# 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 in an up market with a dual-group investor structure, the overall market herding level is intensified even if each investor group has lower herding tendency; however, when the market goes down, in-group herding tendency is positively related to overall market herding. In addition, informed investors herd on fundamental factors and uninformed investors herd on non-fundamental factors only in the "post-peak" period.

**Keywords**: Herding behavior, Herding tendency, Institutional investors, Chinese stock markets.

**JEL classification**: G14; G15; G40

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## 1. Introduction

Research shows that investors herd in stock markets. When investors herd, they tend to trade in the same direction in a short period of time and ignore their private information, as individuals might be better off when they follow the trades of preceding investors (Bikhchandani, Hirshleifer, and Welch, (1992)). Herding can be observed in amateur investors due to less financial knowledge and training (Venezia, Nashikkar, and Shapira, (2011)). It can also happen among professional investors, such as institutional investors (Nofsinger and Sias, (1999)), mutual fund managers (Grinblatt, Titman, and Wermers, (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)). The impact of herding on stock market, however, is not conclusive, as while many studies find that herding causes stock prices deviate from fundamentals and more volatile,[1] some find otherwise.[2]

Herding activities are not only found in the U.S., but also widely detected in international markets. At the market level, Chang, Cheng, and Khorana (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, and the empirical results indicate that investors herding is significant in Japan, South Korea and Taiwan, but not in the U.S. and Hong Kong. Expanding on their study, Chiang and Zheng (2010) document that investors herd at the market level in most advanced stock markets (not in the U.S.) and in seven Asian markets. Following

[1] For example, Wermers (1999), Iihara, Kato, and Tokunaga (2001).
[2] For example, Lakonishok, Shleifer, and Vishny (1992).

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, Demirer, and Hammoudeh (2013, 2014)), East Asian markets (Zheng, Li and Chiang (2017)) and the Turkish stock market (Dalgiç, Ekinici and Oğuz (2019)).

Among the research on herding in emerging markets, many studies focus on China, which has been one of the largest and fastest-growing economies. The existence of herding behavior in Chinese stock markets is mostly supported by the literature, but the evidence is not conclusive. Tan, Chiang, Mason and Nelling (2008) suggest that herding exists in both Chinese A-share markets, which are dominated by domestic individual investors, and B-share markets, which are dominated mainly by foreign institutional investors. Yao, Ma, and He (2014) find that Chinese investors exhibit different levels of herding behavior, more prominently in the B-share markets. Chong (2019) find that cross-herding exists between 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, Li, and Tan (2010) argue that although herding is detected within both the Shanghai and Shenzhen A-share markets, no evidence of herding is detected within 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 nonevidence) of herding at the overall market level, or of one particular group of investors. Very few literature, such as (Li, Rhee & Wang (2017)), attempts to investigate herding across investor groups in Chinese stock markets. Li et al. (2017) divides investors into the institutional investors group and the individual investors group based on their account ID. However, Jones et.al. (2021) find that individual investors with largest account balances behave much more like institutional investors. In our study, we separate investors by their direct trading records instead of their account ID 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 pattern" 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 un-informational factors (investor sentiment (Kumar & Lee (2006), misperceptions of future returns, shifts in risk aversion (Hoffman, Post & Pernnings (2012)). In contrast, institutional investors are more efficient in information acquisition (Kim, Lee & Kim (2014)) and more skillful in risk management, with less disagreement among each other (Choi & Skiba (2015)). Studies on herding document the differences between institutional and individual investors, especially in terms of the cause of herding. Many institutional investors herd due to correlated private information, while individual investors' herding is mostly driven by behavioral factors and emotions (Hsieh (2013), Lin, Tsai and Lung (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 & Roger (2013)), risk management skills (Salganik-Shoshan

(2016)), and preferences (Frijns et al. (2016)) 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 fulfill the gap and contribute to the literature as the following.

Firstly, our research investigates herding activities in Chinese stock markets based on a trading data set with high frequency data[3]. Most previous studies utilize daily, monthly, or even quarterly data to detect investors' herding behavior. However, since information flows fast in the stock markets, investors' trading decision can change within hours or even minutes. As a result, low-frequency data might underestimate the extent of short-term herding (Kremer and Nautz, 2013) while high-frequency data could provide more insights on herding behaviors. Wang, Kim and Suardi (2022) use the trade and quote data with 1-minute interval from the Shanghai Stock Exchange (SSE) to investigate the intra-day herding. They find that even within one day there exists different herding activities driven by different 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 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 not only helps us to detect the different herding patterns but also to 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 measure from the relation between the cross-sectional

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

absolute deviation (CSAD) of stock returns and market returns following the model developed by Chang, Cheng, and Khorana (2000) (CCK model). According to the CCK model, when the market return dispersion (CSAD) decreases with an increase market return, the market herding is detected. 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, 2013)). Furthermore, the CCK model can only detect herding in the whole market, and it cannot provide any insights on herding among different group 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, Rhee, & Wang (2017) as a herding measure (LRW model) by using the 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 be a good complement to the return-based herding measure (CCK). Intuitively, a strong group herding tendency could increase market herding activity. Therefore, we hypothesize that when

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

the group herding tendency increases (trading volume dispersion decreases), investor herding activities intensify at the market level (stock market return is negatively significantly correlated with CSAD measure).

Moreover, we modify the LRW model at least from the following two aspects. First, we divide all investors into three groups (most-informed, least-informed, and investors in the middle) based on direct trading records but Li, Rhee & Wang (2017) separate investors in China's A share market only by their account ID types (institutional vs individual). Some literature (Jones et.al. (2021)) find that individual(retail) investors in China's A stock market are heterogenous in terms of account balance, information and skills. Thus, Li, Rhee & Wang (2017)'s findings on individual investors' herding could mix the behaviors of more-informed individual investors and less-informed individual investors. Our grouping-by-volume method might provide more insights on the heterogeneity of individual investors' trading patterns. Second, Li, Rhee and Wang (2017) directly use the dispersion of trading volume as the in-group herding measure. We add an adjusted factor[5] into LRW measure to capture the daily change of herding tendency from particular groups.

Finally, many studies suggest that heterogeneous herding activities affects 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 (2013) find 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

[5] The Adjusted $\text{Factor}_{\text{j,t}}$ 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 on the effect of daily herding.

markets,[6] especially from different investor group's 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 on the same direction, we expect that market volatility is negatively correlated with herding activities, but the effect could be different between most-informed investors and least-informed investors.

As literature has documented that investors' herding behavior is different between down market (crisis) and up market (tranquil period),[7] we divide the whole sample into two subsamples by the date of June 9th, 2015 when Chinese market indexes reached the peak. The sample period before June 9th, 2015 is defined as "pre-peak" period when the market was generally in the upturn, and after June 9th, 2015 is defined as "post-peak" period when the market was generally in the 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 "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 explains 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

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

[7] For example, Chiang and Zheng (2010)

by applying both our in-group herding measure and traditional 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 (mostly 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 for seven 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 in 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 extra access to external funds. These extra financing channels injected roughly 2 trillion yuan into the stock market and fueled the boom of the stock market from the end of 2014. However, when the government, the People's Bank of China and China Securities Regulatory Commission (CSRC), started to concern about the bubble in stock market, they imposed stricter regulations on leveraged investing and margin

8 The asset thresholds of "preferred clients" differ across security companies, but the minimum is around 500K CNY, or about 75K USD holding position for the last 3 months.

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. First, when the CSRC prohibited securities companies from extending extra financing channels to clients, margin traders (institutional investors and "qualified" individual investors with 500k plus asset 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 big shareholders after the Chinese stock market plunged in June 2015. As a result, we find more significant changes of trading behaviors in larger investors than in smaller investors.

## 3. In-group Herding and Market Herding Measures

*3.3.1 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 the spirit of Lee & 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 the trading volume/value of each trade, and we focus on two groups with largest behavioral differences: trades with trading volume over 50000 shares

[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 first 6 months holding et al. Most of them limit sales of stock, especially for institutional investors.

are grouped as most-informed investors, and trades with trading volume under 500 shares are grouped as least-informed investors. [10]

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%[11] of daily transactions through the sample period[12]. 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 return such as the CCK measure[13].

In 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:

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

where $Trd_{j,it}$ represents the natural log value of the raw trading volume from group $j$ on stock

[10] Trade size is efficient to identify investors unless the order splitting strategies are prevailing in the market, which is not the case in China (See Caglio and Mayhew (2008) for more details). We also use different trade values as the proxy for identity of traders, and the main findings remain the same.
[11] For most-informed group, it ranges from 18.9% to 23.3%. For least-informed group, it ranges from 10.5% to 16.6%.
[12] The percentage of transactions of the most-informed/least-informed investor group is the ratio of trades over 50000/below 500 shares over the total trades on SSE 180 component stocks.
[13] CCK's herding measure is based on a moving window of 25 daily returns and suppress the information contained in the variation of trades within each trading day.

$i$ at day t. $N$ is the number of stocks traded by group $j$ at day $t$[14]. $\mu(Trd)_{j,t}$ is the average trading volume for stocks in group $j$ on day $t$.

As mentioned above, we use trade sizes to identify investor's type. 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 is 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 share per trade, and the least-informed group whose trades are less than 500 share per trade. Our sample helps to detect the change of herding patterns within particular investor group 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 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, Rhee and Wang (2017) directly use this dispersion of trading volume as in-group herding measure. We add an adjusted factor to capture the short-term herding tendency, which represents 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

[14] 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, which means all stocks are traded by both informed investors and uninformed investors every day.

subsequent market return and volatility.

*3.3.2 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, Cheng and Khorana, (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 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 herding behavior is detected by the following specification:

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

As proposed by Chang et al. (2000), the coefficient $\lambda_2$ measures the herding behavior, and a significantly negative $\lambda_2$ 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 affect security returns.[15] Galariotis et al. (2015) employs the unexplained part of CSAD in the factors equation to test the "intentional" herding.

At the first step, CSAD is estimated as follows:

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

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[16]. The fitted values of Equation (5) represent how $CSAD_t$ responds to the fundamental information, and the residual series of Equation (5) captures the deviations not caused by fundamental information. Next, we estimate the following equations similar to Equation (4) but with the fitted values ($CSAD_{Fund,t}$) and the residuals of Equation (5) respectively ($CSAD_{NonFund,t}$).

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

[15] For example, Liew and Vassalou (2000), Gregory et al. (2003), Leite et al. (2020)

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

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

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

*3.3.3 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 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 Equation (4), based on the sample of the 25[17] trading days prior to day *t*; $\sigma_{inf,t}$ and $\sigma_{uninf,t}$ are calculated from Equation (1) and represent the herding tendency within most-informed investors and least-uninformed investors in day *t*. The coefficients $\alpha_1$ and $\alpha_2$ 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 $\alpha_1$ or $\alpha_2$ 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

[17] We use different numbers of trading day for the rolling window, but the main results do not change. Results are available on request.

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 Equation (6) and (7). $\sigma_{In,t}$ and $\sigma_{Uninf,t}$ are defined in Equation (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.

*3.3.4 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, Nashikkar, and Shapira (2011), Kremer and Nautz (2013)).

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 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. Equation (11) and (12) tests how market level herding affects subsequent market returns, and Equation (13) tests how in-group herding tendency affects subsequent market returns.

Follow the same spirit of Venezia, Nashikkar & Shapira (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. Equation (14) tests how market level herding affects market volatility, Equation (15) tests how in-group herding tendency affects market volatility.

## 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[18]. This sample period covers the most recent bull-and-bear cycle in China's A share market, when the SSE index[19] 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 sector of the market which is 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 500k for the past 30 trading days, and therefore locks out some individual investors.

[Table 1]

Table 2 Panel A reports the summary statistics of daily returns of SSE180 during the sample period from June 3rd 2014 to May 31st 2016. China's A share market was very volatile in this period. The mean daily return during the "Pre-Peak" market before it reached the peak on June 9th, 2015 was 0.36%, while it dropped to -0.22% in the next year. It is not surprising that 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 quite 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

[18] Every trading record has the following information: security code, trading date, trading time, current price, trading quantity and trading value.

[19] 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.

are identified based on their trading records. The table shows that the least-informed investors group have 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 $\sigma_{Inf}$ compared to $\sigma_{uninf}$.[20] This is consistent with previous findings that most-informed (mostly institutional) investors herd less than least-informed (mostly individual) investors (Li, Rhee & Wang (2017)). Meanwhile, we find that the dispersion of trading volumes for both groups are 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, Cheng and Khorana (2000), Gleason, Mathur and Peterson (2004), Demireer and Kutan (2006).

[Table 2]

*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 periods and the bull/bear sub-periods. The results are presented in Table 3. Herding is detected when the coefficient $\lambda_2$ in the regressions is negative and significant. We find that $\lambda_2$ for all investors is negative and significant for the whole sample period and post-peak period. This suggests that herding exists in the Chinese stock market, especially when the market collapses. However, the cause for the

[20] 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.

market herding is different between pre-peak and post-peak periods. When the market is rising, 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.

[Table 3]

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

Figure 1 presents the dynamics of the herding tendency for both most-informed and least-informed investors, the market level of herding, and Shanghai Composite Index for the period from 2014/07/07 to 2016/5/31.

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, Figure 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 for 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 for most-informed investors bounced back at 2014/12/25, followed by the rise of herding tendency for least-informed investors at 2015/01/06. However, the former kept rising from then on, while the later 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 changes in fundamental information than to nonfundamental factors. On the other hand, least-informed investors were unaware of the increasing market risk and only changed their trading behavior when the market actually collapsed.

The market herding measure is derived from Equation (4). As Chang et al. (2000) suggest, a negative and significant coefficient $\lambda_2$ testifies 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 $\lambda_2$'s coefficient is significant at 5%. The two spikes of this market herding measure occur in 2014/12 and 2015/05, 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 on investors' trading patterns compared to the return-based herding measure only, especially for a market with a dual-group investor structure.

[Figure 1]

Next, we investigate the relation between market herding and in-group herding tendency and the two different types of herding driven by either fundamental factors or non-fundamental factors. The estimates for Equation (8), (9) and (10) are reported in Table 4A.

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 all 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 $\lambda_2$ are inversely correlated with the level of herding. Therefore, the negative coefficients of $\sigma_{uninf,t}$ and $\sigma_{uninf,t}$ on $\lambda_2$ 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 $\lambda_2$) in terms of the return-based herding measure. Given the fact 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 on 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 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, Rhee and Wang (2017), and different from the situation in developed markets where institutional (more informed) investors dominate the market (Nofsinger and Sias, 1999, Iihara, Kato and Tokunaga (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, Rong & Spyrou (2015)), while uninformed investors herd more on non-fundamental factors like psychological biases (Barber, Odean and Zhu (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, while the increasing herding tendency in least-uninformed investors cause 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 because of the low herding activities in the pre-peak period.[21] It is also possible that during the up market there are abundant financing channels, 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 are aware of the market risk, so herding activities intensified, and the herding pattern became different between informed and least-informed investors.

[Table 4A]

Some may argue that the in-group herding tendency and market level herding are both responding to "common factors", so the relationship of in-group herding on market level herding could be correlational not causal. To address this issue, we follow the spirit of Galariotis, Rong & Spyrou (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 Equation (6), and Equation (7).[22] 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, the residuals series ($\varepsilon_{inf,t}$ or $\varepsilon_{uninf,t}$) from these two regressions

[21] See figure 1.

[22] The regression equations are as the following:

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

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

are used to replace the original herding tendency measures ($\sigma_{inf,t}$ $or$ $\sigma_{uninf,t}$) and we repeat the regressions in Table 4A.

The results of the two-step tests are reported in Table 4B. The results from "Step 1" shows 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 Equations (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 $\sigma_{inf\_net}$ and $\sigma_{uninf\_net}$ 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.

[Table 4B]

*4.4 Consequences of herding on market return and volatility*

In this section, we investigate the effects of the dual-group herding behavior on market return and volatility. We calculate the adjusted in-group herding tendency measure $HT_{j,t}$[23] by subtracting the in-group herding tendency measures ($\sigma_{inf,t}$ $or$ $\sigma_{uninf,t}$) from its 25 days 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 being compared to those using the market herding measure (the CKK 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

[23] As show in Equation (2), higher HT value corresponds to lower value of $\sigma_{inf,t}$ $or$ $\sigma_{uninf,t}$ and indicates high level of in-group herding.

that the overall market herding in NYSE has insignificant impacts on the subsequent short-term returns, which suggests that the herding in NYSE is mostly driven by market information. 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 mothed of Venezia, Nashikkar & Shapira (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 $\lambda_2$ and lagged returns; the second set includes the measure of fundamental herding and nonfundamental herding from equation (6) and (7); the last set includes the adjusted herding tendency measures for most-informed and least-informed investors, and lagged returns.[24]

Previous literature (Scharfstein and Stein (1990), Bikhchandani and Sharma (2001), Barberis and Schleifer (2003), Choi and Sias (2009)) argue that the herding activity driven by fundamental factors merely facilitates the incorporation of information into prices, while 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 & Nautz (2013) 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 are inversely correlated with the actual herding activities, positive and significant coefficients of CKK herding measures are indicative of return

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

reversal.[25] But for adjusted our in-group herding tendency measure, the negative coefficients mean return reversal. The results are reported in Table 5.

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, if 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 hits the peak. The return reversal effect is weaker in the post-peak period, probably because uninformed investors become more risk sensitive and cautious when the market crashes. The positive coefficients of most-informed investor herding during 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 values of adjusted R-squared for the equations using in-group herding tendency measures are higher than those using the CKK herding measure.

[Table 5]

*4.4.2 Impacts of herding on market volatility*

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

The results based on the CKK herding measure provide mixed results. The market level herding decreases subsequent market volatility in post-peak period but increases subsequent

[25] For example, a lower subsequent return caused by a lower value of the CKK market herding measure means it is caused by a higher level of herding tendency in that investors' group.

market volatility for the whole period. Although impact magnitude measured by the absolute value of coefficients is quite small.

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 pre-peak and the whole period but are not significantly associated with the market volatility in post-peak period. It is possible that when the market crashes, other factors such as the lagged market return play more important roles in market fluctuation. Moreover, the results show that the herding from least-informed investor has a slightly greater impact on market volatility than the herding from most-informed investors, although they all raise the market volatility.

[Table 6]

## 5. Concluding remarks

Both most-informed and lest-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 03, 2014, to May 31, 2016, during which the Chines stock market crashes 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 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 risk. Thirdly, we find that least-informed investor herding causes stock price to deviate away from fundamentals while most-informed investor herding usually does not. Lastly, investors' in-group herding activities lead to market volatility, especially during the up market. Our 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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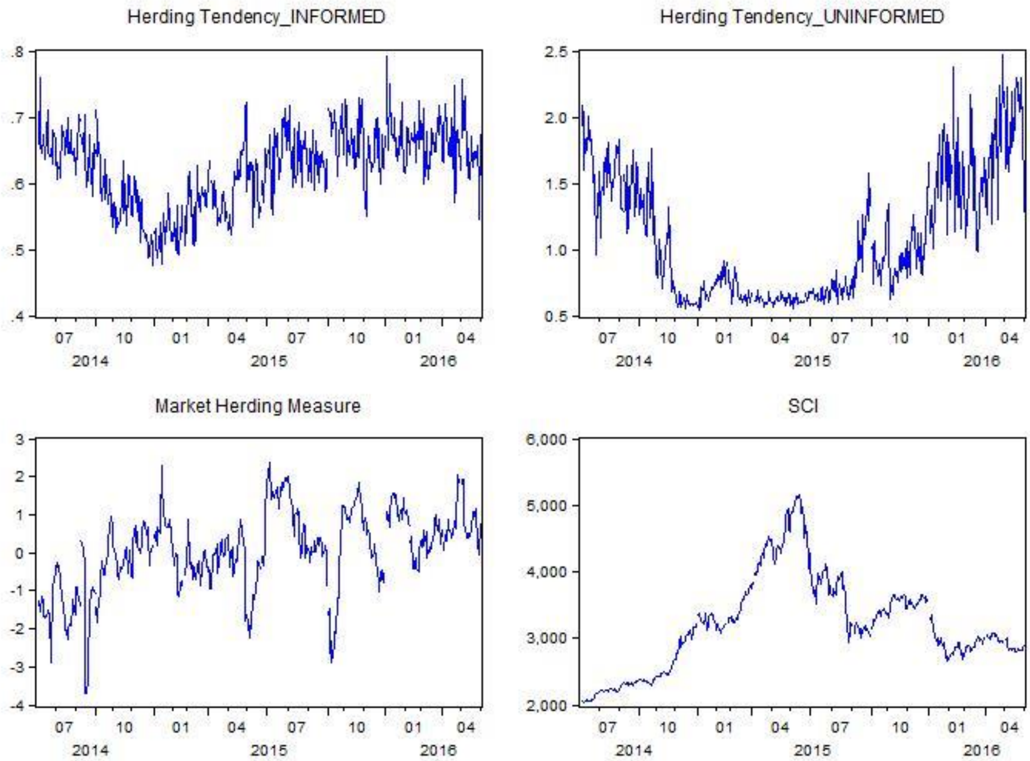
Figure 1 Relation Between In-group Herding Tendency and Market Herding




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 $\lambda_2$, which estimated from $CSAD_t = \lambda_0 + \lambda_1|R_{m,t}| + \lambda_2(R_{m,t})^2 + \varepsilon_t$ (3). SCI stands for Shanghai Composite Index.

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: $\sigma_{j,t} = \sqrt{\frac{\sum_{i=1}^{N}[Trd_{j,it}-\mu(Trd)_{j,t}]^2}{N-1}}$ |
| $HT_{j,t}$ | 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 | $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\lvert R_{i,t} - R_{m,t}\rvert$ |
| $\lambda_2$ | The daily CCK method herding measure | is estimated from Equation: $CSAD_t = \lambda_0 + \lambda_1\lvert R_{m,t}\rvert + \lambda_2(R_{m,t})^2 + \varepsilon_t$ based on daily returns of $R_{i,t}$ and $R_{m,t}$ |
| $\lambda_{2,Fund}$ | The daily "spurious" herding measure | is estimated from Equation: $CSAD_{Fund,t} = \lambda_0 + \lambda_1\lvert R_{m,t}\rvert + \lambda_{2,Fund}(R_{m,t})^2 + \varepsilon_t$, 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: $CSAD_{Nonfund,t} = \lambda_0 + \lambda_1\lvert R_{m,t}\rvert + \lambda_{2,Nonfund}(R_{m,t})^2 + \varepsilon_t$, 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. | |
| $Vol\_SH180_t$ | 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

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 equation (2). The herding tendency is calculated as

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

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) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $CSAD_t$ | $CSAD_{Fund,t}$ | $CSAD_{NonFund}$ | $CSAD_t$ | $CSAD_{Fund,t}$ | $CSAD_{NonFund,t}$ | $CSAD_t$ | $CSAD_{Fund,t}$ | $CSAD_{NonFund,t}$ |
| $\lambda_1$ | 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) |
| $\lambda_2$ | -2.0108 | -1.047*** | 1.3585 | -4.4430*** | 0.6346 | -4.8549*** | - | 0.2168 | -2.7511*** |
| | (-1.4109) | (-2.3130) | (1.5627) | (-3.5506) | (1.1483) | (-5.0906) | 3.9393***( | (0.6111) | (-4.3874) |
| | | | | | | | -4.4109) | | |
| $\lambda_0$ | 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:

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

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

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

Table 4A: 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) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_{2,Fun}$ | $\lambda_{2,NonFund}$ | $\lambda_2$ | $\lambda_{2,Fun}$ | $\lambda_{2,NonFund}$ | $\lambda_2$ | $\lambda_{2,Fun}$ | $\lambda_{2,NonFund}$ | $\lambda_2$ |
| $\sigma_{Inf,t}$ | -5.7132 | -10.4963** | - | 9.1888** | -8.4191* | 0.7696 | 4.7882** | -3.5216 | 1.2666 |
| | (-1.5043) | (-2.3165) | 16.2095*** | (2.4480) | (-1.71327) | (0.1560) | (2.100018) | (-1.1061) | (0.3633) |
| | | | (-3.3654) | | | | | | |
| $\sigma_{Uninf,t}$ | -0.2468 | - | - | -2.0746** | 5.0252*** | 2.9506*** | -1.5317* | -2.9291** | -4.4608*** |
| | (-0.1662) | 11.7825*** | 12.0293*** | (-2.1521) | (4.0270) | (2.3298) | (-1.7509) | (-2.3961) | (-3.3328) |
| | | (-6.6511) | (-6.3879) | | | | | | |
| $\boldsymbol{\alpha_0}$ | 12.6717* | 34.7678*** | 47.4395*** | - | 5.4664 | -6.7318 | -4.8820 | 8.8755* | 3.9935 |
| | * | (5.1450) | (6.6041) | 12.1982*** | (0.7424) | (-0.9009) | (-1.4599) | (1.8992 | (0.7804) |
| | (2.2372) | | | (-2.1447) | | | | | |
| *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 equations (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.

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) | |
|---|---|---|---|---|---|---|
| | $\sigma_{inf}$ | $\sigma_{uninf}$ | $\sigma_{inf}$ | $\sigma_{uninf}$ | $\sigma_{inf}$ | $\sigma_{uninf}$ |
| $CSAD_{Fun,t-1}$ | 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) |
| $\alpha_0$ | 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 |

Notes: This table reports the results for equations

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

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

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

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) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_{2,Fun}$ | $\lambda_{2,NonFund}$ | $\lambda_2$ | $\lambda_{2,Fun}$ | $\lambda_{2,NonFund}$ | $\lambda_2$ | $\lambda_{2,Fun}$ | $\lambda_{2,NonFund}$ | $\lambda_2$ |
| $\varepsilon_{inf,t}$ | -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 | - | -13.9284*** | -1.8868 | 5.5401*** | 3.6532** | -2.3041** | -3.5063** | -5.8078*** |
| | （-0.5007） | 12.8859*** | (-4.6882) | (-1.5263) | (3.4459) | (2.2529) | (-2.0453) | (-2.1833) | (-3.3434) |
| | | (-4.5463) | | | | | | | |
| $\alpha_0$ | 2.4985*** | 2.5295*** | 5.0281*** | -0.1300 | - | -2.6199*** | 1.1445*** | -0.0558 | 1.0887** |
| | (4.9336) | (3.6682) | (6.9564) | (-0.3572) | 2.4898*** | (-5.4847) | (3.6113) | (-0.1237) | (2.2276) |
| | | | | | (-5.2571) | | | | |
| *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: $\varepsilon_{inf,t}$ and $\varepsilon_{uninf,t}$ are the residuals from equation (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.

Table 5: 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) |
| $\alpha_0$ | 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: | $CAR_{m,t+1}$ | | | $CAR_{m,t+3}$ | | | $CAR_{m,t+5}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $\lambda_2$ | 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) |
| $\alpha_0$ | -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 |

Notes: This table reports the results for Equation (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 Equation (3) based on the sample of the 25 trading days prior to day *t*; $HT_{inf,t}$ and $HT_{uninf,t}$ are calculated from Equation (2) and represent the herding tendency within most-informed investors and least-informed investors in day *t*. $\lambda_{2\_unex}$ is the residual series of Equation (7) capturing the component in $\lambda_{2,t}$ that cannot be explained by $\sigma_{In,t}$ and $\sigma_{UnIn,t}$.

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

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

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

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

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 Equation (14) and (15). $\lambda_{2,t}$ is the herding coefficient estimated from Equation (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 Equation (2) and represent the herding tendency within informed investors and un-informed investors at day t.

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

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

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