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Differences in herding: Individual vs. institutional investors☆

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ABSTRACT

Using a trading volume-based measure, we study the differences between institutional and individual investors in herding. First, better-informed institutional investors trade more selectively, whereas less-informed individuals allocate their investments evenly across stocks. Second, individual investors rely more on public information for their trades as they are influenced by market sentiment and attention-grabbing events. Third, institutional investors react asymmetrically to up- and down-market movements, whereas individual investors do not. Finally, despite these differences in herding both individual and institutional investors pay close attention to one another's trades in forming a consensus.

1. Introduction

Herding as a form of correlated behavior happens when investors imitate and follow other investors' decisions while suppressing their own private information and beliefs (Devenow and Welch, 1996 and Avery and Zemsky, 1998). Herding can be either rational or irrational. Herding driven by market sentiment, fad and informational cascades (Banerjee, 1992; Bikhchandani et al., 1992; Barberis and Shleifer, 2003) and positive-feedback trading (Nofsinger and Sias, 1999) can be irrational, driving prices away from fundamental values and generating excess volatility. Whereas herding induced by correlated information (Falkenstein, 1996; Froot et al., 1992; Hirshlerfer et al., 1994), reputation costs (Scharfstein and Stein, 1990; Dasgupta et al., 2011), and underlying security characteristics can be rational, facilitating the incorporation of new information into prices (Wermers, 1999; Galariotis et al., 2015).

Most of previous studies concentrate on institutional herding and provide mixed empirical evidence (Sias, 2004; Choi and Sias, 2009; Dasgupta et al., 2011; Koch, 2014; Choi and Skiba, 2015). There are also several studies that examine individual herding (Nofsinger and Sias, 1999; Merli and Rogerz, 2013). However, little previous studies have formally investigated the behavioral

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differences in herding between institutional and individual investors. Institutions and individuals are two different types of investors, and they have different characteristics. Relative to institutions, individuals are less-informed and more vulnerable to the influence of psychological biases, market sentiment, and attention-grabbing events, such as market return shocks (Kaniel et al., 2008; Barber and Odean, 2008). Under asymmetric information, less-informed investors may rationally behave like price chasers (Wang, 1993, 1994). Nofsinger and Sias (1999) further suggest that individual investors engage in herding as a result of irrational but systematic response to fads or sentiment, while institutional investors engage in herding as a result of agency problems, security characteristics, fads, or the manner in which information is impounded in the market. Naturally, we expect that individual and institutional investors behave differently in herding and that individuals herd more strongly towards the market than institutional investors. Relative to individual investors, institutional investors are more skillful and sophisticated. Using transaction records of French individual investors for the period 1999–2006, Merli and Rogerz (2013) demonstrate that the level of individual herding depends on the investor sophistication degree. Most recently, Salganik (2016) finds that, compared with investors of retail mutual funds, clients of institutional mutual funds use more quantitatively sophisticated criteria such as risk-adjusted return measures and tracking error, demonstrate stronger momentum-driven and herding behaviors. Different types of investors also differ in preferences which will be revealed through their respective trading activities. Mitton and Vorkink (2007) show that the different preferences of different groups of investors affect the valuation of stocks. Extending the framework of Hong and Sraer (2015), Frijns et al. (2016) show that preferences of various investor types, which are revealed through their trading activity, cause the slope of the SML to change, and the sign of the slope depends on which type of investors is more active in the market. Verrecchia (1979, 1981) expresses "total consensus" or total agreement as a situation in which all investors interpret information in some homogeneous fashion. Investors can either achieve consensus beliefs rationally based on public and private information, or by being subject to market waves of sentiment irrationally such as following trend-chasing "popular models" and herding with other investors' movements (e.g., Shleifer and Summers, 1990). On the other hand, disagreement arises when different investors have different information sets or interpret the same set of information differently (Harris and Raviv, 1993; He and Wang, 1995). Carlin et al. (2014) find that increased disagreement among different investors is associated with higher expected returns, higher return volatility, and larger trading volume. Frijns et al. (2016) argue that in a market with different types of investors, some with low disagreement and others with high disagreement, trading activity could reflect disagreement levels among investor types. They suggest that cross-sectionally, individual investors are more likely to have high disagreement because they differ in their ability to interpret noisy signals, whereas institutions are more likely to have low disagreement among each other. Naturally, disagreement level differences among investor types will also be reflected in their trading and herding activities.

In this study we fill in the gap by examining the differences in herding between institutional and individual investors. Our examination is conducted by using trading data from the Chinese stock market where trend-chasing or sentiment-induced herding behavior is more prevalent because of the dominance of individual investors and limited arbitrage opportunities.[1] This unique database, provided by the Shanghai Stock Exchange (SSE), is extracted from the daily trading history of all individual and institutional investors who traded the component stocks of the SSE 180 Index between July 1, 2002 and December 31, 2004. For each component stock we have the aggregated daily RMB trading value of institutional (and individual) investors. On the basis of institutional (individual) buys and sells for each component stock, we compute trading volume-based herding measures to examine the impact of market return movements on the herding behavior of institutional and individual investor groups.

We define the daily standard deviation of the cross-sectional institutional (individual) trading volume for all sample stocks as a proxy of the herding measure of institutional (individual) investor group. Our herding measure is similar to that of Christie and Huang (1995) to the extent that we exploit the information contained in the cross-sectional movement of the market. However, our measure focuses on the cross-sectional variability of trading volumes by different investor groups rather than the returns used in Christie and Huang (1995). Christie and Huang (1995) argue that their measure of dispersions quantifies the average proximity of individual returns to the mean return. Analogous to their argument, our trading-volume based dispersion measure quantifies the average proximity of individual stock trading volumes to the mean. We argue that a low dispersion of trading volume across different stocks represents a high degree of herding towards the market because herding happens when investors imitate and follow other investors' decisions while suppressing their own private information and beliefs (Shalen, 1993; Harris and Raviv, 1993; Kandel and Pearson, 1995). Dispersions therefore are bounded below at zero when all individual stock trading volumes move in perfect unison with the market average, and increase when individual stock trading volumes begin to vary from the market.

In fact, trading volume-based variables have been used extensively as proxy of information in the literature, and trading-volume based herding measures are not new in the literature (Lakonishok et al., 1992; Baker and Stein, 2004; Sias, 2004; Goetzmann and Massa, 2005; Baker and Wurgler, 2006; and Kumar and Lee, 2006). Baker and Stein (2004) find that aggregate measures of share turnover and equity issuance have incremental power for future equal-weighted market returns. Goetzmann and Massa (2005) construct a measure of dispersion of opinion based on the sum of the absolute deviations of the aggregated trades in the top 100 sample stocks by different income, age, and professional groups of investors. Li and Wang (2007) propose a trading volume based measure of dispersion of beliefs to examine the relation between stock returns, consensus beliefs, and investors' trading volume changes. They argue that if investors' trading activities are generated by or at least reflect the inter-temporal changes in their beliefs (Shalen, 1993), then naturally and more directly dispersion of investors' trades can be used to measure the dispersion of beliefs among investors. Jiang and Sun (2014) propose a measure of dispersion in fund managers' beliefs about future stock returns based on their active holdings, they find that both the level of and the change in dispersion positively

[1] During our sample period, short-sales are not allowed and price-limits are imposed in the Chinese stock market.

predict subsequent stock returns. In testing the relationship between disagreement and stock return and volatility, Banerjee (2011) finds that using volume as proxies for disagreement provide empirical evidence that is consistent with investors using prices on average. We argue that since herding is a trading phenomenon, trading volume-based herding measures should at least complement return-based counterparts. For example, return dispersions are predicted to be low when herding occurs, yet low return dispersions by themselves do not necessarily guarantee the presence of herding (Christie and Huang, 1995). Besides, return-based herding measures may not be an ideal proxy when the market is quiet and investors are confident of the direction of market movement (Hwang and Salmon, 2004; Hwang and Salmon, 2009). Our herding measure is constructed by directly using market-wide daily institutional (individual) trading volume, and it is applicable to both quiet and turbulent markets.

It is important to note that our herding measure capture market-wide herding by a group of investors rather than herding by individual retail or institutional investors. At least two different types of herding are observed in the literature: herd towards the market and herd towards particular stocks. Herd towards the market happens when investors tend to move with the market or follow the general market trend. Christie and Huang (1995), Chang et al. (2000), Gleason et al. (2004), and Hwang and Salmon (2004, 2009) capture the herding behavior towards market by applying the stock returns or stock betas based dispersion measures. In contrast, herd towards particular stocks occurs when a group of investors focus only on a subset of securities while neglecting other securities with identical exogenous characteristics (Lakonishok et al., 1992; Hirshlerfer et al., 1994; Wermers, 1999). For example, dispersion in analysts' forecasts is a popular proxy of herding towards individual stocks (Diether et al., 2002), although Goetzmann and Massa (2005) claim that professional analysts' opinions do not necessarily reflect the expectations of the average investors. Instead, they use the absolute deviations of the aggregated trades in the top 100 sample stocks by different groups of investors as a proxy of dispersion of opinions in their study. Choi and Sias (2009) and Demirer et al. (2015) also investigate institutional herding behavior at the industry level.

At least four major findings emerge from our analyses. First, as a group, better-informed institutional investors tend to trade more selectively, whereas less-informed individuals tend to allocate their investments evenly across stocks. Second, individual investors rely more on public information for their trade. They are influenced by market sentiment and attention-grabbing events. Third, institutional investors react asymmetrically to up- and down-market movements, whereas individual investors do not. Finally, both individual and institutional investors pay close attention to one another's trades in forming a consensus. Notably, using return-based herding measure of Christie and Huang (1995), Demirer and Kutan (2006) find no evidence of herding in the Chinese A share markets between 1999 and 2002. In contrast, using the same return-based herding measure and a sample of cross-listed Chinese domestic A- and foreign B-shares, Tan et al. (2008) find herding behavior exists in both A- and B-share markets.[2] However neither of these studies investigates the herding behavioral differences between individual and institutional investors. The rest of the paper is organized as follows. Section 2 describes the data and institutional background of the Chinese market. Section 3 examines the differences in herding behavior between individuals and institutional investors. Section 4 investigates the herding behavior in up- and down-markets. Section 5 presents the interaction between two types of investors. The last section presents the conclusions.

2. Institutional background and the data

Institutional investors in China consist of: (i) investment funds; (ii) Qualified Foreign Institutional Investors (QFIIs);[3] (iii) the National Social Security Fund; (iv) insurance companies; (v) corporate annuity funds; and (vi) authorized securities firms. During our sample period, each investor is allowed to open one trading account on each of the two stock exchanges, the SSE and the Shenzhen Stock Exchange (SZSE).[4] Investors need to register their accounts at the China Securities Depository and Clearing Corporation Limited, which is a national securities registration institute under the supervision of the China Securities Regulatory Commission, before they trade securities. Institutional investors are not allowed to open individual trading accounts, and vise versa. An institutional (individual) investor can only place an order through one branch of a brokerage firm. Therefore, the ownership and trading of shares are clearly identified. By the end of 2004, China's two stock exchanges, SSE and SZSE, had more than 60 million investor accounts, more than 90% of which belonged to individual investors.[5] The number of investor accounts traded on the SSE was 37.87 million, of which 36.82 million (97.23%) were individual investor accounts. The remaining 1.05 million (2.77%) were institutional accounts.[6] Although institutional accounts comprise only a small percentage of the total number of investor accounts, institutional trading accounts for more than 20% of the total trading volume, especially for large-cap stocks.

The SSE has launched a number of stock indexes, with the most important being the SSE Composite Index, which covers all of the stocks listed on the SSE, and the SSE 180 Index. The 180 component stocks are selected from all of the A-share stocks listed on the SSE based on their industrial representation, market capitalization, and liquidity. By the end of December 2005, SSE 180 stocks

[2] In China, the A-share market is dominated by individual investors, while foreign institutional investors are the main participants in the B-share market during our sample period.

[3] In December 2002, China introduced the QFII scheme, which for the first time allowed the entry of foreign investors into the domestic A-share market. The first QFII investment took place in July 2003.

[4] In May 2015, the CSRC announced that now each investor may open multiple accounts on the two stock exchanges.

[5] China Securities Regulatory Commission (CSRC): http://www.csrc.gov.cn/.

[6] Please refer to *SSE Monthly Statistics* (December 2004). Some critics argue that the actual number of institutional investor accounts is larger, as some institutions illegally open individual investor accounts to manipulate share prices, and some individuals do not trade in the secondary market; they use the names of family members and relatives to open multiple accounts to increase their chances of getting IPO allocations. However, there are no official statistics on these factors, and they do not alter the features of individual investor domination in Chinese equity markets.

accounted for 67% of the market capitalization, 56% of the capitalization of floating shares, and 53% of the RMB trading value of the SSE, respectively.

The primary data set for this paper is extracted from the complete transaction records of all trades between all investors, grouped by individuals and institutions, on all of the component stocks of the SSE 180 Index from July 1, 2002, the launch date of the SSE 180 Index, to December 31, 2004. Beside the limitation on data availability, one important reason that we choose a short and early sample period rather than a longer and more recent sample period is that there was one big event happened after 2004, the "split-share structure reform" in China which was initialed in 2005 and completed by the end of 2007. Before the reform, in addition to a minority publicly tradable A-, B-, and H-shares, a typical listed Chinese firm has a substantial portion of nontransferable shares in the form of state-owned shares, legal person shares, and employee shares. The purpose of the reform is to dismantle the dual share structure by converting non-tradable shares into tradable shares. The Removal of floating restrictions on non-tradable shares, however, contribute to abnormal high trading volume and volatility during the reform period which is not desirable for clearly identifying investors' "normal" trading behavior.[7] Our final trading sample consists of all of the 180 component stocks over the 610 trading days. The SSE 180 Index component stock list is adjusted semi-annually (on July 1 and December 31 every year), and on each occasion about 10% or less of the total number of component stocks is added or removed from the list. Over the two and a half years of the sample period, we have a total of 251 component stocks due to these semi-annual adjustments of the list.

Panel A of Table 1 reports the basic statistics of the SSE 180 component stocks. Individual investors dominate the trading in terms of trading value. On average, institutional trading accounts for only 13.7% of the value over the sample period while individual trading represents the remaining 86.3%. Institutional buying and selling account for 14.9% and 12.4%, respectively, which indicates that institutions are net-buyers over the sample period, although at a small margin.

We further divide the SSE 180 stocks into five size portfolios based on their previous half-year average market capitalizations. Consistent with the empirical findings for other stock markets, we find that institutional investors tend to trade more in large stocks. The average percentage of institutional trades in the portfolio of the largest stocks (portfolio 5) is 22%, whereas that in the portfolio of the smallest stocks (portfolio 1) is less than 6%. Overall, the institutional trade increases monotonically with the market capitalization of the portfolios.[8]

Large stocks usually tend to have higher prices; therefore, empirical results based on trading value could be subject to the price effect. However, in our case, the differences in the average stock prices among the quintiles are quite small. Not surprisingly, larger stock portfolios tend to have lower mean returns and higher share volumes and trading volume over the sample period. However, there are no significant differences in turnover among the size quintiles, although the largest and smallest portfolios tend to have slightly higher turnovers.

3. Differences in herding behavior between individuals and institutions

3.1. Herding measures

In the same spirit of Christie and Huang (1995), we use dispersion of trading volume across different stocks as a proxy of herding of a homogenous investor group across different stocks. Specifically, we define the standard deviation of the cross-sectional trading volume for all sample stocks on day t, $\sigma(Trd)_{j,t}$, as a proxy of the herding measure of investor group j, $j = D$ (individuals) and S (institutions):

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

where $Trd_{j,it}$ = the trading volume of group j for stock i at time t; $\mu\,(Trd)_{j,t}$ = the cross-sectional average trading volume of investor group j at time t; and N is the number of stocks in the calculation. We also compute $\sigma(Buy)_{jt}$ and $\sigma(Sell)_{jt}$ to measure buy- and sell-side herd measures, where *Buy* and *Sell* denote the buying and selling volume, respectively. In this paper, we define the trading volume as the change of logarithmic trading value.[9] Following previous studies, we transform the raw trading value by taking the natural log (Ajinkya and Jain, 1989; Falkenstein, 1996).[10] Because daily trading volume in stock market growth dramatically, especially in the emerging markets, the log of volume changes effectively transform the nearly exponential volume series into a linear series (e.g., Andersen, 1996), and using the change in volume helps remove any time trend that may exist in volume

[7] For more information about the split-share structure reform, please see Firth et al. (2010) and Liao et al. (2014).

[8] Over the sample period, the average percentage of no-institutional-trading days for small stocks (17.37%) is also considerably larger than that for large stocks (3.09%). In contrast, individuals traded all of the SSE 180 stocks almost every day, although the difference between individual and institutional investors in no-trading-days for particular stocks can partly be explained by the enormous number of individual investor accounts. We find that only three stocks have no-individual-trading days, and the largest number of no-individual-trading days is three.

[9] Furthermore, as robustness checks, we also use turnover and raw trading value in our analysis, and the results are generally the same.

[10] For example, Ajinkya and Jain (1989) find that the empirical distribution of log transformed trading volume is quite close to the normal distribution.

Table 1
Basic statistics.
This table reports the daily average of return, return standard deviation, price, market capitalization, share and trading value, and turnover for all SSE 180 component stocks and the stocks of each size portfolio from July 1, 2002 to December 31, 2004, respectively. It also reports the average percentage of institutional trade, buy, and sell values for a particular stock over the sample period. The RMB/US$ exchange rate was around RMB8.27/US$1 during the sample period. **, *, and † indicate significance at the 1%, 5%, and 10% levels, respectively.

	No. of stocks	Mean return (%)	Return Stdev. (%)	Mean price (RMB)	Mean market cap. (Mil. RMB)	Mean share volume	Mean RMB volume (RMB)	Turnover	Institutional trade (%)	Institutional buy (%)	Institutional sell (%)
All Stocks	180	−0.064	1.54	8.45	9557.35	3,067,427	23,664,823	1.0141	13.68	14.92	12.43
Portfolio											
1 (Smallest)	36	−0.094	1.54	7.42	2335.04	1,416,696	10,382,306	1.0840	5.65	5.89	5.41
2	36	−0.087	1.54	7.94	3360.22	1,716,817	13,350,644	0.9937	9.92	10.23	9.61
3	36	−0.078	1.52	9.06	4671.51	1,923,951	16,588,228	0.9798	12.68	14.02	11.34
4	36	−0.041	1.47	9.36	7093.34	2,366,451	21,609,916	0.9306	17.93	19.99	15.87
5 (Largest)	36	−0.020	1.34	8.45	30,293.96	7,905,066	56,364,539	1.0813	22.24	24.49	19.99

(e.g., Sullivan and Xiong, 2012).[11] Hasbrouck (1988) indicates that any private information must be inferred from the unanticipated portion of trade rather than total trade, i.e., the trade innovation. The change in trading value can be interpreted as the abnormal or unexpected trading component.

3.2. Differences between institutional and individual investors in herding

Intuitively, if an investor group trades some particular stocks in concert, then its trading value will increase significantly, whereas that for other stocks will decrease or at least not change significantly. As a result, the standard deviation of trading volume or dispersion of this investor group across different stocks should be large. Conversely, if an investor group tends to herd towards market trends, then the dispersion of its trading value should not differ from trends and the magnitude of dispersion should be relatively small. Therefore, a low (high) value of dispersion indicates relatively strong (weak) herding behavior towards the market return.

Institutional investors are superior to individual investors in the acquisition of firm-specific and private information. Institutional investors are also more homogeneous and tend to trade more on particular stocks or particular groups of stocks to take advantage of information asymmetry (Campbell et al., 1993; Harris and Raviv, 1993; He and Wang, 1995). In contrast, less informed individual investors are likely to react to all changes in volume and price as if these changes reflected information. Hence, they may consider it to be optimal to follow market trends, i.e., herd more on the market trend and trade less selectively across different stocks. Therefore, we should observe the following:

H1. On average, the magnitude of the herding measure for institutional investors is larger than that for individual investors if the former have superior information to the latter and trade on that information.

Specifically, we expect that the mean cross-sectional standard deviation of institutional trading value for institutions will be greater than that for individuals:

$$\sigma(Trd)_S > \sigma(Trd)_D.$$

Table 2 reports the herding measures of individuals and institutions for all of the SSE 180 stocks at the market and portfolio levels. Consistent with Hypothesis 1, the magnitude of the average institutional herding measure is larger than that of the individual herding measure in all cases. Another interesting finding is that the magnitude of the herding measures for institutions decreases almost monotonically with the size of the portfolio, whereas individual herding measures increase, although not monotonically, with the size of the portfolio. In other words, institutions herd more on large stocks than on small stocks and they are more selective in picking smaller stocks while individuals usually trade more evenly on small stocks and they are relatively pickier in choosing large stocks. For example, the difference between the average herding measure for institutional trades, $\sigma(Trd)_S$, of the smallest portfolio (Portfolio 1) and that for the largest portfolio (Portfolio 5) is 0.58 and is significant at least the 5% level.[12] In contrast, the difference for individual investors is significantly negative (−0.02).[13]

Panel B of Table 2 provides the correlation matrix between the daily market index return and the mean and dispersion of institutional and individual trading volume. Many previous studies have suggested a positive relation between market returns and

[11] Non-trading days are not included in our computation of dispersion measures. Alternatively, following Ajinkya and Jain (1989), Cready and Ramanan (1991), Llorente et al. (2002), we use RMB1 in the case of zero trading volume for a stock on a given day. The results using this different transformation method are similar to those reported in this paper even though this transformation tends to overstate dispersion measures.

[12] For all of the tests reported in Table 1, we use both the *t*-test and the Wilcox test, and the results are the same except for one case in which the *t*-test result is significant at the 5% level, whereas the Wilcox test result is significant at the 10% level.

[13] As a robustness check, we also use the coefficient of the variation (CV) of the institutional (individual) trading volumes as measures of the dispersion of institutional (individual) trading activity to control for the possible "size effect" of different dollar trading volumes. The results are similar to those that have been reported. To save space, we do not report these results.

Table 2
Cross-sectional standard deviation of trading value.
Panel A of this table reports the cross-sectional averages of the herding measures for individuals and institutions at the market level, including all of the SSE 180 stocks, and at the portfolio level, respectively. The sample period is from July 1, 2002 to December 31, 2004. Panel B provides the correlation matrix between the daily market index return and the mean and standard deviation of institutional and individual trading volume. *Trd, Buy,* and *Sell* are the logarithmic total trading, buy, and sell value changes, respectively. **, *, and † indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Basic statistics

	No. of stocks	Individual trading			Institutional trading		
		$\sigma(Trd)_D$	$\sigma(Buy)_D$	$\sigma(Sell)_D$	$\sigma(Trd)_S$	$\sigma(Buy)_S$	$\sigma(Sell)_S$
All stocks	180	0.5525	0.5997	0.5660	1.5987	1.6358	1.9432
Portfolio 1 (Smallest)	36	0.5139	0.5365	0.5197	1.8697	1.7847	2.0898
Portfolio 2	36	0.5418	0.5751	0.5500	1.7154	1.7659	2.0332
Portfolio 3	36	0.5477	0.5891	0.5599	1.5903	1.6377	1.9688
Portfolio 4	36	0.5735	0.6341	0.5935	1.4366	1.5422	1.8684
Portfolio 5 (Largest)	36	0.5334	0.6046	0.5531	1.2912	1.3946	1.6841
Portfolio 1-Portfolio 5		−0.0195**	−0.0681**	−0.0335**	0.5785**	0.3900**	0.4057**

Panel B: Correlation matrix

		Market return	$\mu(Trd)_S$	$\mu(Trd)_D$	$\sigma(Trd)_S$	$\sigma(Trd)_D$
Market Return (SSE180 Index)	R	1.0000				
Average Institutional Trading value change	$\mu(Trd)_S$	0.2690**	1.0000			
Average Individual Trading value change	$\mu(Trd)_D$	0.3636**	0.7975**	1.0000		
Dispersion of Institutional Trading value	$\sigma(Trd)_S$	−0.0302	0.0148	0.0106	1.0000	
Dispersion of Individual Trading value	$\sigma(Trd)_D$	0.0712†	0.1130**	0.1391**	0.3026**	1.0000

trading volume (Wermers, 1999; Nofsinger and Sias, 1999; Edelen and Warner, 2001). Consistent with these studies, we find that the correlations among market returns and average institutional and individual trading volume are all significantly positive. The behavioral finance literature suggests that return-volume relations should be stronger in the trading of individual investors than in the trading of institutional investors (Griffin et al., 2003). We provide direct evidence to support this argument: we find that the estimated correlation coefficient between market returns and trading volume is substantially larger for individual investors (0.36) than it is for institutional investors (0.27). Moreover, we find evidence that the dispersions of institutional and individual trading volumes are positively correlated (0.30), and that institutional and individual trading volumes are highly correlated (0.79). These results are consistent with the argument that investors closely watch and filter information from each other's trades.

3.3. Differences in reaction to market returns between individual and institutional investors

Frankel and Froot (1990) suggest that, in the short run, investors tend to form expectations by extrapolating from recent trends. Shalen (1993) claims that investors tend to filter private information about the sequence of future prices from current prices. Romer (1993) argues that uncertainty about the quality of other investors' information can cause investors to incorrectly, but rationally, place too much weight on market prices and too little on their own information. Hence, when there are significant changes in market prices, it is relatively easy for investors to form "consensus forecasts" (Barberis et al., 1998) of short-run market movements.

Intuitively, if investors herd towards the market trends, then when there are significant changes in market return, their trading volumes will increase while the dispersion of their trades decreases. Naturally, a low (high) value of dispersion indicates relatively strong (weak) herding behavior towards the market return. Furthermore, relative to institutional investors, individual investors rely more on public information when making their investment decisions. The trading behavior of individual investors is more heavily influenced by market return shocks, sentiment, and other attention-grabbing events. Therefore, we expect that the herding measure of individual investor group is more sensitive to market return movements, which leads to our second hypothesis.

H2. The herding measure is negatively related to the contemporaneous absolute market return for both individual and institutional investors, and individual investors exhibit more a sensitive herding reaction to market return movements than do institutional investors.

First, we test whether the herding measure decreases when the absolute value of market returns increases after controlling for the average trading volume, as shown below.

$$\begin{bmatrix} \sigma(Trd)_{S,t} \\ \sigma(Trd)_{D,t} \end{bmatrix} = \begin{bmatrix} \alpha_S \\ \alpha_D \end{bmatrix} + \begin{bmatrix} \lambda_S & 0 \\ 0 & \lambda_D \end{bmatrix} \begin{bmatrix} \mu(Trd)_{S,t} \\ \mu(Trd)_{D,t} \end{bmatrix} + \begin{bmatrix} \beta_S \\ \beta_D \end{bmatrix} |RM|_t + \begin{bmatrix} \varepsilon_S \\ \varepsilon_D \end{bmatrix}, \tag{2}$$

where $\mu(Trd)_{j,t}$ is the cross-sectional average of trading volume for investor group j; $j = S, D$ at time t; and RM_t is the market index (proxied by the SSE 180 Index) return. If H_2 is true, then we expect that the estimates of β_S and β_D should be significantly negative.

Second, if, relative to institutional investors, the herding measure of individual investors is more sensitive to market return movement, then we should observe that $\beta_D < \beta_S$. To test this, rather than estimate model (2) for institutions and individuals separately, we estimate the following pooled regression model (3).

$$\sigma(Trd)_t = \alpha + \alpha_D I_D + \lambda_S \mu(Trd)_t + \lambda_{D-S} I_D \mu(Trd)_t + \beta_S |RM_t| + \beta_{D-S} I_D |RM_t| + \varepsilon_t \tag{3}$$

where $\sigma(Trd) = \begin{bmatrix} \sigma(Trd)_S \\ \sigma(Trd)_D \end{bmatrix}$; $\mu(Trd) = \begin{bmatrix} \mu(Trd)_S \\ \mu(Trd)_D \end{bmatrix}$; and I_D is an individual investor dummy variable.

An increase in trading volume may lead to an increase in returns (Gervais et al., 2001). To control for the possible impact of the correlation between absolute return and volume, we use the General Moment Method (GMM) to estimate model (3). Table 3 reports the estimates of model (3) for each of the dispersion measures, $\sigma(Trd)$, $\sigma(Buy)$, and $\sigma(Sell)$, respectively.

Consistent with Hypothesis 2, in the trade herd equation ($\sigma(Trd)$), the estimated coefficient for the absolute market return (β_S) is significantly negative in the case of "All stocks" and for all five portfolios, which suggests that the herding measure for institutional trade is negatively related to the contemporaneous absolute market return.

Second, we find that the relation between the herding measure and the absolute market return for institutional investors differs in the buy herd equation ($\sigma(Buy)$) and the sell herd equation ($\sigma(Sell)$). Whereas β_S is significantly negative in the case of "All stocks" and for most of the portfolios in the sell herd equation, it is only significantly negative for the largest portfolio in the buy herd equation. In other words, when making buying decisions, institutions are less sensitive to market return movements.

Furthermore, we find that the estimates of $\beta_{D\text{-}S}$ are significantly negative in most of the cases in both the buy and sell equations, and a couple of cases in the trade equation. As $\beta_D = \beta_{D\text{-}S} + \beta_S$, this implies a much stronger herding tendency towards market portfolio by individual investors, regardless of buying or selling. In other words, less-informed individual investors herd more in stock trading, and this is consistent with herding theories based on informational heterogeneity among market participants.

Overall, the results in Table 3 indicate that: (i) the herding measures for both individuals and institutions are negatively related to absolute market returns and positively related to the average trading volume; and (ii) individual herding measure is more sensitive to market movement. In other words, when there are clear signals of market return movements, whether increases or decreases, the dispersion of beliefs on market movement declines. As the result, herding towards market movement intensifies, especially that of individual investor group.

Table 3
Relation between the dispersions of change in trading value and the absolute market return (GMM estimates).
$\sigma(Trd)_t = \alpha + \alpha_D I_D + \lambda_S \mu(Trd)_t + \lambda_{D-S} I_D \mu(Trd)_t + \beta_S |RM_t| + \beta_{D-S} I_D |RM_t| + \varepsilon_t$ (3)
RM is the SSE 180 Index return. $\mu(Trd)_t$ is the cross-sectional average change of total trading value for institutional and individual investors; $\sigma(Trd)$, $\sigma(Buy)$, and $\sigma(Sell)$ are the scaled dispersion measures of total trading, buying, and selling value changes for individuals and institutions. All of the trading value variables are in logarithm.
**, *, and † indicate significance at the 1%, 5%, and 10% levels, respectively.

	All			Portfolio 1			Portfolio 2			Portfolio 3			Portfolio 4			Portfolio 5		
	Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value	
$\sigma(Trd)$																		
α	1.0309	91.83	**	1.0315	68.15	**	1.0229	71.28	**	1.0290	61.47	**	1.0452	60.49	**	1.0560	52.53	**
α_D	0.0178	1.15		0.0202	0.95		0.0163	0.81		0.0373	1.65	†	0.0082	0.35		0.0110	0.39	
λ_S	0.0302	2.27	*	0.0074	0.54		0.0309	2.23	*	0.0415	2.48	*	0.0212	1.18		0.0590	2.51	*
$\lambda_{D\text{-}S}$	0.1035	4.13	**	0.0951	3.41	**	0.0933	2.95	**	0.1390	3.80	**	0.1730	5.40	**	0.1451	3.42	**
β_S	−3.5398	−4.27	**	−3.6263	−3.37	**	−2.6155	−2.47	*	−3.2994	−3.01	**	−5.1959	−4.12	**	−6.4277	−3.76	**
$\beta_{D\text{-}S}$	−2.0167	−1.70	†	−2.2903	−1.53		−1.8520	−1.21		−4.2707	−2.62	**	−0.8850	−0.50		−1.2103	−0.51	
Adjusted R^2	0.0596			0.0264			0.0205			0.0383			0.0446			0.0487		
$\sigma(Buy)$																		
α	0.9999	86.47	**	1.0109	55.78	**	0.9884	56.64	**	0.9810	54.46	**	1.0100	58.88	**	1.0272	51.26	**
α_D	0.0455	2.77	**	0.0371	1.60		0.0507	2.23	*	0.0834	3.45	**	0.0417	1.66	†	0.0226	0.79	
λ_S	0.0127	1.04		0.0314	1.78	†	−0.0076	−0.47		0.0045	0.26		0.0123	0.67		0.0188	0.90	
$\lambda_{D\text{-}S}$	0.1124	4.43	**	0.0778	2.59	**	0.1380	4.38	**	0.1667	4.52	**	0.1830	5.56	**	0.1207	2.91	**
β_S	0.0174	0.02		−1.2333	−0.86		1.3280	1.08		2.1890	1.85	†	−1.1500	−0.93		−3.1254	−2.11	*
$\beta_{D\text{-}S}$	−5.1944	−4.45	**	−4.2392	−2.42	*	−5.7810	−3.48	**	−9.5442	−5.68	**	−4.7354	−2.73	**	−2.5548	−1.15	
Adjusted R^2	0.0353			0.0156			0.0138			0.0294			0.0267			0.0175		
$\sigma(Sell)$																		
α	1.0196	105.91	**	1.0080	61.79	**	1.0172	68.43	**	1.0194	67.91	**	1.0286	68.95	**	1.0334	53.28	**
α_D	0.0275	1.95	†	0.0445	1.99	*	0.0211	1.05		0.0434	2.05	*	0.0172	0.80		0.0353	1.23	
λ_S	0.0156	1.33		−0.0125	−0.70		−0.0007	−0.05		0.0158	0.94		0.0122	0.74		0.0336	1.66	†
$\lambda_{D\text{-}S}$	0.1130	4.73	**	0.1068	3.50	**	0.1169	3.72	**	0.1630	4.44	**	0.1547	4.94	**	0.1751	4.42	**
β_S	−2.2431	−2.86	**	−0.9319	−0.77		−1.9773	−1.78	†	−2.2184	−2.08	*	−3.2874	−2.75	**	−3.8312	−2.40	*
$\beta_{D\text{-}S}$	−3.1267	−2.70	**	−5.0722	−3.14	**	−2.3854	−1.54		−4.9462	−3.04	**	−1.9208	−1.13		−3.9974	−1.73	†
Adjusted R^2	0.0505			0.0147			0.0151			0.0319			0.0279			0.0382		

3.4. Robustness test: extreme market conditions

A large cross-sectional variation of trading volume could be due to large shocks in the market or due to large dispersion of sensitivity of volume. To control for this possibility, as a robustness test, we estimate model (4) with a dummy variable capturing extreme market shocks:

$$\sigma(Trd)_t = \alpha + \alpha_D I_D + \alpha\lambda_S I_D \mu(Trd)_t + \alpha\lambda_{D-S} I_D \mu(Trd)_t + \beta_S |RM_t| + \beta_{D-S} I_D |RM_t| + \theta D_t + \varepsilon_t \tag{4}$$

where the dummy variable D_t is defined as:

$$D_t = \begin{cases} 1, & \text{if the market return is extremely high or extremely low;} \\ 0, & \text{otherwise.} \end{cases}$$

The cut-off point for extreme market movement is $\pm 1\%$ daily changes of the SSE 180 Index returns.

Table 4 reports the estimates of model (4) for each of the herding measures. Consistent with Hypothesis 2 and the results in Table 3, in the equation for the dispersion of trading volume ($\sigma(Trd)$), the estimated coefficient for the absolute market return (β_S) is significantly negative in the case of "All stocks" and for most of the portfolios. Second, institutional buying is less sensitive to market return movements than institutional selling. Finally, the estimates of $\beta_{D\text{-}S}$ are significantly negative in a majority of the cases in both the buy and sell equations, suggesting that there is a stronger herding tendency towards market portfolio by individual investors. On the other hand, the estimate of the coefficient for extreme market shocks (θ) tends to be negative but is not significant for all cases except for the smallest portfolio in the selling equation. These results indicate that the negative relation between our herding measure and the contemporaneous absolute market return cannot be attributed to large shocks in the market or due to large dispersion of sensitivity of volume with respect to those shocks.

Table 4
Relation between dispersion and extreme market returns (1%) (GMM estimates).
$\sigma(Trd)_t = \alpha + \alpha_D I_D + \alpha\lambda_S I_D \mu(Trd)_t + \alpha\lambda_{D-S} I_D \mu(Trd)_t + \beta_S |RM_t| + \beta_{D-S} I_D |RM_t| + \theta D_t + \varepsilon_t$ (4)
RM is the SSE 180 Index return. $\mu(Trd)_t$ is the cross-sectional average change of total trading value for institutional and individual investors; $\sigma(Trd)$, $\sigma(Buy)$, and $\sigma(Sell)$ are the scaled dispersion measures of total trading, buying, and selling value changes for individuals and institutions. *Up* is the dummy variable for the up market, which takes a value of 1 if the market is extremely high, and *D* is a dummy variable for extreme market return shocks, which takes a value of 1 if the market is extremely low or extremely high. The criterion for extreme is set at 1%, which implies that the daily changes in the SSE 180 Index returns are greater than or equal to 1% in both directions. All of the trading value variables are in logarithm. **, *, and † indicate significance at the 1%, 5%, and 10% levels, respectively.

	All			Portfolio 1			Portfolio 2			Portfolio 3			Portfolio 4			Portfolio 5		
	Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value	
$\sigma(Trd)$																		
α	1.0301	92.17	**	1.0293	68.07	**	1.0236	71.86	**	1.0280	62.01	**	1.0452	60.46	**	1.0553	52.13	**
α_D	0.0177	1.15		0.0200	0.94		0.0163	0.81		0.0373	1.64		0.0082	0.35		0.0110	0.38	
λ_S	0.0303	2.28	*	0.0080	0.59		0.0310	2.24	*	0.0416	2.48	*	0.0212	1.18		0.0592	2.52	*
$\lambda_{D\text{-}S}$	0.1031	4.12	**	0.0937	3.35	**	0.0934	2.95	**	0.1386	3.78	**	0.1730	5.39	**	0.1447	3.42	**
β_S	−3.0846	−2.86	**	−2.2700	−1.62		−3.0217	−2.32	*	−2.6731	−1.85	†	−5.1885	−3.10	**	−5.9884	−2.75	**
$\beta_{D\text{-}S}$	−2.0089	−1.69	†	−2.2626	−1.51		−1.8538	−1.21		−4.2635	−2.60	**	−0.8849	−0.50		−1.2018	−0.50	
θ	−0.0097	−0.65		−0.0290	−1.41		0.0085	0.44		−0.0133	−0.58		−0.0002	−0.01		−0.0094	−0.37	
Adj. R^2	0.0592			0.0271			0.0199			0.0378			0.0438			0.0480		
$\sigma(Buy)$																		
α	0.9992	86.87	**	1.0095	55.39	**	0.9888	56.93	**	0.9793	54.29	**	1.0106	58.77	**	1.0263	50.91	**
α_D	0.0454	2.77	**	0.0369	1.59		0.0507	2.23	*	0.0833	3.45	**	0.0418	1.66	†	0.0225	0.79	
λ_S	0.0128	1.05		0.0318	1.80	†	−0.0076	−0.47		0.0047	0.27		0.0123	0.67		0.0190	0.91	
$\lambda_{D\text{-}S}$	0.1120	4.42	**	0.0769	2.56	*	0.1380	4.37	**	0.1661	4.48	**	0.1833	5.56	**	0.1202	2.91	**
β_S	0.4682	0.47		−0.4141	−0.23		1.1290	0.76		3.2379	2.01	*	−1.4981	−0.93		−2.5642	−1.29	
$\beta_{D\text{-}S}$	−5.1868	−4.43	**	−4.2225	−2.42	*	−5.7819	−3.48	**	−9.5320	−5.63	**	−4.7417	−2.74	**	−2.5439	−1.14	
θ	−0.0096	−0.62		−0.0175	−0.76		0.0042	0.19		−0.0223	−0.96		0.0074	0.35		−0.0120	−0.43	
Adj. R^2	0.0349			0.0152			0.0130			0.0293			0.0260			0.0169		
$\sigma(Sell)$																		
α	1.0186	106.07	**	1.0044	61.47	**	1.0186	68.22	**	1.0189	68.72	**	1.0282	68.93	**	1.0328	53.07	**
α_D	0.0274	1.94	†	0.0441	1.98	*	0.0211	1.05		0.0434	2.05	*	0.0171	0.79		0.0353	1.23	
λ_S	0.0158	1.35		−0.0114	−0.64		−0.0004	−0.03		0.0159	0.95		0.0123	0.74		0.0337	1.66	†
$\lambda_{D\text{-}S}$	0.1124	4.71	**	0.1045	3.40	**	0.1171	3.71	**	0.1628	4.42	**	0.1545	4.92	**	0.1748	4.41	**
β_S	−1.6355	−1.59		1.2820	0.80		−2.8175	−2.05	*	−1.9003	−1.41		−3.0814	−1.88	†	−3.4642	−1.74	†
$\beta_{D\text{-}S}$	−3.1163	−2.69	**	−5.0270	−3.07	**	−2.3892	−1.54		−4.9425	−3.03	**	−1.9170	−1.13		−3.9903	−1.72	†
θ	−0.0129	−0.91		−0.0473	−2.20	*	0.0177	0.87		−0.0068	−0.31		−0.0044	−0.20		−0.0078	−0.30	
Adj. R^2	0.0504			0.0172			0.0149			0.0312			0.0271			0.0375		

4. Herding behavior differences in up- and down-markets

Previous studies have suggested that investors tend to react differently to good and bad news (e.g., Grinblatt et al., 1995 and Keim and Madhavan, 1995). In the herding literature, some studies find that herding tends to be more prevalent in extreme market conditions (Christie and Huang, 1995; Zhou and Lai, 2009), while other studies suggest that herding is independent of market conditions (Hwang and Salmon, 2004). Chang et al. (2000) document mixed findings for a number of emerging and developed markets. Whether or not herding is independent of market conditions remains an empirical issue. In this study, we find that the herding does exist in the Chinese stock market and the dispersion measure is negatively related to the absolute market return. In this section, we further examine whether the herding behavior is asymmetrical to up- and down-market price movements and whether there is any difference in herding between individual and institutional investors. To meet this end, we formulate our third hypothesis.

H3. If investors respond to good and bad news differently, then the herding measure differs in up- and down-markets.

To test Hypothesis 3, we estimate the following regression model using the GMM:

$$\sigma(Trd)_t = \alpha + \alpha_D I_D + \lambda_S \mu(Trd)_t + \lambda_{D-S} I_D \mu(Trd)_t + \delta_S Up_t + \delta_{D-S} I_D Up_t + \gamma_S Dn_t + \gamma_{D-S} I_D Dn_t + \varepsilon_t \tag{5}$$

where the two dummy variables Up and Dn are defined as:

$$Up_t = \begin{cases} 1, & \text{if the market return is significantly high;} \\ 0, & \text{otherwise.} \end{cases}$$

$$\text{and} \quad Dn_t = \begin{cases} 1, & \text{if the market return is significantly low;} \\ 0, & \text{otherwise.} \end{cases}$$

The two dummy variables signify significant upward and downward market return movements, respectively. The cut-off point for significant market movement is $\pm 1\%$ daily changes of the SSE 180 Index returns.[14] The estimated coefficients of the up- and down-market dummy variables, β and γ, should differ significantly either in their sign or magnitude to indicate differential reactions. Furthermore, this model allows us to test the differences between individual and institutional investors. As $\delta_{D\text{-}S} = \delta_D - \delta_S$ (and $\gamma_{D\text{-}S} = \gamma_D - \gamma_S$), a negative estimate of $\delta_{D\text{-}S}$ ($\gamma_{D\text{-}S}$) implies that the herding measure of individual investors is more negatively related to large market return increases (decreases) than that of institutional investors.

Table 5 reports the estimates of the regression model (5). In the trade herd ($\sigma(Trd)$) equation, the estimates of both δ_S and γ_S are significantly negative, whereas those of both $\delta_{D\text{-}S}$ and $\lambda_{D\text{-}S}$ are negative, although not significant, at the overall market level and in most cases at the portfolio level. These results indicate that: (i) the herding measure of both institutional and individual trading narrows in the presence of large market changes, and (ii) the herding measure of individual trading is more negatively (but not significantly) related to large market changes.

In the buy herd equation ($\sigma(Buy)$), the estimates of neither δ_S nor γ_S are significant, whereas the estimates of both $\beta_{D\text{-}S}$ and $\lambda_{D\text{-}S}$ are significantly negative at the 5% and 10% level, respectively. This implies that the institutional buy herd measure is not generally sensitive to large changes in market returns. In contrast, the individual buy herd declines significantly, suggesting that individual buy herd is sensitive to large changes in market returns.

Finally, in the sell herd equation ($\sigma(Sell)$), the estimates of β_S are significantly negative, whereas those of γ_S are negative, but insignificant, in most cases. These results imply that the institutional sell herd measure declines significantly when there are large up market movements, but it does not decrease significantly with large down market movements. The estimates of $\lambda_{D\text{-}S}$ are significantly negative in most cases, whereas those of $\delta_{D\text{-}S}$ are generally negative, but not significant, which implies that the individual sell herd measure declines more significantly in the presence of down market movements.

In summary, we find evidence of herding towards the market portfolio when there are large up- and down-market movements. This result is consistent with the finding of Hwang and Salmon (2004) for the U.S. and Korean markets. Second, we find that individual trades tend to react symmetrically to up and down market movements, whereas institutional trades tend to exhibit asymmetrical responses. Relative to institutions, the individual buy herd measure is more sensitive to both up and down market movements, whereas that for individual sell herd is more sensitive only to down market movements. These results are also consistent with the herding prediction in Christie and Huang (1995) in that because investors are more likely to suppress their own beliefs in favor of the market consensus during periods of unusual market movements, herd behavior would most likely emerge during periods of market stress.

5. Interactions between individual and institutional investors

Motivated by Bikhchandani et al. (1992) and Welch (1992), we examine whether one type of investors is concerned with the beliefs and trading activities of the other type. A number of studies have suggested that investors are concerned with the beliefs

[14] We also test all of the models with a $\pm$ 2% cut-off point. The overall results remain unchanged.

Table 5
Relation between Dispersion, Change in Trading Value, and Up-and-Down Markets (1%) (GMM Estimates).
$\sigma(Trd)_t = \alpha + \alpha_D I_D + \lambda_S \mu(Trd)_t + \lambda_{D-S} I_D \mu(Trd)_t + \delta_S Up_t + \delta_{D-S} I_D Up_t + \gamma_S Dn_t + \gamma_{D-S} I_D Dn_t + \varepsilon_t$ (5) $\mu(Trd)_t$ is the cross-sectional average change of total trading value for institutional and individual investors; $\sigma(Trd)$, $\sigma(Buy)$, and $\sigma(Sell)$ are the scaled dispersion measures of total trading, buying, and selling value changes for individuals and institutions. *Up* is the dummy variable for the up market, which takes a value of 1 if the market is extremely high, and *Dn* is the dummy variable for the down market, which takes a value of 1 if the market is extremely low. The criterion for extreme is set at 1%, which implies that the daily changes in the SSE 180 Index returns are greater than or equal to 1% in both directions. All of the trading value variables are in logarithm. **, *, and † indicate significance at the 1%, 5%, and 10% levels, respectively.

	All			Portfolio 1			Portfolio 2			Portfolio 3			Portfolio 4			Portfolio 5		
	Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value		Estimate	*t*-Value	
$\sigma(Trd)$																		
α	1.0162	101.78	**	1.0189	76.42	**	1.0109	78.43	**	1.0174	65.80	**	1.0215	67.67	**	1.0286	62.01	**
α_D	0.0084	0.64		0.0109	0.60		0.0079	0.46		0.0144	0.72		0.0049	0.24		0.0047	0.20	
λ_S	0.0243	1.88	†	0.0054	0.40		0.0302	2.14	*	0.0414	2.46	*	0.0090	0.52		0.0481	2.18	*
$\lambda_{D\text{-}S}$	0.0806	3.44	**	0.0831	2.87	**	0.0865	2.84	**	0.0964	2.68	*	0.1569	4.84	**	0.1229	3.26	**
δ_S	−0.0572	−3.14	**	−0.0630	−2.52	*	−0.0553	−2.22	*	−0.0684	−2.70	*	−0.0586	−2.07	*	−0.0939	−2.62	*
$\delta_{D\text{-}S}$	−0.0157	−0.63		−0.0413	−1.18		−0.0303	−0.89		−0.0189	−0.51		−0.0246	−0.63		−0.0097	−0.20	
γ_S	−0.0417	−2.70	*	−0.0524	−2.21	*	−0.0142	−0.64		−0.0385	−1.53		−0.0702	−2.99	**	−0.0800	−3.06	**
$\gamma_{D\text{-}S}$	−0.0318	−1.59		−0.0250	−0.81		−0.0179	−0.61		−0.0629	−1.92	†	−0.0042	−0.14		−0.0152	−0.41	
Adjusted R^2	0.0409			0.0211			0.0148			0.0264			0.0297			0.0332		
$\sigma(Buy)$																		
α	1.0000	97.71	**	1.0054	67.25	**	0.9940	65.46	**	0.9927	62.30	**	1.0041	67.94	**	1.0127	60.69	**
α_D	0.0229	1.64		0.0225	1.18		0.0244	1.28		0.0403	1.93	†	0.0189	0.89		0.0142	0.60	
λ_S	0.0033	0.29		0.0263	1.48		−0.0095	−0.58		0.0009	0.05		0.0061	0.33		0.0037	0.19	
$\lambda_{D\text{-}S}$	0.0965	4.06	**	0.0720	2.32	*	0.1294	4.21	**	0.1332	3.64	**	0.1551	4.59	**	0.1207	3.13	**
δ_S	0.0323	1.91	†	0.0140	0.47		0.0395	1.32		0.0637	2.23	*	0.0023	0.09		−0.0069	−0.21	
$\delta_{D\text{-}S}$	−0.1032	−4.09	**	−0.1148	−3.00	**	−0.1187	−3.12	**	−0.1565	−4.00	**	−0.0701	−1.80	†	−0.0899	−1.80	†
γ_S	−0.0254	−1.61		−0.0396	−1.33		0.0008	0.03		−0.0107	−0.46		−0.0240	−1.04		−0.0638	−2.42	*
$\gamma_{D\text{-}S}$	−0.0410	−1.93	*	−0.0301	−0.85		−0.0358	−1.10		−0.0926	−2.94	**	−0.0446	−1.43		−0.0037	−0.10	
Adjusted R^2	0.0298			0.0144			0.0093			0.0228			0.0176			0.0136		
$\sigma(Sell)$																		
α	1.0121	116.27	**	1.0107	71.07	**	1.0066	78.69	**	1.0126	73.39	**	1.0147	74.92	**	1.0181	60.77	**
α_D	0.0113	0.94		0.0196	1.04		0.0111	0.67		0.0157	0.85		0.0083	0.44		0.0155	0.65	
λ_S	0.0185	1.58		−0.0119	−0.67		0.0035	0.25		0.0194	1.15		0.0070	0.42		0.0390	1.91	†
$\lambda_{D\text{-}S}$	0.0796	3.58	**	0.0875	2.80	*	0.1057	3.55	**	0.1126	3.12	**	0.1416	4.55	**	0.1283	3.55	**
δ_S	−0.0580	−3.17	**	−0.0105	−0.36		−0.0653	−2.67	*	−0.0630	−2.48	*	−0.0476	−1.80	†	−0.1036	−2.73	*
$\delta_{D\text{-}S}$	−0.0077	−0.31		−0.0856	−2.23	*	−0.0186	−0.55		−0.0075	−0.20		−0.0352	−0.96		0.0132	0.26	
γ_S	−0.0189	−1.38		−0.0504	−2.03	*	0.0160	0.64		−0.0175	−0.72		−0.0420	−1.81	†	−0.0154	−0.58	
$\gamma_{D\text{-}S}$	−0.0542	−2.89	**	−0.0367	−1.17		−0.0439	−1.41		−0.0779	−2.43	*	−0.0149	−0.48		−0.0925	−2.48	*
Adjusted R^2	0.0387			0.0139			0.0144			0.0212			0.0193			0.031		

and uncertainties of other investors and that they filter additional information by observing the trades of other investors. Using the Granger causality test, we examine whether individual (institutional) investors are concerned with the trading activities of institutional (individual) investors. Specifically, we test the following hypothesis.

H4. Institutional (individual) herding is not only related to their own lagged trading, but also to that of individual (institutional) investors.

We use the Granger causality test based on the following vector auto-regression model (VAR) with k lags.[15]

$$\begin{bmatrix} \sigma(Trd)_{D,t} \\ \sigma(Trd)_{S,t} \end{bmatrix} = \begin{bmatrix} c_D \\ c_S \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} \mu(Trd)_{D,t-1} \\ \mu(Trd)_{S,t-1} \end{bmatrix} + \begin{bmatrix} e_{D,t} \\ e_{S,t} \end{bmatrix}, \tag{6}$$

where $A_{ij} = \sum_{k=1}^{K} a_{ij}(k) L^{k-1}$, for $i,j = 1,2$. For example, if a standard *F*-test does not reject the hypothesis that $A_{22} = 0$, then institutional trading volumes ($\mu(Trd)_S$) does not Granger-cause individual herding ($\sigma(Trd)_D$).

The test results summarized in Table 6 are consistent with Hypothesis 4 (H4). We find strong interactions between individuals and institutions in their trading levels and herding. At the market level, the institutional trading variables Granger-cause the herding of not only institutions but also that of individuals, although at the portfolio level, however, the Granger causality test result is mixed. The same observation applies to individual investors. These results are consistent with the argument that investors are concerned with the beliefs and uncertainty of other investors (Romer, 1993) and imitate earlier investors (Bikhchandani et al., 1992 and Welch, 1992), as the initial market reaction to news does not fully reflect investor assessments of that news, and further trading reveals additional information about these assessments.

[15] We estimate the VAR model (5) with $K = 5$, 10, and 15, respectively, and the results are mainly the same. To save space, we only report the results for $K = 5$.

Table 6
Causal Relation between Institutional and Individual Investor Trading Value and the Dispersion Measure.
This table presents the Granger causality test results based on the following VAR model:

$$\begin{bmatrix} \sigma(Trd)_{D,t} \\ \sigma(Trd)_{S,t} \end{bmatrix} = \begin{bmatrix} c_D \\ c_S \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} \mu(Trd)_{D,t-1} \\ \mu(Trd)_{S,t-1} \end{bmatrix} + \begin{bmatrix} e_{D,t} \\ e_{S,t} \end{bmatrix} \quad (5)$$

The figures are *F*-statistics with their *p*-values in brackets. *R* is the SSE 180 Index return for the case of "All stocks," and it is the portfolio mean return for the other cases (i.e., for each of the five portfolios). $\mu(Trd)_j$, $\mu(Buy)_j$, and $\mu(Sell)_j$ are the average total trading, buying, and selling value changes, respectively, and $\sigma(Trd)_j$, $\sigma(Buy)_j$, and $\sigma(Sell)_j$ are the corresponding dispersion measures for investor group *j*, $j = D$ (individuals) and *S* (institutions), respectively. All of the trading value variables are in logarithm.

	All		Portfolio 1		Portfolio 2		Portfolio 3		Portfolio 4		Portfolio 5	
	F-test	*P*-value	*F*-test	*P*-value	*F*-test	*P*-value	*F*-test	*P*-value	*F*-test	*P*-value	*F*-test	*P*-value
H_0: $\mu(Trd)_S \rightarrow \sigma(Trd)_D$	5.12	[0.000]	0.81	[0.545]	1.54	[0.176]	0.47	[0.798]	1.21	[0.304]	2.13	[0.061]
H_0: $\mu(Buy)_S \rightarrow \sigma(Buy)_D$	1.92	[0.090]	0.55	[0.737]	1.98	[0.080]	0.43	[0.828]	0.43	[0.830]	0.44	[0.823]
H_0: $\mu(Sell)_S \rightarrow \sigma(Sell)_D$	4.28	[0.001]	0.18	[0.969]	0.88	[0.495]	0.30	[0.914]	1.11	[0.353]	1.78	[0.115]
H_0: $\mu(Trd)_D \rightarrow \sigma(Trd)_S$	5.46	[0.000]	0.41	[0.845]	3.44	[0.005]	3.95	[0.002]	4.10	[0.001]	5.29	[0.000]
H_0: $\mu(Buy)_D \rightarrow \sigma(Buy)_S$	2.39	[0.037]	1.51	[0.184]	0.78	[0.566]	1.38	[0.231]	0.29	[0.920]	2.45	[0.033]
H_0: $\mu(Sell)_D \rightarrow \sigma(Sell)_S$	3.46	[0.004]	0.97	[0.436]	1.01	[0.408]	1.84	[0.103]	1.52	[0.181]	2.07	[0.068]

6. Conclusion

In this paper, by using daily individual and institutional trading data, we construct a set of dispersion measures to study the differences of herding behavior between individual and institutional investors. We find that cross-sectionally, the magnitude of the average individual dispersion measures is smaller than those of institutional investors, which implies that less-informed individual investors tend to trade towards the market movement and less selectively across different stocks.

Second, we find that dynamically, both the individual and institutional herding measures are negatively related to the absolute market return and positively related to the average trading volume. Although both individual and institutional investors place greater weight on market returns and filter information from returns and trading, the herding measure of the former is more sensitive to total trading and market return movement. This finding remains robust with extreme market shocks controlled for. Furthermore, we find that relative to institutions, the individual buy herd measure is more sensitive to both up- and down-market movements, whereas the individual sell herd measure is more sensitive only to down-market movements.

Finally, we find that, at the market level, institutional herding is not only Granger-caused by its own lagged trades but also that of individuals. The same observation applies to individual investors. These results indicate that, both individual and institutional investors pay close attention to one another's trading activities in forming a consensus.

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