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Herding in Chinese stock markets: Evidence from the dual-investor-group

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ABSTRACT

Employing the group-specific herding measure, we explore the herding behavior in Chinese stock markets where a dual-group investor structure exists. Using high-frequency trading data, we find that the in-group herding tendency for most-informed investors and least-informed investors exhibits different patterns and has distinct effects on the market level herding as well as on subsequent market performances. Those effects are different in the "pre-peak" period and "post-peak" period from 7/2014 to 6/2016. Specifically, the evidence suggests that most-informed investors generally herd less than least-informed investors in the Chinese stock markets, but the gap narrows down when the market collapses and uncertainty increases. In addition, informed investors herd on fundamental factors and uninformed investors herd on non-fundamental factors only in the "post-peak" period.

1. Introduction

Research shows that investors herd in stock markets. When investors herd, they tend to trade in the same direction in a short time and ignore their private information, as individuals might be better off when they follow the trades of preceding investors (Bikhchandani et al., 1992). Herding can be observed in amateur investors due to less financial knowledge and training (Venezia et al., 2011). It can also happen among professional investors, such as institutional investors (Nofsinger and Sias, 1999), mutual fund managers (Grinblatt et al., 1995), and financial analysts (Welch, 2000), etc. Investors may herd intentionally, especially among institutional investors, which could be driven by reputation or compensation causes (Scharfstein and Stein, 1990). Investors may also herd unintentionally when they respond to public information or news unanimously (Bikhchandani and Sharma, 2001). However, the impact of herding on the stock market is not conclusive. Although many studies find that herding causes stock prices to deviate from fundamentals and more volatile,[1] some find otherwise.[2]

Herding activities are not only found in the U.S. but are also widely detected in international markets. At the market level, Chang et al. (2000) propose a model to use the relation between the level of cross-sectional absolute deviation of equity returns (CSAD) and the overall market return to detect herding. The empirical results indicate that investor herding is significant in Japan, South Korea,

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[1] i.e., Wermers (1999), Iihara et al. (2001).
[2] i.e., Lakonishok et al. (1992).

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and Taiwan but not in the U.S. and Hong Kong. Expanding from their studies, Chiang and Zheng (2010) document that investors herd at the market level in most developed stock markets (not in the U.S.) and seven Asian markets. Following a similar approach, researchers find herding activities in many emerging markets, such as Indian stock markets (Lao and Singh, 2011), Gulf Arab stock markets (Balcilar et al., 2013, 2014), East Asian markets (Zheng et al., 2017), and the Turkish stock market (Dalgıç et al., 2019).

Among the research on herding in emerging markets, many studies focus on China, one of the largest and fastest-growing economies. The literature mainly supports the existence of herding behavior in Chinese stock markets, but the evidence is not conclusive. Tan et al. (2008) suggest that herding exists in both Chinese A-share markets, dominated by domestic individual investors, and B-share markets, dominated mainly by foreign institutional investors. Yao et al. (2014) find that Chinese investors exhibit different levels of herding behavior, more prominently in the B-share markets. Chong et al. (2019) finds that cross-herding exists between the Chinese A-share and B-share markets. On the other hand, according to Demirer and Kutan (2006), herd formation does not exist in Chinese markets, and the empirical results support rational asset pricing models and market efficiency. Chiang et al. (2010) argue that although herding is detected within both the Shanghai and Shenzhen A-share markets, no evidence of herding is detected within the B-share markets. Investors' herding activities in China are also affected by stock characteristics, domestic market returns/volatilities, and international stock market conditions, and the significance of herding varies among different industries (Chiang et al., 2010; Chiang and Zheng, 2010; Yao et al., 2014; Zheng et al., 2017).

Although the abovementioned literature, among others, investigate different aspects of herding behavior in Chinese stock markets, they mostly only present the evidence (or non-evidence) of herding at the overall market level, or of one particular group of investors. Very little literature, such as (Li et al. (2017)), attempts to investigate herding across investor groups in Chinese stock markets. For example, Li et al. (2017) divides investors into the institutional investors' group and the individual investors' group based on their account IDs. However, Jones et al., 2020 find that individual investors with the largest account balances behave much more like institutional investors. In our study, we separate investors by their direct trading records instead of their account IDs because of the heterogeneity of trading behaviors among individual investors in China's A-share market. We believe that trading records disclose investors' "true trading patterns" better than their account IDs. Research on trading behaviors has documented the differences between these two groups of investors. Some studies characterize individual investors as "noise traders" as they are more likely to trade on uninformational factors such as investor sentiment (Kumar and Lee, 2006), misperceptions of future returns, and shifts in risk aversion (Hoffmann et al., 2013). In contrast, institutional investors are more efficient in information acquisition (Kim et al., 2014) and more skillful in risk management, with less disagreement among each other (Choi and Skiba, 2015). Studies on herding document the differences between institutional and individual investors, especially regarding the cause of herding. Many institutional investors herd due to correlated private information, while individual investors' herding is mainly driven by behavioral factors and emotions (Hsieh, 2013; Lin et al., 2013). Nofsinger and Sias (1999) suggest that individual investors herd as an irrational response to market turmoil or sentiment, while institutional investors herd mainly due to agency problems or security characteristics. Other factors, including investors' sophistication degree (Merli and Roger, 2013), risk management skills (Salganik-Shoshan, 2016), and preferences (Frijns et al., 2018), also affect the level of herding for those investors. However, the differences between institutional and individual investors might not be constant and distinctive through markets. Therefore, this study intends to fill the gap and contribute to the literature from the following aspects.

Firstly, our research investigates herding activities in Chinese stock markets based on a trading data set with high-frequency data.[3] Previous studies mostly utilize daily, monthly, or quarterly data to detect investors' herding behavior. However, since information flows fast in the stock markets, investors' trading decisions can change within hours or even minutes. As a result, low-frequency data might underestimate the extent of short-term herding (Kremer and Nautz, 2013a, 2013b), while high-frequency data could provide more insights into herding behaviors. Wang et al. (2022) use the trade and quote data with a 1-min interval from the Shanghai Stock Exchange (SSE) to investigate the intra-day herding. They find that even within one day, there exist different herding activities driven by other causes: fundamental and non-fundamental factors. In an attempt to discover the potential heterogeneity in herding patterns, we construct a sample with higher-frequency (level one) transaction records from over 250 million observations from the CSMAR China Security Market Trade & Quote Research Database, which covers the component stocks of the SSE 180 Index from June 03, 2014, to May 31, 2016. The level-one trading data helps us detect the different herding patterns and identify the trader's type.

Secondly, we compare two different herding measures to detect herding activities. We first create a series of return-based herding measures from the relation between the cross-sectional absolute deviation (CSAD) of stock returns and market returns following the model developed by Chang et al. (2000) (CCK model). According to the CCK model, market herding is detected when the market return dispersion (CSAD) decreases with an increase in market return. However, although the CCK model has been used widely to test market herding activities in the literature, it has its limitations. For example, the proxy of herding in the CCK model, low return dispersion, does not necessarily guarantee the presence of herding when the market is quiet, and investors are confident of the direction of market movement (Christie and Huang, 1995; Hwang and Salmon, 2004), so it works better when the market is under crisis (Chiang and Zheng, 2010). In addition, the CCK model doesn't differentiate the cause of herding, i.e., investors could herd with each other intentionally or herd on fundamental information unintentionally (Kremer and Nautz, 2013a). Furthermore, the CCK model can only detect herding in the whole market and cannot provide any insights into herding among different groups of investors. To address the above issues on the return-based herding measures, we construct an in-group herding tendency measure based on those high-frequency trading data. The in-group herding tendency measure is proposed by Li et al. (2017) as a herding measure (LRW model) by using the

[3] Our data set is the Level-1 data from CSMAR China Security Market Trade & Quote Research Database, which collects trading data every 3 s according to its database description.

cross-sectional variability of trading volumes within different investor groups rather than the market-level return and return dispersion.[4] Since herding is a trading phenomenon, the trading volume-based herding measure (LRW) can complement the return-based herding measure (CCK). It is of note that a strong group herding tendency (trading volume dispersion decreases) could increase market herding activity (stock market return is negatively significantly correlated with the CSAD measure), but it is also possible that the herding tendency among different groups could be opposite, and their effects on market level herding cancel each other at the aggregate level.

Moreover, we modify the LRW model from the following two aspects. Firstly, based on direct trading records, we divide all investors into three groups (most-informed, least-informed, and investors in the middle). Although Li et al. (2017) separate investors in China's A share market only by their account ID types (institutional vs. individual). Some literature (Jones et al., 2020) find that individual(retail) investors in China's A stock market are heterogeneous regarding account balance, information, and skills. Thus, individual investors' herding found in Li et al. (2017) could mix the behaviors of more-informed individual investors and less-informed individual investors. Our grouping-by-volume method might provide more insights into the heterogeneity of individual investors' trading patterns. Secondly, Li et al. (2017) directly uses the dispersion of trading volume as the in-group herding measure. We add an adjusted factor[5] into the LRW measure to capture the daily change of herding tendency from particular groups.

Finally, many studies suggest that heterogeneous herding activities affect subsequent stock returns and volatility differently. Among others, Dasgupta et al. (2011) find that persistent institutional trading is negatively associated with long-term returns. Kremer and Nautz (2013a) see return reversals after herding activities in German stock markets. However, very little research examines the herding's impact on subsequent market returns in Chinese stock markets,[6] especially from different investor groups' perspective. As more-informed investors herd more on fundamental factors and less-informed investors herd more on non-fundamental factors, we find that return reversals caused by herding from the least-informed investors' group but not by herding from the most-informed investors' group. In addition, herding could affect stock market volatility as well. From the definition of herding measures that investors herd when they trade in the same direction, we expect that market volatility is negatively correlated with herding activities. Still, the effect could be different between most-informed investors and least-informed investors.

As literature has documented that investors' herding behavior is different between the down market (crisis) and upmarket (tranquil period),[7] we divide the whole sample into two subsamples by date of June 9, 2015, when Chinese market indexes reached their peak. The sample period before June 9, 2015, is defined as the "pre-peak" period when the market was generally upturned. After June 9, 2015, the sample period is defined as the "post-peak" period when the market was generally in a downturn. All tests are performed in "pre-peak", "post-peak", and whole sample periods, respectively. According to the previous literature, we expect that herding activities are more pronounced in the "post-peak" period (down market).

The remainder of this paper is organized as follows: Section 2 discusses Chinese stock markets and investors. Section 3 describes the data and the estimation models for testing herding behavior. Section 4 reports the empirical evidence of herding behavior and possible causes of herding and examines how herding affects future stock market performances by applying both our in-group herding measure and the market herding CCK measure. Section 5 summarizes our findings and concludes the analyses.

2. Investors in the Chinese stock market

One of the unique features of the Chinese stock market is the great magnitude of less-informed investors, unlike developed markets such as the U.S. market, where more informed (primarily institutional) investors dominate the market. In recent years, the Chinese government has employed an "encouraging-institutional-investors policy" in the capital market to stabilize the financial system. The percentage of floating stocks held by institutional investors in China's A shares market increased significantly in past years, from about 25% by the end of 2007 to 81% by the end of 2017. The policy, which includes the Investor Appropriateness Examination, sets a minimum asset requirement for investors to enter certain sectors of the A shares market. Meanwhile, institutional investors are also allowed to short selling of selected stocks and trade index futures and index options. Besides government policies, "preferred clients[8]" investors in the Chinese stock markets also receive extra benefits from securities companies (brokerages), such as commission discounts, direct financing, and additional access to external funds. These extra financing channels injected roughly 2 trillion yuan into the stock market and fueled the stock market's boom from the end of 2014. However, when the government, the People's Bank of China, and the China Securities Regulatory Commission (CSRC), started to be concerned about the bubble in the stock market, they

[4] Although both the CCK model and LRW model are herding measures, there's a distinct difference between these two measures: the CCK model is a herding measure based on stock returns and market returns derived from the CAPM. In contrast, the LRW model measures the uniformity of trading toward specific stocks from a group of investors. Therefore, we believe the LRW herding measure is better for catching the herding tendency within one particular investor group.

[5] The Adjusted $\text{Factor}_{j,t}$ is the moving average of $\sigma(Trd)_{j,t}$ for the past 25 days. We add it to remove the trend of $\sigma(Trd)_{j,t}$ and emphasize the effect of daily herding.

[6] Zheng et al. (2015) find that both short-term and long-term future excess stock returns positively correlate with the herding measure in Chinese stock markets. However, due to data limitations, they could only measure herding activities at a quarterly frequency and, therefore, a much longer test window.

[7] i.e., Chiang and Zheng (2010)

[8] The asset thresholds of "preferred clients" differ across security companies, but the minimum is around 500 K CNY, or about 75 K USD holding position for the last three months.

imposed stricter regulations on leveraged investing and margin trading.[9] Larger investors were influenced more severely than smaller investors by those restrictions and later "rescue" policies when the government tried to stabilize the market in July 2015. These events affected larger investors in at least two ways. Firstly, when the CSRC prohibited securities companies from extending extra financing channels to clients, margin traders (institutional investors and "qualified" individual investors with 500 k plus assets in their accounts) received extensive margin calls and were forced to downsize their portfolios. Secondly, the CSRC placed restrictions on sales of stocks and index futures, especially for large shareholders, after the Chinese stock market plunged in June 2015. As a result, we find more significant changes in trading behaviors in larger investors than in smaller investors.

3. In-group herding and market herding measures

3.1. Trading volume-based measure of in-group herding tendency

Since this study aims to investigate the dynamic of herding behavior within distinct investor groups exhibiting different trading patterns, and trading records contain direct and important information on trading patterns, we follow a similar approach to Lee and Radhakrishna (2000) and use the trade size to identify the type of investors. To discern the differences in herding tendency between informed and uninformed investors, we use the size threshold to separate all trade records into three groups: informed investor trade, uninformed investor trade, and other trade. Investor groups are formed based on each trade's trading volume/value, and we focus on two groups with the largest behavioral differences: trades with trading volume over 50,000 shares are grouped as most-informed investors, and trades with trading volume under 500 shares are grouped as least-informed investors.[10,11]

We find that, on average, the percentage of transactions from the most-informed investors group contributes 20.6% of daily transactions of SSE180 components stocks, while from the least-informed investors group contributes 12.5%[12] of daily transactions over the sample period.[13] The standard deviation of cross-sectional trade volumes within each investor group is calculated to capture their different trading patterns. This trading records-based measure allows us to assess the herding behavior within each group, in different market regimes, and the impact of each on market level herding and market returns. Another benefit of high-frequency data is that we can get information on intra-day herding tendency, which may be omitted by herding measures based on daily stock returns, such as the CCK measure.[14]

On each trading day, we first assign every high-frequency trade record (every five seconds) into three groups based on its volume, then add up the trades from each group j of stock i on day t to get the daily trading volume $Trd_{j,\,it}$, finally calculate the daily dispersion of trading volume $\sigma_{j,\,t}$ for two selected groups (most-informed and least-informed) by the following equation to assess the herding tendency of the group in that trading day:

$$\sigma(Trd)_{j,t} = \sqrt{\frac{\sum_{i=1}^{N}\left[Trd_{j,it} - \mu(Trd)_{j,t}\right]^2}{N-1}} \tag{1}$$

where $Trd_{j,\,it}$ represents the natural log value of the raw trading volume from group j on stock i on day t. N is the number of stocks traded by group j on day t.[15] $\mu(Trd)_{j,\,t}$ is the average trading volume for stocks in group j on day t.

As mentioned above, we use trade sizes to identify investor types. We separate trades into three groups, the most-informed group, the least-informed group, and the group in the middle. The average trades for one stock per day are about 42,000. Since we are interested in the heterogeneity in trading behaviors among investors, we focus on the most-informed group whose trades are over 5000 shares per trade and the least-informed group whose trades are less than 500 shares per trade. Our sample helps to detect the change in herding patterns within particular investor groups on a daily base.

If investors in a group herd more, then $\sigma_{j,\,t}$ becomes smaller. In contrast, if investors in a group herd less and trade stocks more

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[9] Those policies include new restrictions on margin trading on stocks, doubled margin requirements for CSI 500 index futures, no-sales permission for large shareholders for the first six months of holding, etc. Most of them limit sales of stock, especially for institutional investors.

[10] Trade size is efficient for identifying investors unless order-splitting strategies prevail in the market, which is not the case in China (See Caglio and Mayhew (2016) for more details). We also use different trade values as the proxy for the identity of traders, and the main findings remain the same.

[11] Some may argue that value based (RMB trading volume) herding measures could be better than our shares volume based herding measure. However, Lee and Radhakrishna (2000) argue that the dollar-based measure contends a different set of problems/errors. For example, a small price change in a low-price stock could categorize a same trade into different group of investors. To mitigate this price sensitivity problem, Lee and Radhakrishna (2000) suggest setting a buffer zone of medium-sized trades so that the accuracy of investors classification can be greatly improved, and that is exactly what we do in this study.

[12] For the most-informed group, it ranges from 18.9% to 23.3%. For the least-informed group, it ranges from 10.5% to 16.6%.

[13] The percentage of transactions of the most-informed/least-informed investor group is the ratio of trades over 50,000/below 500 shares over the total trades on SSE 180 component stocks.

[14] CCK's herding measure is based on a moving window of 25 daily returns and suppresses the information contained in the variation of trades within each trading day.

[15] It is possible that N is different for different groups if they only trade on a fraction of stocks. But in our sample, it is identical, meaning all stocks are traded by both informed investors and uninformed investors daily.

selectively, $\sigma_{j,\,t}$ increases. We compare $\sigma(Trd)_{j,\,t}$ between most-informed and least-uninformed investor groups and between the whole and sub-sample periods to explore the dynamics of herding behavior within different groups and their effects on market performances.

Li et al. (2017) directly uses this dispersion of trading volume as an in-group herding measure. We add an adjusted factor to capture the short-term herding tendency, representing the change of herding in a group at time t.

$$HT_{j,t} = Adjusted\ Factor_{j,t}{}^{*} - \sigma(Trd)_{j,t} \tag{2}$$

The adjusted trading factor $HT_{j,\,t}$ is the moving average of $\sigma(Trd)_{j,\,t}$ for the past 25 days. A positive value of $HT_{j,\,t}$ means a rising herding tendency in group *j* at time *t*. This adjustment helps us to investigate the short-term dynamics of in-group herding and its effect on subsequent market return and volatility.

3.2. Market herding measure

Herding happens when investors forgo their own decisions and act like others. In empirical work, either "herding to stocks" or "herding to market" is detected by examining the dispersion of trading volumes, of the order direction of trades, or of the return of equity. When herding exists, the examined dispersion decreases. We also follow the CCK (Chang et al., 2000) procedure and apply the return-based herding measure to discover the market-level herding, and further break it into fundamental herding and non-fundamental herding.

According to the CCK procedure, herding is detected when the cross-sectional absolute deviation (CSAD) of returns is negatively correlated with the market return square, and the CSAD is defined as the following:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} | R_{i,t} - R_{m,t} | \tag{3}$$

where $R_{i,\,t}$ is the stock return of stock *i* at time *t*, and $R_{m,\,t}$ is the cross-sectional average return of *N* stocks in the portfolio at time *t*. The following specification detects the herding behavior:

$$CSAD_t = \lambda_0 + \lambda_1 | R_{m,t} | + \lambda_2 \left(R_{m,t}\right)^2 + \varepsilon_t \tag{4}$$

As proposed by Chang et al. (2000), the coefficient λ_2 measures the herding behavior, and a significantly negative λ_2 testifies the existence of herding behavior in the market.

As mentioned before, this study aims to investigate different investor groups' herding behavior and the herding effect on market performance. We hypothesize that more-informed investors' herding is more likely to be driven by fundamental information and less-informed investors' herding is more likely to be driven by non-fundamental factors such as sentiment. In order to verify the causes of herding behaviors, we follow the methodology proposed by Galariotis et al. (2015) to separate the "spurious" herding from the "intentional" herding. Many previous studies have established the link between Fama-French factors (high minus low (HML) and small minus big (SMB)) and fundamental information that affects security returns.[16] Galariotis et al. (2015) employ the unexplained part of CSAD in the factors equation to test the "intentional" herding.

In the first step, CSAD is estimated as follows:

$$CSAD_t = \beta_0 + \beta_1 \left(R_{m,t} - R_{f,t}\right) + \beta_2 HML_t + \beta_3 SMB_t + \varepsilon_t \tag{5}$$

where HML_t is the daily High Minus Low return factor and SMB_t is the daily Small Minus Big return factor for Chinese A shares market.[17] The fitted values of Eq. (5) represent how $CSAD_t$ responds to the fundamental information, and the residual series of Eq. (5) captures the deviations not caused by fundamental information. Next, we estimate the following equations similar to Eq. (4) but with the fitted values ($CSAD_{Fund,\,t}$) and the residuals of Eq. (5) respectively ($CSAD_{NonFund,\,t}$).

$$CSAD_{Fund,t} = \lambda_0 + \lambda_1 | R_{m,t} | + \lambda_{2,Fund} \left(R_{m,t}\right)^2 + \varepsilon_t \tag{6}$$

$$CSAD_{NonFund,t} = \lambda_0 + \lambda_1 | R_{m,t} | + \lambda_{2,NonFund} \left(R_{m,t}\right)^2 + \varepsilon_t \tag{7}$$

Eqs. (4), (6), and (7) are estimated for the entire sample period and the sub-periods, and the results are reported in Table 2.

3.3. Relations between market-level herding and in-group herding tendency

When investors follow others to trade within an investor group, it is possible that the whole market herding activities are more significant. However, it is also possible that investors from different investor groups herd to trade in opposite directions, especially when there's more information asymmetry during crisis periods.

To test the relation between the in-group herding tendency measure and the market herding behavior from the CCK model, we

[16] i.e., Liew and Vassalou (2004), Gregory et al. (2010), Leite et al. (2020)

[17] Daily series for HML and SMB factors in Chinese stock markets are derived from RESSET Finance Database. See www.resset.cn.

write the following regression:

$$\lambda_{2,t} = \alpha_0 + \alpha_1\sigma_{inf,t} + \alpha_2\sigma_{uninf,t} + \varepsilon_t \tag{8}$$

where $\lambda_{2,\ t}$ is the herding coefficient estimated from Eq. (4), based on the sample of the 25[18] trading days before day t; $\sigma_{inf,\ t}$ and $\sigma_{uninf,\ t}$ are calculated from Eq. (1) and represent the herding tendency within most-informed investors and least-uninformed investors in day t. The coefficients α_1 and α_2 capture how the herding tendency of investor groups impacts the market-level herding, respectively. As a smaller $\sigma_{inf,\ t}$ or $\sigma_{inf,\ t}$ suggests a higher level of in-group herding tendency, a positive and statistically significant α_1 or α_2 means that a higher herding tendency in that group is associated with a lower value of $\lambda_{2,\ t}$, suggesting a rising level of market herding, and vice versa.

Furthermore, we also explore the effects of in-group herding tendency on different types of market herding by estimating the following regressions:

$$\lambda_{2,Fund,t} = \alpha_0 + \alpha_{1,Fund}\sigma_{inf,t} + \alpha_{2,Fund}\sigma_{uninf,t} + \varepsilon_t \tag{9}$$

$$\lambda_{2,NonFund,t} = \alpha_0 + \alpha_{1,NonFund}\sigma_{inf,t} + \alpha_{2,NonFund}\sigma_{uninf,t} + \varepsilon_t \tag{10}$$

$\lambda_{2,\ Fund,\ t}$ and $\lambda_{2,\ NonFund,\ t}$ are market herding measures estimated from Eqs. (6) and (7). $\sigma_{In,\ t}$ and $\sigma_{Uninf,\ t}$ are defined in Eq. (8). The coefficients $\alpha_{1,\ Fund}$ and $\alpha_{2,\ Fund}$ capture the effect of in-group herding tendency on the market level of "spurious" herding ($\lambda_{2.\ Fund,\ t}$), when the market herding is caused by fundamental information (see Galariotis et al., 2015). $\alpha_{1,\ NonFund}$ and $\alpha_{2,\ NonFund}$ capture the impact of in-group herding tendency on the "intentional" herding ($\lambda_{2NonFund,\ t}$), when market herding is caused by non-fundamental factors.

3.4. Consequences of herding on market return and volatility

Herding behavior reflects investors' perception of risk and lower risk tolerance, especially when the market is in turmoil periods. This change in trading behavior can consequently affect equity price and return volatility (Foucault et al., 2011; Venezia et al., 2011; Kremer and Nautz, 2013a).

Bikhchandani and Sharma (2001) suggest that herding could be either "spurious herding", which is driven by fundamentals, or "intentional herding", which is caused by investors' intention to follow others. Intentional herding drives stock price away from the fundamental value and consequently leads a return reversal while spurious herding only incorporates information into prices and has no further influence on prices.

With the in-group herding tendency examined, we can investigate the dynamics between the two in-group herding tendencies and subsequent market returns. Specifically, we examine the effect of herding on subsequent market returns using the following regressions:

$$CAR_{m,t+i} = \alpha_0 + \beta_1\lambda_{2,t} + \sum_{j=1}^{k}\beta_j R_{m,t-j} + \varepsilon_t \tag{11}$$

$$CAR_{m,t+i} = \alpha_0 + \beta_2\lambda_{2,Fund} + \beta_3\lambda_{2,NonFund} + \beta_j\sum_{j=1}^{k} R_{m,t-j} + \varepsilon_t \tag{12}$$

$$CAR_{m,t+i} = \alpha_0 + \beta_4 HT_{inf,t} + \beta_5 HT_{uninf,t} + \sum_{j=1}^{k}\beta_j R_{m,t-j} + \varepsilon_t \tag{13}$$

where $CAR_{m,\ t+i}$ is the cumulative returns from day t to day $t + i$; lagged returns are included in the regression according to Schwarz Criterion (SC). Other variables are defined before. Eqs. (11) and (12) test how market level herding affects subsequent market returns, and Eq. (13) tests how in-group herding tendency affects subsequent market returns.

Follow the same spirit of Venezia et al. (2011), we estimate the following regressions to estimate the effect of herding on the market volatility:

$$Std_{m,t} = \gamma_0 + \beta_1\lambda_{2,t-1} + \beta_4 R_{m,t-1} + \beta_5 vol\_SH180_{t-1} + \varepsilon_t \tag{14}$$

$$Std_{m,t} = \gamma_0 + \beta_2 HT_{inf,t-1} + \beta_3 HT_{uninf,t-1} + \beta_4 R_{m,t-1} + \beta_5 vol\_SH180_{t-1} + \varepsilon_t \tag{15}$$

where $Std_{m,\ t}$ is the standard deviation of daily-returns of SSE 180 index based on the past 25 trading days. vol_SH180_{t-1} is the log value of the trading volume of all the component stocks of SEE index for day t − 1. Eq. (14) tests how market level herding affects market volatility, Eq. (15) tests how in-group herding tendency affects market volatility. All variables description are reported in Table 1.

[18] We use different numbers of trading days for the rolling window, but the main results stay the same. Results are available on request.

Table 1
Variables Description.

$\sigma_{j,\ t}$	the daily dispersion of trading volume $\sigma_{j,\ t}$ for each group (informed and uninformed), measure the in-group herding of group j at time t	is calculated from high-frequency trade records of group j at time t: $\sigma_{j,t} = \sqrt{\frac{\sum_{i=1}^{N}\left[Trd_{j,it} - \mu(Trd)_{j,t}\right]^2}{N-1}}$
$HT_{j,t}$	the herding tendency of group j at time t	$HT_{j,\ t}$ = Adjusted $Factor_{j,\ t}$ * $- \sigma(Trd)_{j,\ t}$
$CSAD_t$	the cross-sectional absolute deviation (CSAD) of returns at time t	$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} \mid R_{i,t} - R_{m,t} \mid$
λ_2	The daily CCK method herding measure	is estimated from Equation: $CSAD_t = \lambda_0 + \lambda_1 \mid R_{m,\ t} \mid + \lambda_2(R_{m,\ t})^2 + \varepsilon_t$ based on daily returns *of* $R_{i,\ t}$ *and* $R_{m,\ t}$
$\lambda_{2,\ Fund}$	The daily "spurious" herding measure	is estimated from Equation: $CSAD_{Fund,\ t} = \lambda_0 + \lambda_1 \mid R_{m,\ t}\mid + \lambda_{2,\ Fund}(R_{m,\ t})^2 + \varepsilon_t$, where $CSAD_{Fund,\ t}$ is the fitted value of $CSAD_t = \beta_0 + \beta_1(R_{m,\ t} - R_{f,\ t}) + \beta_2 HML_t + \beta_3 SMB_t + \varepsilon_t$
$\lambda_{2,\ NonFund}$	The daily "intentional" herding measure	s estimated from Equation: $CSAD_{Nonfund,\ t} = \lambda_0 + \lambda_1 \mid R_{m,\ t}\mid + \lambda_{2,\ Nonfund}(R_{m,\ t})^2 + \varepsilon_t$, where $CSAD_{Fund,\ t}$ is the residuals of $CSAD_t = \beta_0 + \beta_1(R_{m,\ t} - R_{f,\ t}) + \beta_2 HML_t + \beta_3 SMB_t + \varepsilon_t$
HML and SMB	Book-to-Market factor and Size factor	Daily series for HML and SMB factors in Chinese stock markets are derived from RESSET Finance Database
$R_{m,\ t}$	The daily return of Shanghai180 index	$R_{m,\ t} = \ln P_t - \ln P_{t-1}$
$Std_{m,\ t}$	the standard deviation of daily-returns of SSE 180 index based on the past 25 trading days.	
Vol_SH180_{t-1}	the log value of the trading volume of all the component stocks of SEE index.	

Notes: The common sample period is from 07/08/2014–5/31/2016. The "Pre-Peak" period is from 2014/07/08 to 2015/06/09, and the "Post-Peak-market" period is from 2015/06/10 to 2016/5/31. All trading data is extracted from CSMAR China Security Market Trade & Quote Research Database

4. Data and empirical evidence

4.1. Data description

We use a data set of high-frequency transaction records from the Shanghai stock exchange, and the data are extracted from CSMAR China Security Market Trade & Quote Research Database. The trading records cover all of the component stocks of the SSE 180 Index from June 03, 2014, to May 31, 2016, including 263 stocks and more than 250 million observations.[19] This sample period covers the most recent bull-and-bear cycle in China's A share market, when the SSE index[20] rose from 2152 points in May 2014, peaked at 5380 points in May 2015, and plunged back to 2821 in March 2016.

Since the primary objective of our study is to investigate differences in herding behaviors from different groups, we need to investigate the market sector accessible to all investors. For that reason, we choose the component stocks of the SSE180 index instead of the Shanghai-Shenzhen 300 Index. The latter includes stocks that cannot be traded by individual investors whose investments are less than 500 k for the past 30 trading days and therefore locks out some individual investors.

Table 2 Panel A reports the summary statistics of daily returns of SSE180 during the sample period from June 3, 2014, to May 31, 2016. China's A-share market was very volatile in this period. The mean daily return during the "Pre-Peak" market before it peaked on June 9, 2015, was 0.36%, while it dropped to −0.22% in the next year. Unsurprising, the annual return standard deviation was 50% higher in the "Post-Peak" market, at 2.49% compared to 1.64% in the "Pre-Peak" market. The trading volume remained relatively stable in the sample period. CSAD slightly jumped from 0.0166 to 0.0171 when the market switched from bull to bear.

Table 2 Panel B reports the herding tendency measures in the two investor groups, which are identified based on their trading records. The table shows that the least-informed investors' group has a relatively higher herding tendency than the most-informed investors' group in the whole sample period, as well as in pre-peak and post-peak sub-periods, which is testified by a lower mean value of σ_{unInf} compared to σ_{inf}.[21] This result is consistent with previous findings that most-informed (mostly institutional) investors herd less than least-informed (mostly individual) investors (Li et al., 2017). Meanwhile, we find that the dispersion of trading volumes for both groups is smaller in the down market when the dispersion of trading volume for the most-informed investors group declined from 1.7090 to 1.5374 and the least-informed investors group decreased from 1.2106 to 0.9925. This result confirms that investors herd more during the crisis period (Chang et al., 2000; Gleason et al., 2004; Demirer and Kutan, 2006).

[19] Every trading record has the following information: security code, trading date, trading time, current price, trading quantity, and trading value.
[20] Shanghai-Shenzhen 300 index is calculated using the component stocks chosen from both Shanghai and Shenzhen exchanges, which is one of the most inclusive indexes for the Chinese stock market.
[21] The differences between the herding tendency measures of most-informed investors and least-informed investors are statistically significant for all pre-peak, post-peak, and whole sample periods. See Panel C of Table 2 for details.

Table 2
Data Descriptive.

Panel A: Market									
	Pre-Peak	Post-Peak	All	Pre-Peak	Post-Peak	All	Pre-Peak	Post-Peak	All
	SH180_RETURN (%)			*SH180_VOL*			*CSAD*		
Mean	0.36	−0.22	0.07	23.2899	23.1200	23.2039	0.0166	0.0171	0.0168
Std.	1.64	2.49	2.12	0.7874	0.6163	0.7131	0.0069	0.0090	0.0080
Ske.	−0.7244	−0.8359	−0.9955	−0.3144	0.4098	−0.0063	0.8810	2.1683	1.8233
Obs.	226	239	465	226	239	466	226	239	465
Panel B: Herding Measures									
	$\sigma_{inf,\ t}$			$\sigma_{uninf,\ t}$					
Mean	1.7090	1.5374	1.6210	1.2106	0.9925	1.0986			
Std.	0.1683	0.0986	0.1616	0.4305	0.3839	0.4212			
Obs.	226	239	465	226	239	465			

Panel C: Test for Equality of Herding Measure Means			
Test for Equality of Means	Pre-peak	Post-peak	Whole period
Anova F-test	−1.450***	−1.476***	−1.928***
	(263.0962)	(451.5551)	(622.627)
Welch F-test	−1292.917***	1269.259***	−1597.918***
	(263.0962)	(451.5551)	(622.627)

Notes: The daily return of Shanghai180 index (*SH180_RETURN)* is calculated as $R_{m,\ t} = \ln P_{m,\ t} - \ln P_{m,\ t-1}$. The standard deviation of the daily return of SSE180 index (*SH180_STD)* is calculated on the past 250 trading days. The daily trading volume (*SH180_VOL*) is the log value of the trading volume of all the component stocks of SEE index. CSAD is the cross-sectional absolute deviation of returns, calculated from Eq. (2). The herding tendency is calculated as

$$\sigma(Trd)_{j,t} = \sqrt{\frac{\sum_{i=1}^{N}\left[Trd_{j,it} - \mu(Trd)_{j,t}\right]^2}{N-1}} \tag{1}$$

Table 3
Results for CCK Herding Test.

	Pre-Peak (2014/7/08–2015/6/09)			Post-Peak (2015/6/10–2016/5/31)			Whole-period (2014/7/08–2016/5/31)		
	$CSAD_t$	$CSAD_{Fund,\ t}$	$CSAD_{NonFund,\ t}$	$CSAD_t$	$CSAD_{Fund,\ t}$	$CSAD_{NonFund,\ t}$	$CSAD_t$	$CSAD_{Fund,\ t}$	$CSAD_{NonFund,\ t}$
λ_1	0.2899***	0.0726***	−0.0568	0.3905***	0.0012	0.2983***	0.3640***	0.0223	0.1651***
	(3.6519)	(2.9240)	(−1.1302)	(4.5438)	(0.0323)	(4.4777)	(6.2435)	(0.9691)	(3.9594)
λ_2	−2.0108	−1.047***	1.3585	−4.4430***	0.6346	−4.8549***	−3.9393***	0.2168	−2.7511***
	(−1.4109)	(−2.3130)	(1.5627)	(−3.5506)	(1.1483)	(−5.0906)	(−4.4109)	(0.6111)	(−4.3874)
λ_0	0.0144***	0.016***	−0.0138***	0.0133***	0.016***	−0.0120***	0.0137***	0.016***	−0.0009**
	(18.8999)	(70.5861)	(−16.8018)	(14.0584)	(39.4484)	(−10.5635)	(22.4943)	(6935068)	(−2.2773)
Obs.	226	226	226	239	239	239	465	465	465
Adj. R^2	0.1171	0.0449	0.6382	0.0861	0.0360	0.3579	0.0960	0.0279	0.4797

Notes: This table reports results for the following equations:

$$CSAD_t = \lambda_0 + \lambda_1 \mid R_{m,t} \mid + \lambda_2 \left(R_{m,t}\right)^2 + \varepsilon_t \tag{4}$$

$$CSAD_{Fund,t} = \lambda_0 + \lambda_1 \mid R_{m,t} \mid + \lambda_{2,Fund} \left(R_{m,t}\right)^2 + \varepsilon_t \tag{6}$$

$$CSAD_{NonFund,t} = \lambda_0 + \lambda_1 \mid R_{m,t} \mid + \lambda_{2,NonFund} \left(R_{m,t}\right)^2 + \varepsilon_t \tag{7}$$

The lagged CSAD variable is also included in the equations above to eliminate AR effects, but due to space limitation they are not reported. The results are available upon requests. ***, **, * Indicate statistical significance at 1%, 5% and 10%, respectively.

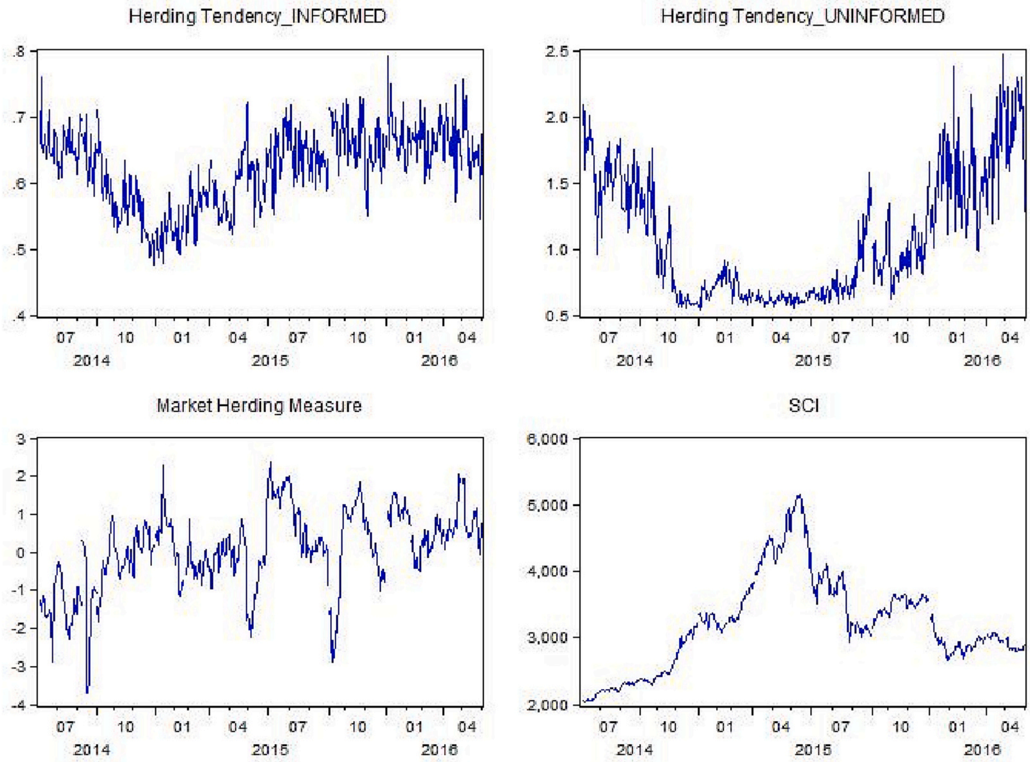

Fig. 1. Relation Between In-group Herding Tendency and Market Herding.
Notes: Herding Tendency for most-informed (INFORMED) investors and least-informed investors (UNINFORMED) are captured by $1/\sigma_{inf,\ t}$ and $1/\sigma_{uninf,\ t}$ respectively. Market Herding Measure is the negative of t-stats for the series of coefficient λ_2, which estimated from $CSAD_t = \lambda_0 + \lambda_1 \mid R_{m,\ t}\mid + \lambda_2 (R_{m,\ t})^2 + \varepsilon_t$ (3). SCI stands for Shanghai Composite Index.

4.2. Herding behavior in the market

Besides the in-group herding measure, we further apply the CCK model to test the existence of market-level herding during the whole two-year period and the bull/bear sub-periods. The results are presented in Table 3. Herding is detected when the coefficient λ_2 in the regressions is negative and significant. We find that λ_2 for all investors is negative and significant for the whole sample period and post-peak period. This finding suggests that herding exists in the Chinese stock market, especially when the market collapses. However, the cause for the market herding differs between the pre-peak and post-peak periods. When the market rises, market herding is more likely to be driven by fundamental factors. In a collapsing market, market herding is more likely to be driven by non-fundamental factors. We will further investigate the reasons in the next section.

4.3. Effect of in-group herding tendency on market level of herding

Fig. 1 presents the dynamics of the herding tendency for both most-informed and least-informed investors, the market level of herding, and the Shanghai Composite Index from July 7, 2014, to May 31, 2016.

As we argue above, the smaller the dispersion of trading volume for one investor group, the higher the level of herding tendency in this group. Therefore, Fig. 1 shows the reciprocal of $\sigma_{inf,\ t}$ representing the herding tendency for most-informed investors and $\sigma_{uninf,\ t}$ for least-informed investors.

The herding tendencies of most-informed and least-informed investors both declined when the market started to boom. When the market reached its first peak around the end of 2014, the herding tendency of most-informed investors bounced back on December 25, 2014, followed by the rise of the herding tendency for least-informed investors on Jan.6, 2015. However, the former kept rising, while the latter stayed relatively low until the market collapsed. It is possible that this difference of in-group herding tendency happened when most-informed investors sensed the increasing market risk and reacted more to fundamental information changes than non-fundamental factors. On the other hand, least-informed investors were unaware of the rising market risk and only changed their trading behavior when the market collapsed.

We use Eq. (4) to calculate the market herding measure. As Chang et al. (2000) suggest, a negative and significant coefficient λ_2 testifies to the existence of herding behavior in the market. In our empirical tests, the market-level return-based herding is detected when the absolute value of the t-stat of λ_2's coefficient is significant at 5%. The two spikes of this market herding measure occur in

Table 4A
In-group herding tendency and market level herding.

A: Effect of in-group herding on market level herding									
	Pre-Peak 2014/7/08–2015/6/09			Post-Peak 2015/6/10–2016/5/31)			Whole-period (2014/7/08–2016/5/31)		
	$\lambda_{2,\ Fun}$	$\lambda_{2,\ NonFund}$	λ_2	$\lambda_{2,\ Fun}$	$\lambda_{2,\ NonFund}$	λ_2	$\lambda_{2,\ Fun}$	$\lambda_{2,\ NonFund}$	λ_2
$\sigma_{Inf,\ t}$	−5.7132	−10.4963**	−16.2095***	9.1888**	−8.4191*	0.7696	4.7882**	−3.5216	1.2666
	(−1.5043)	(−2.3165)	(−3.3654)	(2.4480)	(−1.71327)	(0.1560)	(2.100018)	(−1.1061)	(0.3633)
$\sigma_{Uninf,\ t}$	−0.2468	−11.7825***	−12.0293***	−2.0746**	5.0252***	2.9506***	−1.5317*	−2.9291**	−4.4608***
	(−0.1662)	(−6.6511)	(−6.3879)	(−2.1521)	(4.0270)	(2.3298)	(−1.7509)	(−2.3961)	(−3.3328)
$\boldsymbol{\alpha_0}$	12.6717**	34.7678***	47.4395***	−12.1982***	5.4664	−6.7318	−4.8820	8.8755*	3.9935
	(2.2372)	(5.1450)	(6.6041)	(−2.1447)	(0.7424)	(−0.9009)	(−1.4599)	(1.8992	(0.7804)
Obs.	226	226	226	239	239	239	465	465	465
Adjusted R-squared	0.0086	0.307	0.3376	0.028666	0.0602	0.0156	0.0066	0.0223	0.0236

Notes: This table reports the results for Eqs. (8), (9) and (10).

$$\lambda_{2,t} = \alpha_0 + \alpha_1\sigma_{Inf,t} + \alpha_2\sigma_{Uninf,t} + \varepsilon_t \tag{8}$$

$$\lambda_{2,Fund,t} = \alpha_0 + \alpha_{1,Fund}\sigma_{inf,t} + \alpha_{2,Fund}\sigma_{Uninf,t} + \varepsilon_t \tag{9}$$

$$\lambda_{2,NonFund,t} = \alpha_0 + \alpha_{1,NonFund}\sigma_{inf,t} + \alpha_{2,NonFund}\sigma_{Uninf,t} + \varepsilon_t \tag{10}$$

T-values are in parenthesis. Level of significance are indicated by *, ** and *** for 10%, 5% and 1% respectively.

December 2014, and May 2015, coinciding with the change of in-group herding of most-informed and least-informed investors. It suggests that our trading volume-based herding tendency measure provides additional insights into investors' trading patterns compared to the return-based herding measure only, especially for a market with a dual-group investor structure.

Next, we investigate the relation between market herding and in-group herding tendency, and fundamental factors or non-fundamental factors drive the two different types of herding. Table 4A reports the estimates for Eqs. (8), (9), and (10).

The first finding of Table 4A is that the coefficients of both $\sigma_{inf,\ t}$ and $\sigma_{uninf,\ t}$ in the 3rd column of the pre-peak period are negative and significant. These coefficients capture the effects of in-group herding tendency on overall market herding when the market is rising. As mentioned above, both $\sigma_{j,\ t}$ and λ_2 are inversely correlated with the level of herding. Therefore, the negative coefficients of $\sigma_{uninf,\ t}$ and $\sigma_{uninf,\ t}$ on λ_2 indicate that when the in-group herding tendency decreased (higher $\sigma_{inf,\ t}$ or $\sigma_{uninf,\ t}$) in the pre-peak period (anti-herding), the market herding level increased (lower λ_2) in terms of the return-based herding measure. Given that herding behavior was not significant in overall Chinese markets during the pre-peak period, a possible explanation is that investors might herd within each of those two groups (most-informed and least-informed), but the effect canceled out at the aggregate level, so there was no consensus on trading in the whole market. This evidence could lead to further investigation into market herding, where different types of investors are considered. In the post-peak period, however, market herding is only significantly and positively correlated with the least-informed investors' group. This result is consistent with studies on the Chinese stock market that document a stronger herding tendency in individual investors (less informed) than in institutional (more informed) investors (Li et al., 2017), and different from the situation in developed markets where institutional (more informed) investors dominate the market (Nofsinger and Sias, 1999; Iihara et al., 2001).

The second finding is how in-group herding tendency affects fundamental and non-fundamental herding. Previous literature suggests that informed investors herd more on fundamental factors (Galariotis et al., 2015), while uninformed investors herd more on non-fundamental factors like psychological biases (Barber et al., 2009), investors' trading location (Feng and Seasholes, 2004) and past herding behaviors (Merli and Roger, 2013). The results in the post-peak period confirm the arguments above that the coefficients of in-group herding tendency are positive and significant for informed investors when investors herd on fundamental factors and for uninformed investors when investors herd on non-fundamental factors (9.1888 for the coefficient of $\sigma_{inf,\ t}$ on $\lambda_{2,\ Fund}$, and 5.0252 for the coefficient of $\sigma_{uninf,\ t}$ on $\lambda_{2,\ NonFund}$). It indicates that an increasing herding tendency in most-informed investors increases the market herding driven by fundamental factors. In contrast, the growing herding tendency in least-uninformed investors causes the market herding on non-fundamental factors to rise. The results, however, are inconsistent with the pre-peak period and the whole sample period. It might be because of the low herding activities in the pre-peak period.[22] It is also possible that there are abundant financing channels during the upmarket, and investors herd in different directions, so at the market level, herding decreased (negative coefficients). After the market shifts to the downturn regime when those extra financing channels are closed, investors become more cautious and aware of the market risk. As a result, herding activities intensified, and the herding pattern differed between most-informed and least-informed investors.

Some may argue that the in-group herding tendency and market-level herding respond to "common factors", so the relationship between in-group herding on market-level herding could be correlational, not causal. To address this issue, we follow Galariotis et al. (2015) and apply a two-step procedure to discover the "net" effect of in-group herding on market-level herding.

In the first step, we regress in-group herding measures ($\sigma_{inf,\ t}$ *or* $\sigma_{uninf,\ t}$) on the lagged CSAD measures we obtained from Eqs. (6) and (7).[23] The lagged CSAD measures, based on both fundamental and non-fundamental factors, capture the stock market fundamental information that could affect both market-level herding and in-grouping herding tendency. In the second step, we use the residuals series ($\varepsilon_{inf,\ t}$ or $\varepsilon_{uninf,\ t}$) from these two regressions to replace the original herding tendency measures ($\sigma_{inf,\ t}$ *or* $\sigma_{uninf,\ t}$), and we repeat the regressions in Table 4A.

Table 4B reports the results of the two-step tests. The results from "Step 1" show that the herding tendency measures and lagged CSAD variable are highly correlated for both Pre-peak and Post-peak subsamples, and the whole sample. After replacing the original herding tendency measures with the error term from Eqs. (16) and (17), the results in "Step 2" of Table 4B show similar results to Table 4A and are mostly consistent with previous literature, especially in the post-peak period. The positive coefficients of σ_{inf_net} and σ_{uninf_net} suggest that most-informed investors are more likely to do "spurious herding", and the least-informed investors are more likely to do "intentional herding" at the market level.

4.4. Consequences of herding on market return and volatility

This section investigates the effects of dual-group herding behavior on market return and volatility. We calculate the adjusted in-group herding tendency measure $HT_{j,\ t}$ [24] by subtracting the in-group herding tendency measures ($\sigma_{inf,\ t}$ *or* $\sigma_{uninf,\ t}$) from its 25 days

[22] See Fig. 1.

[23] The regression equations are as the following:

$$\sigma_{inf,t} = \alpha_0 + \alpha_1 CSAD_{Fun,t-1} + \alpha_2 CSAD_{NonFund,t-1} + \varepsilon_{inf,t} \tag{16}$$

$$\sigma_{uninf,t} = \alpha_0 + \alpha_1 CSAD_{Fun,t-1} + \alpha_2 CSAD_{NonFund,t-1} + \varepsilon_{uninf,t} \tag{17}$$

[24] As shown in Eq. (2), a higher HT value corresponds to a lower value of $\sigma_{inf,\ t}$ *or* $\sigma_{uninf,\ t}$ and indicates a higher level of in-group herding.

Table 4B
Effect of in-group herding on market herding (Two-step procedure).

Step 1:

	Pre-Peak 2014/7/08–2015/6/09		Post-Peak 2015/6/10–2016/5/31)		Whole-period (2014/7/08–2016/5/31)	
	σ_{inf}	σ_{uninf}	σ_{inf}	σ_{uninf}	σ_{inf}	σ_{uninf}
$CSAD_{Fun,\ t-1}$	19.7629***	17.3466**	4.1464***	0.5384	7.2521***	3.9326
	(4.3310)	(2.0560)	(2.6307)	(0.1089)	(3.2114)	(0.8551)
$CSAD_{NonFund,\ t-1}$	10.3083***	51.2871***	2.9736***	2.3400***	5.9663***	37.9988***
	(6.5948)	(17.7457)	(3.9847)	(12.7628)	(6.1317)	(19.1758)
α_0	1.3723***	0.8922***	1.4665***	0.9766***	1.4967***	1.0186***
	(17.7433)	(6.2389)	(53.5622)	(11.3749)	(38.6033)	(12.8996)
Obs.	226	226	239	239	465	465
Adjusted R-squared	0.2140	0.5868	0.0799	0.4033	0.0901	0.4417

Step2:

	Pre-Peak 2014/7/08–2015/6/09			Post-Peak 2015/6/10–2016/5/31)			Whole-period (2014/7/08–2016/5/31)		
	$\lambda_{2,\ Fun}$	$\lambda_{2,\ NonFund}$	λ_2	$\lambda_{2,\ Fun}$	$\lambda_{2,\ NonFund}$	λ_2	$\lambda_{2,\ Fun}$	$\lambda_{2,\ NonFund}$	λ_2
$\varepsilon_{inf,\ t}$	−7.3365*	−9.1346*	−16.4712***	9.1957**	−7.2074	1.9883	0.7001	−3.4620	−2.7619
	(−1.9062)	(−1.7460)	(−2.9985)	(2.3721)	(−1.4296)	(0.3910)	(02726)	(−0.9465)	(−0.6976)
$\varepsilon_{uninf,\ t}$	−1.0424	−12.8859***	−13.9284***	−1.8868	5.5401***	3.6532**	−2.3041**	−3.5063**	−5.8078***
	(−0.5007)	(−4.5463)	(−4.6882)	(−1.5263)	(3.4459)	(2.2529)	(−2.0453)	(−2.1833)	(−3.3434)
$\boldsymbol{\alpha_0}$	2.4985***	2.5295***	5.0281***	−0.1300	−2.4898***	−2.6199***	1.1445***	−0.0558	1.0887**
	(4.9336)	(3.6682)	(6.9564)	(−0.3572)	(−5.2571)	(−5.4847)	(3.6113)	(−0.1237)	(2.2276)
Obs.	226	226	226	239	239	239	465	465	465
Adjusted R-squared	0.017	0.1411	0.1910	0.028666	0.0602	0.0156	0.0046	0.0093	0.0223

Notes: This table reports the results for equations

$$\sigma_{inf,t} = \alpha_0 + \alpha_1 CSAD_{Fun,t-1} + \alpha_2 CSAD_{NonFund,t-1} + \varepsilon_{inf,t} \quad (16)$$

$$\sigma_{uninf,t} = \alpha_0 + \alpha_1 CSAD_{Fun,t-1} + \alpha_2 CSAD_{NonFund,t-1} + \varepsilon_{uninf,t} \quad (17)$$

T-values are in parenthesis. Level of significance are indicated by *, ** and *** for 10%, 5% and 1%, respectively.

Notes: $\varepsilon_{inf,\ t}$ and $\varepsilon_{uninf,\ t}$ are the residuals from Eqs. (16) and (17). They represent the remaining part of in-group herding tendency which is not directly caused by last period market herding. This procedure can, at least partly, address the causality problem between in-group herding and market level herding. T-values are in parenthesis. Level of significance are indicated by *, ** and *** for 10%, 5% and 1%, respectively.

moving average. This new measure could capture the dynamic impact of in-group herding tendency on subsequent market returns and volatility. The results are also compared to those using the market herding measure (the CCK model).

4.4.1. *Impacts of herding on market return*

Herding behavior may have a significant effect on asset prices and subsequent returns. Quite a few studies have investigated the impact of herding on market returns. Lee (2017) finds that the overall market herding in NYSE has insignificant impacts on the subsequent short-term returns, which suggests that market information mainly drives herding in NYSE. However, the effect of herding behavior on consequent market returns in emerging markets such as China may be different because of the large number of uninformed investors.

Applying the same method of Venezia et al. (2011) to our dual-group herding framework, we regress subsequent cumulative market returns for 1, 3, and 5 trading days on three sets of variables: the first set includes the market herding measure λ_2 and lagged returns; the second set includes the measure of fundamental herding and nonfundamental herding from Eqs. (6) and (7); the last set includes the adjusted herding tendency measures for most-informed and least-informed investors, and lagged returns.[25]

Previous literature (Scharfstein and Stein, 1990; Bikhchandani and Sharma, 2001; Barberis and ShleiferStyle, 2003; Choi and Sias, 2009) argue that the herding activity driven by fundamental factors merely facilitates the incorporation of information into prices, although the herding activity triggered by non-fundamental factors drives prices away from fundamental values and destabilizes the market. When the latter happens, the existence of herding is followed by return reversals as the market corrects the deviation. Kremer and Nautz (2013a, 2013b) argue that this return reversal should be tested in a short horizon as the arbitrageurs act fast. Therefore, we use the cumulative returns for the subsequent 1, 3, and 5 trading days to test return reversals after herding.

As the market herding measures inversely correlate with the actual herding activities, positive and significant coefficients of CCK herding measures are indicative of return reversal.[26] But for our adjusted in-group herding tendency measure, the negative coefficients mean return reversal. The results are reported in Table 5.

Panel A of Table 5 suggests that the market herding (the CCK measure) has no significant effect on subsequent market returns for all three time-windows during both pre-peak and post-peak periods. However, when we replace them with the adjusted in-group herding tendency measures (HT_{inf} and HT_{uninf}) in the equation, we find that the least-informed investors' herding causes significant return reversals, especially before the market's peak. The return reversal effect is weaker in the post-peak period, might because uninformed investors become more risk-sensitive and cautious when the market crashes. The positive coefficients of most-informed investor herding during the pre-peak period are consistent with previous findings that informed investors herd on market information and facilitate information incorporation, although those coefficients are insignificant. Furthermore, the adjusted R-squared values for the equations using in-group herding tendency measures are higher than those using the CCK herding measure.

To further investigate the impact of herding on market returns from buy herding and sell herding separately, we divide the whole sample into two groups based on trading record data and re-run Eq. (13).[27] Test results are reported in Panel B of Table 5, and most of them are consistent with the results in Panel A that the uninformed investors herd on non-fundamental factors as either their buy herding or sell herding causes significant return-reversal in both pre and post peak periods. The results for informed investors are somehow different. Before the market crashed in June 2015, the informed investors herd on fundamentals and facilitate the incorporation of information into prices. There's no significant relation between their buy herding and sell herding, and future market returns. However, in the post-peak period, the sell herding of informed investors does cause return reversals while the buy-herding still stabilizes the market. As discussed previously, institutional investors are affected more in the down-market when "rescue policies" are imposed by government. The shut-down of financing channels, the restriction on sales of stocks and purchase of index futures force institutional investors to downsize their portfolio. Those sales are not driven by information but need of liquidity, and consequently, might drive the price away from their fundamental value.[28]

4.4.2. *Impacts of herding on market volatility*

In this section, we examine the effects of investors' herding behavior on market volatility by applying both the CCK herding measure and our adjusted in-group herding tendency measures. Table 6 reports the estimation results for Eqs. (14) and (15).

The results based on the CCK herding measure provide mixed results. The market level herding decreases subsequent market volatility in the post-peak period but increases subsequent market volatility for the whole period. Although the impact magnitude measured by the absolute value of coefficients is relatively small.

[25] The coefficients of two lagged market returns are not reported in Table 5 but are available upon request. The coefficients of lagged returns are not significant.

[26] For example, a lower subsequent return caused by a lower value of the CCK market herding measure means it is caused by a higher level of market herding.

[27] In CSMAR level-1 data, all the trades in SSE Main Board are marked as "B" for active buying trade, and "S" for active selling trade. The buy and sell herding measures are calculated based on the trading volumes of active buying and selling trades, respectively.

[28] To validate our results on buy herding and sell herding, we also add an interaction term between each of the herding measures and the market return variable into Eqs. (11)–(13) and re-run the regressions. The results are in consistent with our findings that for both buy-side and sell-side herding, market herding (measured by λ_2) does not cause market return reversals, and uninformed investors who herd on non-fundamental factors do cause significant market return reversals, especially in the pre-peak period. The results are not reported to save space but are available upon request.

Table 5
The impacts of herding on stock returns.

Part A. The impacts of herding on future stock market returns

	Pre-Peak (2014/07/08–2015/06/09)								
Dependent Variables:	$CAR_{m,\ t+1}$			$CAR_{m,\ t+3}$			$CAR_{m,\ t+5}$		
$\lambda_{2,\ t}$	−9.84E-06			−0.0001			4.45E-05		
	(−0.1038)			(−0.6111)			(0.4707)		
$\lambda_{2,\ Fund,\ t}$		0.0001			0.0004			0.0009***	
		(1.0406)			(15463)			(2.8221)	
$\lambda_{2,\ NonFund,\ t}$		−7.59E-05			−0.0003			−0.0004**	
		(−0.7203)			(−1.6516)			(−2.1311)	
$HT_{inf,\ t}$			0.0087			0.0061			0.0081
			(0.8523)			(0.3532)			(0.3693)
$HT_{uninf,\ t}$			−0.01855***			−0.0502***			−0.0712***
			(−2.8009)			(−4.4718)			(−5.0218)
α_0	0.0039***	0.0037***	0.0029**	0.0123***	0.0115***	0.0090***	0.0038***	0.0185***	0.0157***
	(3.2006)	(2.9592)	(2.4565)	(5.7178)	(5.3468)	(4.4810)	(3.0589)	(6.8724)	(6.1923)
Obs.	226	226	226	226	226	226	226	226	226
Adjusted R-squared	−0.0044	0.0001	0.0257	−0.0027	0.0199	0.0749	−0.0035	0.0583	0.0947

	Post-Peak (2015/06/10–2016/5/31)								
Dependent Variables:	$CAR_{m,\ t+1}$			$CAR_{m,\ t+3}$			$CAR_{m,\ t+5}$		
λ_2	4.82E-05			0.0002			0.0001		
	(0.2201)			(0.7579)			(0.3003)		
$\lambda_{2,\ Fund}$		0.0001			0.0003			0.0003	
		(0.3734)			(0.6615)			(0.4388)	
$\lambda_{2,\ NonFund}$		3.48E-05			0.0002			9.98E-05	
		(0.1476)			(0.6615)			(0.1927)	
$HT_{inf,\ t}$			−0.0079			−0.0230			−0.0034
			(−0.4604)			(−0.7838)			(−0.0896)
$HT_{uninf,\ t}$			−0.0081			−0.0372**			−0.0274
			(−0.8551)			(−2.3062)			(−1.3096)
α_0	−0.0022	−0.0021	−0.0017	−0.0064**	−0.0059**	−0.0045	−0.0113***	−0.0110***	−0.0098***
	(−1.3084)	(−1.2237)	(−1.0228)	(−2.1710)	(−1.9988)	(−1.5774)	(−2.9921)	(−2.9048)	(−2.6087)
Obs.	238	238	238	236	236	236	234	234	234
Adjusted R-squared	−0.0040	−0.0079	−0.0047	−0.0018	−0.0056	0.0150	−0.0039	−0.0077	−0.0012

Part B: The Impacts of Sell Herding and Buy Herding om Market Return

	Pre-Peak (2014/07/08–2015/06/09)					
Dependent Variables:	$CAR_{m,\ t+1}$		$CAR_{m,\ t+3}$		$CAR_{m,\ t+5}$	
$HT_{sell\_inf,\ t}$	−0.0006		−0.0198		−0.0174	
	(−0.0576)		(−1.0080)		(−0.6980)	
$HT_{sell\_uninf,\ t}$	−0.0186**		−0.0415***		−0.0617***	
	(−2.1475)		(−2.8023)		(−3.2782)	
$HT_{buy\_inf,\ t}$		0.0074		0.0306*		0.0289
		(0.7589)		(1.8566)		(1.3675)
$HT_{buy\_uninf,\ t}$		−0.0353***		−0.0729***		−0.0898***
		(−3.8541)		(−5.1393)		(−4.9229)
α_0	0.0029**	0.0027**	0.0103***	0.0090***	0.0174***	0.0162***
	(2.3602)	(2.1951)	(4.6810)	(4.2264)	(6.2431)	(5.9191)
Obs.	226	226	226	226	226	226
Adjusted R-squared	0.0516	0.0602	0.0425	0.1126	0.0526	0.1010

	Post-Peak (2015/06/10–2016/5/31)					
Dependent Variables:	$CAR_{m,\ t+1}$		$CAR_{m,\ t+3}$		$CAR_{m,\ t+5}$	

(continued on next page)

Table 5 (*continued*)

	Post-Peak (2015/06/10–2016/5/31)					
Dependent Variables:	$CAR_{m,\ t+1}$		$CAR_{m,\ t+3}$		$CAR_{m,\ t+5}$	
$HT_{sell\_inf,\ t}$	−0.0400**		−0.0775***		−0.0656*	
	(−2.3558)		(−2.6259)		(−1.6801)	
$HT_{sell\_uninf,\ t}$	−0.0317***		−0.0383**		−0.0203	
	(−2.9801)		(−2.0662)		(−0.8358)	
$HT_{buy\_inf,\ t}$		−0.0266		0.0598**		0.08561**
		(−1.6163)		(2.0852)		(2.2958)
$HT_{buy\_uninf,\ t}$		−0.0333***		−0.0341*		−0.0131
		(−3.1824)		(−1.8711)		(−0.5552)
α_0	−0.0009	−0.0008	−0.0047*	−0.0052*	−0.0101***	−0.0109***
	(−0.5610)	(−0.5332)	(−1.6682)	(−1.8242)	(−2.7305)	(−2.9487)
Obs.	226	226	226	226	226	226
Adjusted R-squared	0.0460	0.0413	0.0342	0.0256	0.0055	0.0154

Notes: This table reports the results for Eqs. (11), (12) and (13). $CAR_{m,\ t+i}$ is the cumulative returns from day t to day $t+i$. $\lambda_{2,\ t}$ is the herding coefficient estimated from Eq. (3) based on the sample of the 25 trading days prior to day t; $HT_{inf,\ t}$ and $HT_{uninf,\ t}$ are calculated from Eq. (2) and represent the herding tendency within most-informed investors and least-informed investors in day t. λ_{2_unex} is the residual series of Eq. (7) capturing the component in $\lambda_{2,\ t}$ that cannot be explained by $\sigma_{In,\ t}$ and $\sigma_{UnIn,\ t}$.

$$HT_{j,t} = Adjusted\ Factor_{j,t}{}^{*} - \sigma(Trd)_{j,t} \tag{2}$$

$$CAR_{m,t+i} = \alpha_0 + \beta_1\lambda_{2,t} + \beta_j\sum_{j=1}^{k} R_{m,t-j} + \varepsilon_t \tag{11}$$

$$CAR_{m,t+i} = \alpha_0 + \beta_2\lambda_{2,Fun} + \beta_3\lambda_{2,NonFund} + \beta_j\sum_{j=1}^{k} R_{m,t-j} + \varepsilon_t \tag{12}$$

$$CAR_{m,t+i} = \alpha_0 + \beta_4 HT_{uninf,t} + \beta_5 HT_{uninf,t} + \beta_j\sum_{j=1}^{k} R_{m,t-j} + \varepsilon_t \tag{13}$$

T- values are in parenthesis. Level of significance are indicated by *, ** and *** for 10%, 5% and 1% respectively.

Table 6
The impacts of herding on market volatility.

	Pre-Peak (2014/07/08–2015/06/09)		Post-Peak (2015/06/10–2016/5/31)		Whole-period (2014/7/08–2016/5/31)	
$\lambda_{2,\ t-1}$	3.84E-06		3.35E-05**		−0.0002***	
	(0.3801)		(2.3803)		(−10.8517)	
$HT_{inf,\ t-1}$		0.0040***		2.92E-06		0.0044*
		(5.4388)		(0.0025)		(1.6908)
$HT_{uninf,\ t-1}$		0.0045***		−0.0007		0.0100***
		(8.9385)		(−1.2078)		(6.3735)
$R_{m,\ t-1}$	−0.0103*	−0.0007	0.0111***	0.0107**	−0.0188	−0.0065
	(−1.6933)	(−0.1433)	(2.6667)	(2.4683)	(−1.5953)	(−0.5096)
Vol_SH180_{t-1}	0.0020***	0.0021***	−0.0029***	−0.0028***	−0.0030***	−0.0017***
	(10.9467)	(16.9571)	(−17.3043)	(−16.6599)	(−7.6211)	(−5.9775)
C	−0.0346***	−0.0369***	0.0929***	0.0907***	0.0889***	0.0588***
	(−7.9826)	(−12.6101)	(23.4586)	(22.7691)	(9.6721)	(5.9775)
Obs	225	225	236	236	461	461
Adjusted R-squared	0.4122	0.6358	0.5664	0.5466	0.2524	0.1454
Schwarz Criterion	−10.0213	−10.4805	−9.9628	−9.9119	−7.5320	−7.3870

Notes: This table reports the results for Eqs. (14) and (15). $\lambda_{2,\ t}$ is the herding coefficient estimated from Eq. (4) based on the sample of the 25 trading days prior to day t; $HT_{inf,\ t-1}$ and $HT_{uninf,\ t-1}$ are calculated from Eq. (2) and represent the herding tendency within informed investors and un-informed investors at day t.

$$Std_{m,t} = \gamma_0 + \beta_1\lambda_{2,t-1} + \beta_4 R_{m,t-1} + \beta_5 vol\_SH180_{t-1} + \varepsilon_t \tag{14}$$

$$Std_{m,t} = \gamma_0 + \beta_2 HT_{inf,t-1} + \beta_3 HT_{uninf,t-1} + \beta_4 R_{m,t-1} + \beta_5 vol\_SH180_{t-1} + \varepsilon_t \tag{15}$$

T-values are in parenthesis. Level of significance are indicated by *, ** and *** for 10%, 5% and 1% respectively.

The results based on our adjusted in-group herding tendency measures are consistent with previous studies (De Long et al., 1990; Danielsson, 2008; Persaud, 2000; Foucault et al., 2011). All adjusted in-group herding measures are positively associated with the market volatility in the pre-peak and whole periods but not in the post-peak period. It is possible that when the market crashes, other factors, such as lagged market returns, play more important roles in market fluctuation. Moreover, the results show that the herding from the least-informed investors has a slightly greater impact on market volatility than the herding from most-informed investors, although they all raise market volatility.

5. Concluding remarks

Both most-informed and least-informed investors can herd in a stock market. In a market like China, where no particular group has the dominating position, in-group herding tendency could affect market herding in different ways and consequently impact the market performance. Including the component stocks of the SSE 180 Index, our sample covers the period from June 3, 2014, to May 31, 2016, during which the Chinese stock market crashed on June 9, 2015. We discern the distinct herding tendencies of most-informed and least-informed investors based on the trading records and find the following results. Firstly, most-informed investors generally herd less than least-informed investors in the Chinese stock market; however, the gap narrows down when the market collapses and uncertainty increases. Secondly, previous literature suggests that informed investors herd more on fundamental factors, and uninformed investors herd more on non-fundamental factors. We find that in the Chinese stock markets, this pattern is only significant in a “down” market when investors become more cautious and aware of the risk. Thirdly, we find that least-informed investor herding causes stock prices to deviate away from fundamentals while most-informed investor herding usually does not, except that the sell herding of informed investors also causes return reversals in the post-peak period. Lastly, investors’ in-group herding activities lead to market volatility, especially during the upmarket. The findings also suggest that our in-group herding tendency measures are better than the traditional market herding CCK measure to detect investors’ herding activities and impacts in the Chinese stock markets.

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