Industry Herding and Market States: Evidence from Chinese Stock Markets. *Quantitative Finance*, 13(7), 1091–1113.

Li, W., Rhee, G., Wang, S., 2017. Differences in Herding: Individual vs. Institutional Investors. *Pacific-Basin Finance Journal*, 45(C), 174–185.

Li, X., Geng, Z., Subrahmanyam, A., Yu, H., 2017. Do Wealthy Investors Have an Informational Advantage? Evidence Base on Account Classifications of Individual Investors. *Journal of Empirical Finance*, 44, 1–18.

Merli, M., Roger, T., 2013. What Drives the Herding Behavior of Individual Investors?. *Finance*, 34(3), 67–104.

Newey, W., West, K., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3), 703-708.

Niederle, M., Vesterlund, L., 2007. Do Women Shy Away from Competition? Do Men Compete Too Much?. *Quarterly Journal of Economics*, 122(3), 1067–1101.

Nofsinger, J., Sias, R., 1999. Herding and Feedback Trading by Institutional and Individual Investors. *Journal of Finance*, 54(6), 2263–2295.

Rajan, R., 1994. Why Bank Credit Policies Fluctuate: A Theory and Some Evidence. *Quarterly Journal of Economics*, 109(2), 399–441.

Scharfstein, D., Stein, J., 1990. Herd Behavior and Investment. *American Economic Review*, 80(3), 465–479.

Shyu, J., Sun, H., 2010. Do Institutional Investors Herd in Emerging Markets? Evidence from the Taiwan Stock Market. *Asian Journal of Finance & Accounting*, 2(2), 1–20.

Sundén, A., Surette, B., 1998. Gender Differences in the Allocation of Assets in Retirement Savings Plans. *American Economic Review*, 88(2), 207–211.

Tan, L., Chiang, T., Mason, J., Nelling, E., 2008. Herding Behavior in Chinese Stock Markets: An Examination of A and B Shares. *Pacific-Basin Finance Journal*, 16(1–2), 61-77.

Venezia, I., Nashikkar, A., Shapira, Z., 2011. Firm Specific and Macro Herding by Professional and Amateur Investors and Their Effects on Market Volatility. *Journal of Banking and Finance*, 35(7), 1599–1609.

Welch, I., 1992. Sequential Sales, Learning, and Cascades. *Journal of Finance*, 47(2), 695–732.

Wermers, R., 1999. Mutual Fund Herding and the Impact on Stock Prices. *Journal of Finance*, 54(2), 581–622.

Yap, C., 2013. China's Consumers Show Growing Influence in Gold Market. *Wall Street Journal*. https://www.wsj.com/articles/chinas-consumers-show-growing-influence-in-gold-market-1376318964?tesla=y (visited on 02/12/2019).

Zhang, X., Zhang, L., 2015. How Does the Internet Affect the Financial Market? An Equilibrium Model of Internet-Facilitated Feedback Trading. *MIS Quarterly*, 39(1), 17–38.

Zhou, R., Lai, R., 2009. Herding and Information Based Trading. *Journal of Empirical Finance*, 16(3), 388–393.

Table 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 2 Herding behavior under different market conditions sorted by investor groups

This table shows the comparison of herding tendencies between females and males in different market conditions. 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. Herding behavior 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 up-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. 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)

Table 3 Herding and market conditions

This table reports the summary statistics of herding tendencies for female and male investors in different market conditions. Only individuals with A-share stocks at a large brokerage firm, whose gender and ages are known, are recorded. Individual investors are divided into female and male groups based on the person who opened the account. Lakonishok et al.'s (1992) herding behavior method of measurement is utilized daily for each group. The first sub-period is between 1st January 2007 and 16th October 2007, during which the Chinese stock market hit its highest point of the 21st century. The second sub-period is between 17th October 2007 and 28th October 2008. During this period, the market index dropped from 6,124 points to 1,664 points. Panel A presents the summary statistics of herding tendency for females in both up-market and financial-crisis conditions, while Panel B summarizes the herding tendency statistics for males in both sub-periods. The t-values are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

Panel A. Female herding tendencies during different market conditions			
	Sub-period 1 (2007/01/01-2007/10/16)	Sub-period 2 (2007/10/17-2008/10/28)	Diff (1)-(2)
LSV	0.0539 (0.0090)	0.0444 (0.0100)	0.0095*** (10.35)
Buy LSV	0.0488 (0.0103)	0.0362 (0.0114)	0.0126*** (11.95)
Sell LSV	0.0587 (0.0124)	0.0509 (0.0157)	0.0078*** (5.64)
Panel B. Male herding tendencies during different market conditions			
LSV	0.0395 (0.0059)	0.0371 (0.0070)	0.0025*** (3.96)
Buy LSV	0.0355 (0.0077)	0.0303 (0.0088)	0.0052*** (6.43)
Sell LSV	0.0429 (0.0081)	0.0416 (0.0107)	0.0012 (1.31)

Table 4 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

Table 5 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 6 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 5. 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***
	(-1.3e+02)	(-1.3e+02)
High Age	-0.0390***	-0.0590***
	(-88.04)	(-1.7e+02)

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)	(-1.3e+02)

Table 7 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* Low Experience*				0.0032
				(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

Table 8 Benchmark adjusted CAR before and after Investors' Herding

This table shows the benchmark adjusted cumulative abnormal returns (CAR) 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 9 Zero-investment calendar-time portfolios of investors in different groups

This table presents the average returns of zero-investment calendar-time portfolios of 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. Panel A shows the zero-investment portfolio returns of investors in four herding*turnover groups. For each calendar month, investors are divided into four groups by double sorting the herding tendency and portfolio turnover. Thereafter, the calendar-time portfolios of stocks bought and sold are constructed for investors in each group. The return of each stock on the buy-side and sell-side is adjusted by matching a value-weighted portfolio return of A-share stocks, following the method of Daniel et al. (1997). Afterward, for the buy-side (sell-side) portfolio in each group, the equally weighted cumulative abnormal returns are calculated in the preceding one-, two-, and three-month portfolio formation period. We then construct a zero-investment portfolio for each group by holding the buy-side portfolio and shorting the sell-side portfolio. In Panel B, investors are grouped into two herding and two turnover groups, respectively. The zero-investment portfolios are constructed by using the same method. The t-statistics are given in the parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

Panel A. Differences of buy-sell calendar-time portfolio double sorted by turnover and herding intensity			
Buy-sell portfolio return (%)	One month after formation period	Two months after formation period	Three months after formation period
A: Low herding low turnover	0.776***	1.337***	1.359***
	(3.38)	(4.62)	(4.34)
B: Low herding high turnover	0.421	0.787**	0.912**
	(1.65)	(2.30)	(2.37)
C: High herding low turnover	-0.558*	-1.055***	-1.225**
	(-1.92)	(-2.85)	(-2.73)
D: High herding high turnover	-0.821***	-1.384***	-1.500***
	(-3.30)	(-4.06)	(-3.81)
Diff =(A-B)	0.355	0.550	0.447
	(1.03)	(1.23)	(0.90)
Diff =(C-D)	0.263	0.329	0.275
	(0.69)	(0.65)	(0.46)
Diff =(A-C)	1.334***	2.392***	2.584***
	(3.60)	(5.09)	(4.73)
Diff =(B-D)	1.242***	2.171***	2.413***
	(3.48)	(4.50)	(4.38)
Panel B. Differences of buy-sell calendar-time portfolio sorted by turnover and herding intensity, respectively			
Buy-sell portfolio return (%)	One month after formation period	Two months after formation period	Three months after formation period
Low herding	0.626**	1.204***	1.175***
	(2.66)	(3.81)	(3.36)
High herding	-0.750***	-1.241***	-1.401***
	(-2.83)	(-3.42)	(-3.25)
Diff	1.375***	2.446***	2.577***
	(3.88)	(5.08)	(4.64)
Low turnover	-0.021	-0.140	-0.145
	(-0.10)	(-0.48)	(-0.48)
High turnover	-0.620***	-0.767***	-0.862***
	(-3.72)	(-3.44)	(-3.05)
Diff	0.599**	0.627*	0.717*
	(2.25)	(1.72)	(1.73)

Table 10 Benchmark adjusted CAR before and after investors herd during bull-market and financial-crisis periods

This table reports the benchmark adjusted cumulative abnormal returns (CAR) 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)										
Up-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)

Up-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)

Up-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 11 **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 (CAR) 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)

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

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)

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 (daily, 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 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.

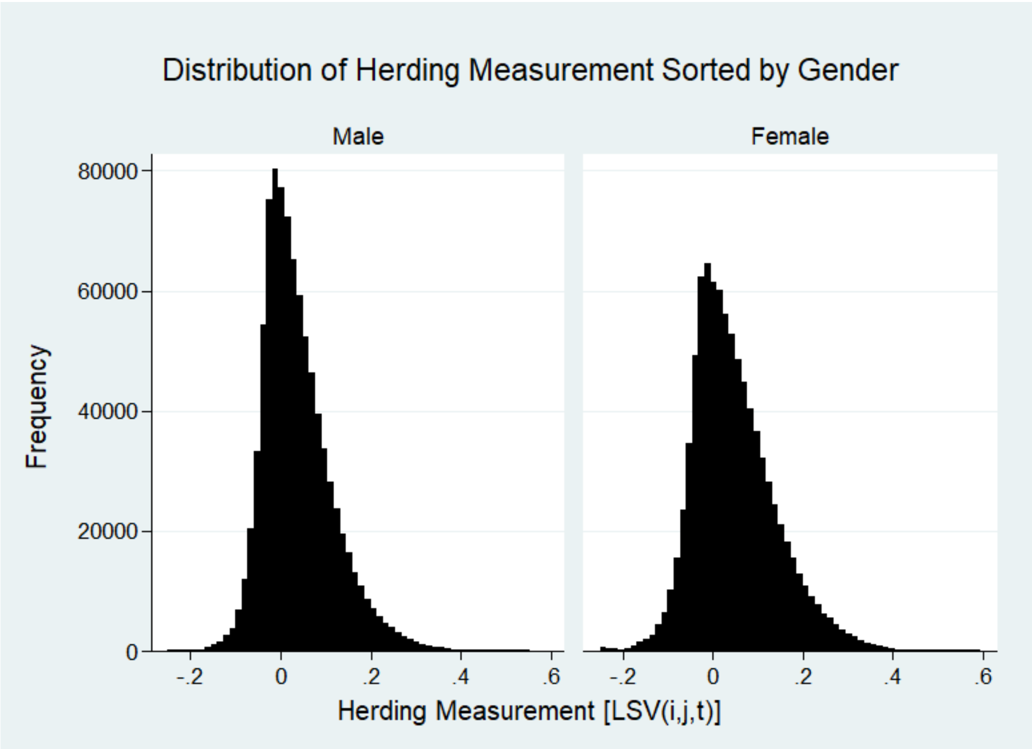

Figure 2 CAR after herding

This figure shows the benchmark adjusted cumulative abnormal returns (CAR) 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.