When Will Investors Herd?

--Evidence from the Chinese Stock Markets

Gongmeng Chen, Oliver M. Rui and Yexiao Xu*

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Abstract

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JEL Classification Code: G15

Keywords: Cross-sectional Dispersion, GARCH, Herding behavior, Momentum, Trading Volume

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* Chen is with the School of Accounting and Finance at the Hong Kong Polytechnic University, Rui is at the Faculty of Business Administration of The Chinese University of Hong Kong, and Xu is at the School of Management in the University of Texas at Dallas. Address correspondence to: Yexiao Xu, School of Management; the University of Texas at Dallas; Richardson, TX 75083. Email: yexiaoxu@utdallas.edu

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Abstract

The institutional characteristics of the Chinese stock markets provide a unique perspective to study the herding behavior of investors. If domestic investors are more knowledgeable or informed about individual stocks than foreign investors, herding behavior is most likely to occur among foreign investors. Our empirical results indicate that during periods of extreme price movements, the relative equity return dispersions for both Shanghai-B and Shenzhen-B actually have decreased, which provides evidence for herd behavior. This result is robust to a different specification which controls for informational trading. However, for both Shanghai-A and Shenzhen-A, we find mixed and weaker results to support for herding. Since B-share investors are foreign investors, the differential herding behavior of local and foreign investors suggest that in the presence of inefficient information disclosure, foreign participants tend to trade according to other signals and to herd due to lack of fundamental and private information on firms. We also propose an alternative approach that involves trading volume to detect herding behavior. After controlling for informational effect, we continue to find strong support for herding activities in the B-share markets. Our findings are robust in terms of portfolio size, industry grouping, and GARCH specifications.

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1. Introduction

A central paradigm of financial economics is the efficient markets hypothesis. Schwert (2003) has summarized the different types of anomalies identified by academics. However, the interpretation of these anomalies is by no means straightforward. The attempt to do so has led to resurgence in the study of behavior finance in recent years[1]. While the importance of this line of research is still debatable, it does seem that the trading behavior of investors might influence asset prices to some degree, at least in the short run. Without getting into detail about the rationale behind certain kinds of trading behavior, it is equally important to know from an empirical perspective if such behavior indeed exists and when it might occur. Herding behavior has been widely documented among analysts and portfolio managers. Several studies on forecasting and institutional investors have also reported the existence of herding behavior. As documented by Givoly and Lakonishok (1984), the earnings forecasts of analysts are biased. Mikhail, Walther, and Willis (1999) found that analysts whose forecasts were less accurate than their peers were likely to turn over. Stickel (1990) documented that changes in the consensus forecast of analysts were positively related to subsequent revisions in such forecasts. Graham (1999) tested whether analysts followed the *value line* in their market timing recommendations, and found that both highly reputable newsletters and those that were not reputable were more likely to follow the *value line*. Wermers (1994) and Grinblatt et al. (1995) examined whether mutual funds herded in their purchasing decisions. In particular, Wermers (1994) studied the trading patterns of 274 mutual funds. After controlling for fund investment objectives, he found that both simultaneous and sequential purchases of the same stocks were significant. Welch (2000) showed that the buy or sell recommendations of a security analyst had a significantly positive influence on the recommendations of other analysts. Kodres and Pritsker (1997) reported herding in daily trading by large futures market institutional traders such as broker-dealers, banks, and hedge funds.

For institutional investors, herding can emerge from either a rational or irrational form of investor behavior. According to Welch (2000), the irrational view focuses on investor psychology, where investors disregard their prior beliefs and blindly follow the actions of other investors. The rational view, in contrast, focuses on the principal-agent problem in which managers mimic the actions of others. Thus, managers may completely ignore their own private information in order to maintain their reputational capital in the market (see for example, Froot et al. 1992; Scharfstein and Stein 1990; and Trueman 1994).

Herding can also occur among individual investors when a group of investors intensively buys and sells the same stock at the same time. However, for individual investors, the rational view may not be applicable since most investors are anonymous. Christie and Huang (1995) argued that because individuals are more likely to suppress their own beliefs in favor of the market consensus during periods of unusual market movements, herd behavior is most likely observed during periods of market stress. Chang et al. (2000) suggested that such behavior may be due to a high degree of government intervention, a low quality of information disclosure, or the presence of more speculators with relatively short investment horizons. In this study, we aim to contribute to the study of investors' herding behavior by investigating its presence when herds are most likely to form in the immature equity markets using robust methods. In particular, we utilize a unique data set from Chinese capital markets where the same company issues different classes of shares with equal rights. Since different shares are traded by different investors in different markets, this offers a unique laboratory for the investigation of herding behavior by investors.

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[1] Hirshleifer (2001) has provided a comprehensive summary on this issue.

China established its securities market in 1992 in Shenzhen and Shanghai to allow listed companies to issue shares. Since then, the securities market has grown and become the place for the corporationization of state-owned enterprises.[2] Statistics show that the total market capitalization of the Chinese securities market stood at US$520 billion and US$570 billion at the end of the 2001 and 2002, respectively. It accounted for about half of China's GDP, making China's capital market the third largest in the Asia-Pacific region behind Japan and Hong Kong (Hong Kong Securities, 2002). As of July 2001, there were more than 60 million stock accounts in China, which were held by approximately 5% of the entire population.[3] Most investors are individuals who trade speculatively. In 2000, the annual turnover rate was 477.19% on the Shanghai Stock Exchange and the Shenzhen Stock Exchange combined.

The institutional characteristics of Chinese stock markets differ from those of other countries. A distinguishing feature of the Chinese markets is that some firms issue two types of shares. Class A-shares, denominated in RMB, are traded among Chinese citizens, while B-share stocks, denominated in U.S. dollars, are traded among non-Chinese citizens or overseas Chinese.[4] Other than segmentation by ownership, these two classes of shares are similar. In

[2] For more detailed information about China's stock markets, please refer to Sun and Tong (2003).

[3] About two-thirds of the accounts are inactive. However, over 85% of the country's population lives in poor rural areas, and have no ability to own stocks. Therefore, over 10% of the city population owns stock accounts.

[4] For the purpose of B-shares on the two Chinese stock exchanges, overseas investors are described as foreign legal and natural persons, including those from Hong Kong, Macao, and Taiwan, and other investors who are approved by the People's Bank of China. However, the State Council has ruled that Chinese who are living overseas and who remit money are permitted to trade in B-shares. This exception has created conditions whereby local traders can open accounts in the name of overseas relatives and friends. In 2001 the restrictions were eased. Domestic investors who have access to foreign currencies (U.S. dollars and Hong Kong dollars) can now buy B-shares. As a consequence of this change in policy, A- and B-share prices are now much closer, although the former still trades at a premium. There are also H-shares and N-shares. H- and N-shares are similar to B-shares, except that they are listed and traded on the Hong Kong Stock Exchange and the New York Stock Exchange, respectively. Chui and Kwok (1998) have provided other background information on the Chinese stock markets.

particular, owners have equal rights to cash flows and voting privileges. However, the B-share markets are less liquid and active than the A-share markets, as shown by the average rate of turnover of the B-share markets, which is around one-third that of the A-share markets. Such a unique institutional feature can provide additional insights into the mystery of investor herding behavior regarding the circumstances under which it might occur in a "controlled environment." Apparently, A- and B-share investors are very different because of differences in culture and geographic location. It is less likely that herding behavior will occur simultaneously in these two groups of investors. In the post-WTO period, investing opportunities for foreign investors in China will definitely increase. In 2002, the Chinese authorities announced that they are planning to allow foreign enterprises to apply to list on the A share market and to participate in mergers and acquisitions as well as in takeover activities in the A share market (Hong Kong Securities, 2002). Therefore, the Chinese securities market is not only unique in feature; it is an important emerging capital market of considerable interest to global investors in the future. This is particularly so because China will be of gigantic economic significance in the coming decades.

An individual's thoughts, feelings, and actions can be influenced by several means: by words, by observations of actions, and by observations of the consequences of actions (such as individual payoffs, market prices, or trading volume). Kelly and O'Grada (2000) found that social interactions between individuals affect their decisions on equity participation and other financial decisions. Rather than a measurement of herd behavior (social influence) per se, this is an indirect measure of the tendency for some groups of investors to react in a common way during periods of extreme shocks more so than at other times. If herding behavior does exist, it is most likely to occur at times of extreme market price movements. Therefore, the buy and sell actions of investors will be seen being more "coordinated" than otherwise. As a consequence, cross-sectional standard deviations of security returns will be low during the herd period. Following this line of thinking, a number of recent studies have investigated the herding behavior of investors in stock markets. Christie and Huang (1995) studied the magnitude of the cross-sectional dispersion of individual stock returns during periods of extreme changes in the market. However, they were unable to detect herd behavior in the U.S. Chang et al. (2000) proposed an alternative approach that uses a non-linear regression specification to examine the relationship between the level of equity return dispersion and the overall market return. Their findings stated that, in the presence of herding, the return dispersion will decrease with an increase in the market return. Using market data from the U.S., Hong Kong, Japan, Korea, and Taiwan, they found evidence of herding in Korea and Taiwan.

In contrast, we study the same issue by utilizing the unique characteristics of Chinese stock market data and relying on more powerful tests. First, it is well documented that R^2s from a market model are especially high for emerging markets. Therefore, the cross-sectional dispersion measure of Christie and Huang (1995) could be highly influenced by a market movement due to the cross-sectional dispersion in betas. While this is not an issue in their study since R^2s are very small for U.S. stocks, it is an important issue when applying data from emerging markets. We thus propose a relative cross-sectional measure of dispersion. Second, we also apply the unique institutional features of Chinese stock markets to control for a possible informational effect while detecting the herding behavior. Third, the special A- and B-share structures and the differences in the possession of information among different groups of investors allow us to identify when herding behavior might occur. Fourth, although momentum trading can be regarded as a special form of herding behavior, it is likely to persist over time.

We disentangle these two effects in this study and construct a more powerful test in a GARCH framework. Finally, we also incorporate information on trading volumes into our study.

We have found evidence of herding in the Chinese equity markets. We also observe that herding behavior is more likely to occur among less informed B-share investors than A-share investors. In addition, investors tend to behave differently in the up and down markets because there are restrictions on short sales in the Chinese markets. The remainder of the paper is organized as follows. Section 2 presents our new methodologies. The empirical results are discussed in Section 3. Section 4 studies the robustness of our conclusions. Section 5 offers concluding comments.

2. Methodology

2.1 The cross-sectional dispersion measure

Christie and Huang (1995) examined the investment behavior of market participants in the U.S. equity markets. They argued that, when herding occurs, individual investors usually suppress their own information and valuations, resulting in a more uniform change in security returns. Therefore, they employed a cross-sectional standard deviation of returns (CSSD) as a measure of the average proximity of individual asset returns to the realized market average:[5]

$$CSSD_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2} \tag{1}$$

where $R_{i,t}$ is the stock return on firm *i* at time *t*, and $R_{m,t}$ is the equally weighted average of the *N* returns in the aggregate market portfolio at time *t*. If a market model with $R_{m,t}$ holds, CSSD can be equivalently written as:

$$CSSD_t = \sqrt{\frac{1}{N-1}R_{m,t}^2\sum_{i=1}^{N}(\beta_i^2 - 1) + \frac{1}{N-1}\sum_{i=1}^{N}\varepsilon_{i,t}^2} \tag{2}$$

where β_i and $\varepsilon_{i,t}$ are the beta coefficient and the idiosyncratic return from a market model, respectively. Clearly, this is a good proxy for cross-sectional dispersion in the idiosyncratic returns when R^2 from a market model (or the first term in equation (2)) is small. Unfortunately, different from U.S. stocks, this implicit assumption does not hold for emerging market stocks. For example, the average adjusted R^2s are 47% and 45% for Shanghai A-shares and Shenzhen-A

[5] Chang et al. (2000) developed a cross-sectional absolute deviation of returns (CSAD) as a measure of dispersion. They have shown that regressing CSAD on $|R_m|$ and $(R_m)^2$ should result in a statistically insignificant coefficient estimate on the second term when there is no herding. This result is derived based on computing CSAD using the expected return. However, since we can only use the realized returns in estimation, it is easy to see that the CSAD measure is a nonlinear function of the market return. In other words, in the absence of herding, one tends to find a significant coefficient on $(R_m)^2$.

shares, respectively, as shown in Table 1. Therefore, a more powerful test should be constructed based on the cross-sectional dispersion of idiosyncratic returns instead.

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Please Insert Table 1 Here

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The ARCH literature has suggested that volatility tends to increase following large price movements. Given this fact, a certain level of cross-sectional dispersion occurring after a large price movement should constitute a relatively lower level of dispersion than the same absolute level of cross-sectional dispersion after a small change in price. In other words, the cross-sectional dispersion should be measured relative to a measure of conditional volatility. Therefore, we propose the following measure of relative cross-sectional dispersion of idiosyncratic return (RCSDI),

$$RCSDI_t = \sqrt{\frac{1}{N-1}\frac{1}{h_{m,t}}\sum_{i=1}^{N}(\varepsilon_{i,t} - \bar{\varepsilon}_t)^2} \tag{3}$$

where $\bar{\varepsilon}_t = \frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i,t}$ is the average cross-sectional idiosyncratic return, and $h_{m,t}$ is the conditional volatility of market returns estimated using a GARCH(1,1) model.

The unique institutional structure of Chinese stock markets provides a great opportunity to study herding behavior. Most Chinese companies issue A-shares for domestic investors and B-shares for overseas investors. These two groups of investors are likely to be different in terms of their behavior. Overseas investors tend to rely more on publicly available macro information or on information that is largely unreliable, while domestic investors may possess more firm-specific information obtained by gleaning through the local news media, private information, and personal experience with the products of such firms. Therefore, domestic investors can be more informed and trade more aggressively at the same time. In contrast, B-share investors as a whole are less informed about a company's future potential. As a result, B-share stocks tend to move more closely with the market than A-share stocks. This is exactly the case, as shown in Table 1. The adjusted R^2s are 47% and 45% for Shanghai A-shares and Shenzhen A-shares, respectively. For B-shares, the adjusted R^2s are higher than for A-shares, with 53% and 56% for Shanghai B-shares and Shenzhen B-shares, respectively. The difference is not due to possible large outliers as supported by the distribution of the adjusted R^2s. We have also performed statistical tests on the differences in the adjusted R^2s for stocks offering both A- and B-shares. Table 1 suggests that the average difference is statistically significant at the 1% level.

B-share stocks also differ from A-share stocks in their liquidity, which may also arise from differences in the available information. As shown in Table 1, the average daily trading volumes were 0.53% and 0.62% for Shanghai A-shares and Shenzhen A-shares, respectively. These are twice as large as those of B-share stocks. Moreover, daily trading volumes are also positively skewed, as shown from the distribution in Table 1. This is part of the reason for using log volume in the following empirical study. Because of liquidity reasons, or more specifically because of differential information, B-share stock returns should be more volatile than those of A-share stocks. The average daily volatility for Shanghai B-shares was 3.68%, which is 45% more volatile than A-share stocks. Similar results hold for stocks traded on the Shenzhen stock exchange. Such a difference in volatility is statistically significant at the 1% level. It is also interesting to note that high volatility in the B-share market is not purely due to large betas, as discussed above. The test statistics for the difference in idiosyncratic volatility suggests that B-share stocks have relatively large idiosyncratic volatilities.

Most studies on herding did not differentiate information trading from true herding behavior. Due to the unique structure of Chinese stock markets, we can use A-share returns as a control variable for information-based trading behavior or for possible coordinated herding between the two markets. In other words, for companies that issue both classes of shares we can use A-share stock returns to control for both market-wide and firm-specific information. Since betas for different classes of shares of the same stock differ, it is better to use the residual returns of the two-classes of shares in order to avoid possible contamination from market returns. This suggests the following measure of relative cross-sectional dispersion of controlled residuals (RCSDCR),

$$\varepsilon_{i,t}^{B} = a_0 + a_1 \varepsilon_{i,t}^{A} + \eta_{i,t}^{B} \tag{4}$$

$$RCSDCR_t = \sqrt{\frac{1}{N-1} \frac{1}{h_{m,t}} \sum_{i=1}^{N} (\eta_{i,t}^{B} - \overline{\eta}_t^{B})^2}\ , \tag{5}$$

where $\varepsilon_{i,t}^{A}$ and $\varepsilon_{i,t}^{B}$ are residual returns from a market model for A- and B-shares, respectively, η^B is the differential residual return of a B-share stock, and $\overline{\eta}_t^{B} = \frac{1}{N} \sum_{i=1}^{N} \eta_{i,t}^{B}$ is the cross-sectional average of differential residual returns. For the same reason discussed above, we have also scaled the measure by the conditional volatility of market returns $h_{m,t}$ estimated using a GARCH(1,1) model.

2.2 Testing the herding behavior based on the cross-sectional dispersion measure

Because individuals are more likely to suppress their own beliefs in favor of the market consensus during periods of unusual market movements, herd behavior will most likely emerge during periods of market stress. Christie and Huang (1995) examined whether equity return dispersions were significantly lower than average during periods of extreme market movements. Based on their argument, we estimate the following empirical model.

$$CD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \qquad (6)$$

where CD_t represents different measures of cross-sectional dispersion proposed in equations (1), (3), and (5). $D_t^L(D_t^U)$ is a dummy variable that equals 1 when the market return day *t* lies in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The extreme tail of the return distribution is defined as *x* percent of observations in the upper and lower tail of the market return distribution. For robustness, we choose *x* to be 1%, 2%, and 5%. The dummy variables capture differences in investor behavior during extreme market movements. During periods of abnormally large average price movements or market stress, the differential predictions of rational asset pricing models and herd behavior are most pronounced. Rational asset pricing models predict that periods of market stress induce increased levels of dispersion, because individual securities differ in their sensitivities to the market returns. In contrast, as a result of herding, security prices tend to move in the same direction with a similar proportion, which translates into a reduced level of dispersion across individual security returns around the market. Thus, rational asset pricing models predict positive coefficients β^L and β^U with one caveat discussed in the next subsection, while negative estimates of β^L and β^U are consistent with the presence of herd behavior.

2.3 Momentum versus herding

A momentum trading strategy requires buying recent winners and selling recent losers. Since it is purely based on information on past stock returns, the use of the momentum trading strategy is considered a special type of herd behavior. Thus, when investors pursue a momentum trading strategy, return volatilities will be exacerbated. As documented by Jagadeesh and

Titman (1993), implementing a momentum strategy was most profitable using individual stocks. This suggests that momentum opportunities occur randomly among individual stocks, otherwise there will be market-wide momentums. Therefore, cross-sectional dispersion at any point in time will increase due to momentum in individual stocks. Since it is difficult to short sell a stock especially in China, individual investors will more likely adopt momentum strategies in an "up" market than in a "down" market. This suggests that increases in cross-sectional dispersion in individual stock returns will be asymmetric. Therefore, both β^U and β^L should be positive, with β^U being larger than β^L in the presence of momentum trading. However, if momentum only exists in common factors, it will also reduce cross-sectional dispersion. Therefore, β^U will be more negative than β^L.

2.4 Detecting herding using trading volume

Trading volume provides important information in a different dimension. Volume could be low when price changes are large, and vice versa. Therefore, in observing herding behavior, a large price swim is neither a necessary nor a sufficient condition, but a plausible one. In contrast, a large trading volume is a necessary condition for the existence of herding behavior among investors since it is a voluntarily coordinated action. By the same argument as in Christie and Huang (1995), the cross-sectional dispersion should be negatively correlated with trading volume when herding occurs. However, this is only a necessary condition. Information could also lead to a high trading volume.

As herding is a coordinated action, there need to be some observable signals that investors can follow. Trading volume could have served as one such common signal. In order for market participants to herd and ignore their own priors, the volume signal has to be large enough to persuade investors that other things might be happening. Consequently, investors may come to believe that it is in their best interest to follow the crowd. In other words, herd behavior is more likely to occur following high trading volumes in the previous period. This suggests that the cross-sectional dispersion should be negatively correlated with the lagged volume variable.

Trading volume could also be high due to informational trading. By definition, information arrives randomly, which suggests that changes in trading volume can serve as a proxy for differential information. The rational asset pricing theory suggests that when information increases, the cross-sectional dispersion should widen. Thus, we control for the informational effect in the following empirical specification:

$$\ln(RCSDI_t) = \alpha_0 + \alpha_1 \ln(RCSDI_{t-1}) + \alpha_2 \ln(V_{t-1}) + \alpha_3 \Delta \ln(V_t) + e_t \, , \tag{12}$$

where V_t is the aggregate trading volume for A or B shares. In order to cope with the apparent heteroscedasticity in the residual and due to the fact that both volatility and trading volume are positive, we take a natural log for all variables. Due to persistence in the cross-sectional dispersion measure, the lagged *RCSDI* variable is used in equation (12) to control for autocorrelation in the residual. Since the *RCSDCR* measure has already discounted the possible informational effect, the following empirical model will be used instead:

$$\ln(RCSDCR_t) = \alpha_0 + \alpha_1 \ln(RCSDCR_{t-1}) + \alpha_2 \ln(V_{t-1}) + e_t \, . \tag{12'}$$

To further account for the possibility of heteroscedasticity and autocorrelation in cross-sectional dispersion measures, we estimate each model using the generalized method of moments (GMM), which in these circumstances is asymptotically more efficient than ordinary least squares estimates (Hansen, 1982).

2.5 The GARCH approach

The up and down market dummy variable approach may have some drawbacks. For example, the number of events for extreme market movement may be relatively small. This means that the dummy variables will be zero most of time. Moreover, this approach does not tell us the true informational effect from herding behavior except for a special case where we can use A-shares as a control variable. The microstructure effect may also be a concern when dealing with individual stock returns. Therefore, we should also use more elaborate approaches on characteristics sorted portfolios. In particular, when there is herding behavior among investors, most stocks should move in the same direction, which increases the co-movement. Therefore, the market components and the idiosyncratic components of the returns for a portfolio should increase and decrease, respectively. This logic leads to the following tests based on the GARCH approach.

$$\begin{cases} \tilde{r}_{m,t+1} = \sigma_{m,t}\xi_{m,t+1} \\ \sigma^2_{m,t} = \omega_m + \gamma_m \sigma^2_{m,t-1} + \alpha_m \xi^2_{m,t} \\ \tilde{r}_{i,t+1} = \sigma_{i,t}\xi_{i,t+1} \\ \sigma^2_{i,t} = \omega_i + \gamma_i \sigma^2_{i,t-1} + \alpha_i \xi^2_{i,t} + \lambda_i \xi^2_{m,t} \end{cases} \tag{7}$$

where $\tilde{r}_{m,t}$ and $\tilde{r}_{i,t}$ are the ***demeaned*** market return and the *i*-th portfolio return, respectively. The conditional idiosyncratic volatility can be defined as the difference between the total volatility of the portfolio $\sigma^2_{i,t}$ and the market volatility $\sigma^2_{m,t}$.[6] In other words, when equation (7.4) is subtracted from equation (7.2), we have the following result:

$$(\sigma^2_{i,t} - \sigma^2_{m,t}) = (\omega_i - \omega_m) + (\gamma_i \sigma^2_{i,t-1} - \gamma_m \sigma^2_{m,t-1}) + \alpha_i \xi^2_{i,t} + (\lambda_i - \alpha_m)\xi^2_{m,t} . \tag{8}$$

When $\gamma_i = \gamma_m$, equation (8) can be further simplified as:

$$\sigma^2_{I,i,t} = \omega_{I,i} + \gamma_{I,i}\sigma^2_{I,i,t-1} + \alpha_i \xi^2_{i,t} + \lambda_{I,i}\xi^2_{m,t} , \tag{9}$$

where $\sigma^2_{I,i,t}$ is the conditional idiosyncratic volatility, and coefficient $\lambda_{I,i} = (\lambda_i - \alpha_m)$ captures the herding behavior discussed in the previous section. As motivated in the previous section, the coefficient estimate $\lambda_{I,i}$ should be negative when herding behavior exists. When $\gamma_i \neq \gamma_m$ in equation (8), we can directly specify the conditional idiosyncratic volatility of equation (9) in the GARCH system as:

$$\begin{cases} \tilde{r}_{m,t+1} = \sigma_{m,t}\xi_{m,t+1} \\ \sigma_{m,t}^2 = \omega_m + \gamma_m \sigma_{m,t-1}^2 + \alpha_m \xi_{m,t}^2 \\ \tilde{r}_{i,t+1} = \sigma_{i,t}\xi_{i,t+1} \\ \sigma_{i,t}^2 = \sigma_{I,i,t}^2 + \sigma_{m,t}^2 \\ \sigma_{I,i,t}^2 = \omega_{I,i} + \gamma_{I,i}\sigma_{I,i,t-1}^2 + \alpha_i \xi_{i,t}^2 + \lambda_{I,i}\xi_{m,t}^2 \end{cases} \tag{10}$$

This framework also facilities our study of the asymmetric response to herding behavior in the up market versus the down market. Specifically, we can replace equation (10.5) with the following equation:

$$\sigma_{I,i,t}^2 = \omega_{I,i} + \gamma_{I,i}\sigma_{I,i,t-1}^2 + \alpha_i \xi_{i,t}^2 + \lambda_{I,i}[|\,\xi_{m,t}\,| - c_{I,i}\xi_{m,t}\,]\,. \tag{11}$$

The responses to the up and down markets are captured by $\lambda_{I,i}(1\text{-}\ c_{I,i})$ and $\lambda_{I,i}(1+\ c_{I,i})$, respectively. When the herding hypothesis is rejected, i.e. $\lambda_{I,i}$ is positive, a significant negative estimate of $c_{I,i}$ suggests possible momentum trading, as discussed in section 2.3.

[6] This definition is motivated by the work of Xu and Malkiel (2003) and is based on the fact that we are using portfolios. The beta from a market model for a portfolio tends to be close to one.

3. Empirical results

We obtained daily stock price data for the entire population of Chinese firms and the equally weighted market index along with the year end market capitalization for each firm from the China Stock Market & Accounting Research Database, which is compiled and maintained at the Hong Kong Polytechnic University. It is believed that herd behavior is a very short-lived phenomenon. In this study, we use daily stock return data over the sample period, from January 1996-December 2002. Although daily return data are available starting from December 1990, there were very few stocks in the beginning. For example, in 1991 only eight stocks were traded. The total number of stocks increased to 14 and 53 in the beginning of 1992 and 1993, respectively. Moreover, return volatilities fluctuated widely prior to 1996 when China implemented a 10% price limit rule[7]. Including the early period will bias our results, since the dummy variable will only take the value of one in the early period. Therefore, we are focusing on the more mature and recent sample period.

3.1 Descriptive statistics

We report the descriptive statistics for daily mean returns and the CSSD and RCSDI of the returns for Shanghai and Shenzhen A- and B-shares. The average daily return ranges from a low of 0.0935 for Shanghai A to a high of 0.1418 for Shenzhen B. In general, B-share stocks outperformed A-share stocks by about three basis points. Chinese stock returns are characterized by higher magnitudes of volatility, with standard deviations ranging from 1.9045% for Shanghai

[7] We adjust for the effects of stock dividends, stock placing, and ex-dividends for all stocks. We also exclude the first trading day of IPO stocks. Both stock exchanges adopted the ST system on March 16, 1998. Firms that have incurred losses for two consecutive years, or whose net assets are lower than the par value of their stocks, are known as special treatment (ST) firms. There were about 67 ST stocks in China by the end of 1999. The price limits for ST shares are +/- 5%, based on the preceding day's closing price.

A to 2.8814% for Shenzhen B. These returns exhibit non-normal distributions, with A- and B-shares being positively and negatively distributed, respectively, as can be seen from the summary statistics on distribution shown in Table 3. B-share returns are also different from A-share returns in their predictability. A-shares have a virtually zero autocorrelation while the autocorrelations of B shares are comparable to the U.S. data.

The average daily RCSDI ranges from a low of 105% for Shenzhen B to a high of 126% for Shanghai A, while the average daily CSSD ranges from a low of 2.04% for Shanghai A and a high of 2.44% for Shenzhen B. Although these two measures of cross-sectional dispersion are very persistent as shown in Table 3, the unit root (Dickey-Fuller) hypothesis is rejected at a 1% level for all RCSDI and CSSD series. These results indicate that all RCSDI and CSSD series exhibit stationary and conditional heteroscedasticity. Accordingly, we estimate the model using the generalized method of moments (GMM) in our later estimation.

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3.2 Herding around extreme market activities

We begin our investigation of the presence of herd behavior by employing dummy variable regression tests of equation (6). Different from Christie and Huang (1995), we use both the *RCSDI* and the CSSD as our measures of dispersion. The coefficients on the dummy variables capture differences in the dispersion and shed light on the extent of herd behavior across trading days with extreme upward or downward price movements. Table 3 reports the GMM estimated coefficients of equation (6) using 1%, 2%, and 5% of the price movement days as our definition of extreme price movement. For the CSSD measure, except for Shanghai B- and

Shenzhen A-shares under the 1% criterion, the estimates of β^{U} and β^{L} are all positive and significant, at least at the 5% level. This measure suggests that there was no herding activity in either market. The conclusion seems to be at odds with common belief of market participants.

In contrast, when applying the RCSDI measure, the coefficient estimates of β^{L} are negative for all four stock markets and almost exclusively significant at the 1% level under the 1% and 2% extreme price movement criteria. With the 5% criterion, β^{L}s are still very significant for B share stocks. The estimates of β^{U} are generally less significant for A-share stocks than for B-share stocks. For example, Shanghai B-shares are all statistically significant at the 1% level under all criteria, while A-shares are significant at the 1% level only under the 1% criterion. The β^{U} estimates are much weaker for stocks traded on the Shenzhen stock exchange. These results indicate that the RCSDI measure is more likely to catch the herding behavior than CSSD. In general, the herding behavior of market participants is more apparent in the B-share markets. Moreover, herds tend to occur asymmetrically. In particular, investors tend to suppress their own beliefs more easily in a down market and in an up market. We are likely to observe herding behavior in B-share investors.

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Please Insert Table 3 Here

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As we have argued that domestic investors may possess more information than foreign investors and given the finding that B-share investors are more likely to herd than A-share investors, we can use A-share returns to control for informational trading for firms that issue both classes of shares. In other words, we can also use the RCSDCR measure. Under the 5% criterion, both β^{U} and β^{L} estimates are statistically significant at the 1% level. Therefore, the decrease in the cross-sectional dispersion of B-share stocks during periods of market stress is not due to informational trading. It is a result of herding behavior. It is also interesting to see that both estimates β^U and β^L are not very different from each other, as the F test indicates in Table 3. Therefore, the RCSDCR measure has also eliminated the momentum effect.

Although the CSSD measure is incapable of detecting herding behavior, the estimates of β^U are generally greater than those of β^Ls. The differences are even statistically significant for stocks traded on the Shenzhen Stock Exchange. Similar to the situation under our RCSDI measure, β^L estimates are more negative and significant than β^U estimates. As discussed in section II.3, these results might indicate momentum trading behavior, since short sales are not allowed in China when markets are low. This finding could not be due to the directional asymmetry documented by McQueen et al. (1996), whose evidence indicates that in the U.S. all stocks react quickly to negative macroeconomic news, but some small stocks adjust to positive news about the economy with a delay. In other words, when the market reacts quickly to negative news, a wider than average dispersion in the down markets should be observed. This is contrary to what we have found.

3.3 A further look at herding behavior using volume information

The extreme market movement may simply correspond to policy changes in China. It is important to investigate the issue from a volume perspective, as discussed in section 2.4. In this section, we reexamine the equity return dispersion and trading volume relationships using the regression model (12). As shown in the last section, the CSSD measure is not very useful in detecting herding behavior; thus, we only report in Table 4 the empirical results under both RCSDI and RCSDCR measures. Although the natural log of the two measures is very persistent with the α_1 estimates ranging from 0.71 to 0.85, a unit root test is rejected at the 1% level. Therefore, the reported asymptotic t-ratios from the GMM estimates are valid.

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Please Insert Table 4 Here

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First of all, changes in log trading volume $\Delta\ln(V)$ significantly affect the cross-sectional dispersion, as indicated by the coefficient estimates α_3. For example, the α_3 estimates are 0.31 and 0.34 for Shanghai A-shares and Shenzhen A-shares, respectively. Both estimates are statistically significant at the 1% level. Similar results hold for B-share stocks. Since the RCSDI measure is persistent, changes in volume have a prolonged impact on cross-sectional dispersion. In other words, the positive informational effect will last for a period of time when changes in volume reflect information. Such an informational effect on cross-sectional dispersion is more than two times larger for the A-share stocks than for the B-share stocks. This seems to be at odds with the fact that the idiosyncratic volatilities are generally larger for B share stocks than for A-share stocks. If volume differential represents information flow, the impact on dispersion for B-shares should be large to account for the large idiosyncratic volatilities, other things being equal. At the same time, trading volume can be considered as a proxy for liquidity. Low volumes in the B share market will likely be associated with high liquidity risks, which induce high volatility. Therefore, the differential impact could be simply due to the liquidity effect.

Chang et al. (2000) argued that in the presence of inefficient disclosure of information, market participants tend to lack fundamental information on firms, which may cause them to trade according to other signals. B-share investors are foreign investors. Foreign shareholders are known to suffer from greater problems of information asymmetry than local shareholders (Kang and Stulz 1997). This is one of the main reasons why investors prefer to invest locally rather than globally, despite the obvious benefits that diversification can bring. Moreover, B-shares suffer from a serious problem of illiquidity, part of which is due to the nature of their ownership type and restrictions (Chen, Lee, and Rui 2001). This is the primary reason why B-shares are priced at a discount to A-shares, despite the fact that both have equal rights to cash flows. Therefore, because B-shares have serious issues of information asymmetry and liquidity, which are two costly frictions for efficient markets, we believe that B-share investors are more likely to suppress their own beliefs during periods of extreme market movements.

If investors do herd by observing the volume signal in the last period, the estimate α_2 should be negative. For both Shanghai A- and Shenzhen A-shares, the α_2 coefficients are positive but statistically insignificant. This is in contrast to the weak herding results for A-share stocks found in Table 3. Meanwhile, consistent with the results in Table 3, the α_2 estimates are significantly negative for both Shanghai B and Shenzhen B shares. Fore example, a 1% increase in trading volume will result in 0.3% decrease in the cross-sectional dispersion. In other words, there herding exists in both B-share markets. We can further study herding behavior using the RCSDCR measure. Since the RCSDCR measure has already been discounted for informational effect, we exclude the last term in equation (12), which is equation (12)'. The result in Table 4 indicates that α_2 is also negative and significant at the 1% level. Therefore, our alternative tests using trading volume also strongly support the finding of herding behavior in the B-share market. More important, the results in Table 4 support our conjecture that herding behavior is more likely to emerge when there is less information in the market.

4. Robust analysis

As we employ an equally weighted measure, the aggregate results that are reported in Table 4 may be influenced by the smaller stocks in each market. An examination of the relative influence of small versus large stocks is especially important in light of the fact that small stock portfolios may react differently under different conditions than large stock portfolios. We reexamine the relationship between cross-sectional dispersion and trading volume in detecting herding using size-based quintile portfolios for each market. Moreover, herding may occur in different sectors of the market. We will also examine the issue using industry portfolios.

4.1 Size-based and industry-ranked portfolio tests

Since the results are not very different between Shanghai A and Shenzhen A, or between Shanghai B and Shenzhen B, we combine the two A-share markets together and the two B-share markets together. We categorize each stock in a given market into quintiles according to its market capitalization at the end of the year that immediately preceded the measurement year. These portfolios are reconstructed each year to reflect any changes in the market capitalization of individual stocks in the aggregate portfolio. We compute the RCSDI measure and estimate equation (12) for each portfolio. The results for all of the portfolios under different classes are reported in Table 5.

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Please Insert Table 5 Here

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Except for the estimates of α_2, the general results for quintile portfolios resemble those from the aggregate market. In particular, for the A-share markets, the estimates of α_2 are not only similar, but are also significant at the 1% level. The estimates of α_2, however, are now also significant at the 1% level. This suggests that investors may have pursued a momentum trading strategy on individual stocks in the size portfolios instead of herding. The fact that this effect is not strong in Table 4 indicates that momentum strategy is implemented only on a few stocks at any given time. In contrast, the results for the B share markets are very similar to those in Table 4. We continue to see that the estimates of α_2 are negative and very significant. Therefore, herding exists across different sizes of stocks in the market. At the same time, the estimates of α_2 seem to decrease in absolute value with the size of the portfolio. This suggests that herding easily occurs among small stocks. This makes perfect sense, since there is less information for small stocks than for large stocks in general.

Similar to size groups, one might argue that stocks from different industries have experienced different herding behavior. Anecdotal evidence and conversations with institutional investors suggest that investors tend to show extreme interest in stocks in some industry groups. We thus sort all A-share stocks into thirteen industry portfolios according to the standard Chinese classifications, including Agriculture, Mining, Manufacturing, Utilities, Construction, Transportation, Information Technology, Wholesale and Retail, Finance and Insurance, Real Estate, Services, and Telecommunications. Since there are too few stocks in Agriculture, Mining, Finance and Insurance, and Telecommunications for the B-share markets, we exclude these industries in our sample. We have estimated the RCSDI measure for each industry and carried regressions of equation (12) in Table 6.

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Please Insert Table 6 Here

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Except for the Mining industry, both α_2 and α_3 estimates are positive and statistically significant at the 1% level. Therefore, the no herding conclusion continues to hold even at the industry level. As been argued above, the positive coefficient α_2 may indicate momentum trading activities. By comparing the magnitude of the α_2 estimates across industries, we find that momentum trading activities are more frequent in the Utilities, Construction, Transportation, Finance, Services, and Telecommunications industries. For the B-share markets, α_2 estimates are negatively significant at the 1% level for seven out of the nine industries examined, even though there are only five significant α_3 estimates. In other words, there is herding behavior in most of the industry groups in the B-share markets. Utilities and Construction are the two large industries that lack evidence of herding behavior. This makes sense, since these are mature, predictable and well-known industries. Therefore, herding exists in most of the industry groups of the B-share markets.

4.2 Testing herding based on GARCH model specifications

When investors herd in a particular sector of the market, not only will the cross-sectional dispersion of returns decrease, the portfolio return itself will move closer to the overall market movement since the returns of individual stocks will be similar at that particular time. In other words, the conditional idiosyncratic volatility of the portfolio will move counter cyclically to the absolute market movement. In order to assess the possible effects of heteroscedasticity during large price movements, the market microstructure effect, and the effect of the idiosyncratic components of different portfolios on the herding behavior, we use the more elaborate GARCH model (10) with the last equation replaced by equation (11) to account for possible asymmetry in the up and down market. In particular, we first form five portfolios in each of the four markets. The corresponding results are reported in Table 7.

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For size-ranked portfolios, both estimates of the autoregressive and moving average coefficients γ_I and α for the conditional idiosyncratic volatility are very small. For example, the γ_I estimates range from 0.05 to 0.16 and are all significant at the 1% level, while the α estimates are mostly insignificant at the conventional level. Therefore, innovations in the returns of individual portfolios do not affect conditional idiosyncratic volatilities. At the same time, innovations in the market returns impact the conditional idiosyncratic volatilities of the portfolio in an important way. As shown in Table 7, for A-shares, the λ estimates are all significant at the 1 % level. Although most λ coefficient estimates are positive, it is negative for the smallest size portfolio. We thus conclude that there is no herding activity in A-share markets, except among small stocks. In contrast, the λ estimates are all negative and statistically significant at the 1% level for B-share size portfolios. Once again, evidence form the GARCH model specifications strongly support herding behavior in the B-share markets.

Our GARCH specification also allows us to study the asymmetry of the herding behavior. This is captured by the coefficient c_I. As shown in Table 7, c_Is are all negative and significant at the 1% level for B-share size portfolios. From equation (11), this could simply mean that the herding effect is stronger for the up market than for the down market. This could also suggest momentum trading in the up market, as argued before.

As shown in Table 6, herding behavior may vary across industries. We therefore apply the same GARCH model of equations (10) and (11) to the thirteen industries for A-shares in Table 8. For all of the industries in each market, the coefficient estimates γ_I are significant at the

1% level. The persistence measure ($\gamma_1 + \alpha$) seems to be much larger than that using size portfolios. The herding estimates λ are all positive and statistically significant at the 1% level. This indicates that there is no herding in all of the industry groups in the A-share markets. Moreover, most of the asymmetric parameter estimates cs are negative and significant, which means that investors trade more actively and aggressively in the up market. This finding is inconsistent with the directional asymmetry documented by McQueen et al. (1996), which suggests that volatilities will increase more in a down market than in an up market since stocks react quickly to negative macroeconomic news, but some small stocks adjust to positive news about the economy with a delay. Instead, it could be due to momentum trading in the up market since short sales are prohibited in Chinese markets. It is also potentially consistent with the "Disposition Effect," since investors tend to unload their winning stocks more often than they will sell their losing stocks.

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For the B-share market, all of the λ coefficient estimates for different industry groups are now negative and statistically significant at the 1% level. It seems that the evidence of herding behavior in the B-share markets is both strong and robust to different specifications. The asymmetry parameters are as strong as those in the A-share market.

5. Concluding comments

Our empirical results indicate that during periods of extreme price movements, the relative equity return dispersions for both Shanghai-B and Shenzhen-B actually have decreased, which provides evidence supporting the presence of herding behavior. This result is robust to a different specification which controls for informational trading. However, for both Shanghai-A and Shenzhen-A stocks, we have found mixed and weaker results to support for herding. Since B-share investors are foreign investors, the differential herding behavior of local and foreign investors suggests that, in the presence of inefficient information disclosure, foreign participants tend to lack fundamental and private information on firms, which may cause them to trade according to other signals. We have also found that herd behavior may be more relevant on the downside than on the upside. Consistent with other studies, we have documented that both the systematic and idiosyncratic risks in the B-share market were higher than that in the A-share market. Relatively large idiosyncratic volatility in the B-share market may partly due to a liquidity reason. Despite that, the average R^2 for B-share stocks was larger than that of A-share stocks. In other words, the systematic risk has accounted for a relatively large portion of the overall security risk in the B-share markets. This evidence is consistent with the view that the relative scarcity of rapid and accurate firm-specific information in B-share market may cause investors to focus more on macroeconomic information.

In this study, we have also used an independent trading volume variable to construct tests for herding behavior. After controlling for informational trading indicated by the volume variable, we again have found herding behavior limited to the B-share markets. As anecdotal evidence suggests that herding might occur in some parts of the market, we have also investigated size portfolios and industry portfolios. The results have indicated that the herding phenomenon in the B-share markets is not driven by either large or small capitalization stocks. In addition, there might be some herding behavior among small stocks in the A-share markets. These results are robust to a GARCH specification.

This study provides a new insight as when investor might herd. Since the herding evidence limited to the B-share markets and the Chinese equity markets as a whole is inefficient and premature, it suggests that market efficiency is not sufficient to observe the herding behavior among investors. Therefore, lack of information and knowledge about the business of individual firms are more likely to cause investors to herd.

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Table 1. Market Model Regression Results

In panel A, we report the mean, 10%, 50%, and 90% percentiles of the adjusted R^2 value, where adjusted R^2 is the statistics from the market model regressions. The mean, 10%, 50%, and 90% percentiles of volatility are reported in panel B, where volatility is computed as the standard deviation of the returns for each stock. We also report differences in characteristics for stocks that issue both A and B shares in Panel C. BD stands for ($\beta_B - \beta_A$), where β_A and β_B are beta estimates from a market model fitted to the returns from A and B share stocks, respectively. "Total Volt." and "Idio. Volt." are total volatility and idiosyncratic volatility from a market model, respectively. T-statistics are computed as SQRT(N_1)*(Average CD)/(Std of CD) in brackets, where CD is the adjusted R^2, Beta, "Total Volt.," or "Idio. Volt."

Panel A: Market model adjusted R^2

Markets/Samples	Mean	10% percentile	50% percentile	90% percentile
Shanghai A	0.4695	0.3184	0.4563	0.6641
Shenzhen A	0.4493	0.3246	0.4558	0.5648
Shanghai B	0.5345	0.3838	0.5537	0.6768
Shenzhen B	0.5644	0.4241	0.5734	0.6884

Panel B: Volatility

Markets/Samples	Mean	10% percentile	50% percentile	90% percentile
Shanghai A	0.0253	0.0193	0.0256	0.0308
Shenzhen A	0.0277	0.0221	0.0274	0.0336
Shanghai B	0.0368	0.0331	0.0363	0.0414
Shenzhen B	0.0384	0.0331	0.0379	0.0453

Panel B: Trading volume ratio

Markets/Samples	Mean	10% percentile	50% percentile	90% percentile
Shanghai A	0.0053	0.0021	0.0047	0.0088
Shenzhen A	0.0062	0.0027	0.0056	0.0101
Shanghai B	0.0024	0.0012	0.0022	0.0034
Shenzhen B	0.0022	0.0007	0.0015	0.0047

Panel C: Difference in characteristics between B and A shares

	Adjusted R^2	Beta	Total Volt.	Idio. Volt.
Average Difference	0.1150	0.0140	0.0079	0.0029
t-ratio	(8.94)	(13.41)	(24.17)	(6.39)

Table 2. Summary Statistics of the Returns, *CSSD*s, *RCSDI*s and *RCSDCRs* for the Four China Markets

We require a stock with a minimum of 60 daily observations (about 3 months) and exclude observations with daily returns exceeding 50%. $R_{i,t}$ is the stock return of firm *i* at time *t* and $R_{m,t}$ is the equally weighted average of the *N* returns in the aggregate market portfolio at time *t*. $CSSD_t$ is the cross-sectional standard deviation computed as, $CSSD_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}$. $RCSDI_t$ is the relative cross-sectional dispersion of idiosyncratic returns computed as, $RCSDI_t = \sqrt{\frac{1}{N-1}\frac{1}{h_{m,t}}\sum_{i=1}^{N}(\varepsilon_{i,t} - \bar{\varepsilon}_t)^2}$,

where $\bar{\varepsilon}_t = \frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i,t}$, $\varepsilon_{i,t}$ is the idiosyncratic return from a market model, and $h_{m,t}$ is the conditional volatility of the market return estimated using a GARCH(1,1) model.

$RCSDCR_t$ is the relative cross-sectional dispersion of controlled residuals computed as, $RCSDCR_t = \sqrt{\frac{1}{N-1}\frac{1}{h_{m,t}}\sum_{i=1}^{N}(\eta_{i,t}^{B} - \bar{\eta}_t^{B})^2}$, whre η is obtained from regressing B share residual returns on A share residual returns of $\varepsilon_{i,t}^{B} = \alpha_0 + \alpha_1\varepsilon_{i,t}^{A} + \eta_{i,t}^{B}$ and $\bar{\eta} = \frac{1}{N_1}\sum_{i=1}^{N_1}\eta_{i,t}^{B}$

Markets/Variables (Sample Period) [Observ. No.]	Mean (%)	Std Dev. (%)	10 percentile %	50 percentile %	90 percentile %	Serial correlation at lag 1	2	3	5	20	Dickey-Fuller *p*-value
Shanghai A Shares (1/2/96 - 31/12/02) [1691]											
R_t	0.0935	1.9045	-1.8090	0.1185	1.9565	0.0060	0.0053	0.0625	0.0169	0.0308	0.0000637612
$CSSD_t$	2.0398	0.7369	1.2302	1.9142	2.9765	0.7631	0.7016	0.6590	0.6378	0.4719	0.0000637612
$RCSDI_t$	125.9486	48.7821	66.8097	120.0945	190.1845	0.7671	0.6805	0.6418	0.5736	0.3300	0.0000637612
Shenzhen A Shares (1/2/96- 31/12/02) [1691]											
R_t	0.1187	2.0977	-2.0650	0.1591	2.3516	0.0275	0.0373	0.0677	0.0177	-0.0148	0.0000637612
$CSSD_t$	2.1354	0.9028	1.2466	1.9508	3.2279	0.7950	0.7130	0.6730	0.6236	0.4320	0.0000637612
$RCSDI_t$	123.7588	50.2406	64.3194	116.7248	187.6453	0.8208	0.7454	0.6916	0.6188	0.2729	0.0000637612
Shanghai B Shares (1/2/96- 31/12/02) [1684]											
R_t	0.1273	2.6205	-2.5780	-0.0300	2.8614	0.1597	-0.0065	0.0426	0.0175	0.0329	0.0000637672
$CSSD_t$	2.3753	1.2057	0.6923	2.4194	3.7739	0.7450	0.7104	0.6722	0.7040	0.5943	0.0000637672
$RCSDI_t$	111.9800	71.9903	34.2393	99.1959	200.7528	0.7796	0.7578	0.6999	0.7171	0.5555	0.0000637672
Shenzhen B Shares (1/2/96- 31/12/02) [1642]											
R_t	0.1418	2.8814	-2.7450	-0.0130	3.1278	0.1862	0.0352	0.0886	0.0381	-0.0275	0.0000638044
$CSSD_t$	2.4395	1.2123	1.0458	2.3000	3.8891	0.6708	0.5886	0.5498	0.5315	0.4081	0.0000638044
$RCSDI_t$	105.0948	59.9663	41.5289	93.9967	182.3290	0.6838	0.6317	0.5867	0.5528	0.4527	0.0000638044
Whole market (1/2/96- 31/12/02) [1684]											
$RCSDCR_t$	157.3685	86.7313	55.0382	146.0519	269.3492	0.7796	0.7133	0.6744	0.6055	0.4042	0.0000637663

Table 3. Testing Herding for the Four China Markets during Periods of Extreme Market Movement using Different Measures

This table reports the GMM estimated coefficient of the following regression model,

$$CD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t ,$$

where CD_t are different measures of cross-sectional dispersion: *CSSD*, *RCSDI* and *RCSDCR*. D_t^L (D_t^U) equals 1 when market return day *t* lies in the extreme lower (upper) tail of the return distribution, and 0 otherwise. The 1%, 2%, and 5% criteria refer to the percentage of observations in the upper and lower tail of the market return distribution that are used to define days of extreme price movements. *F*-value shows the difference in significance between β^L and β^U. "***", "**", "*" stand for significance at the 1%, 5%, and 10% levels, respectively.

Markets /Measures	1% Criterion				2% Criterion				5% Criterion			
	α	β^L	β^U	*F-value*	α	β^L	β^U	*F-value*	α	β^L	β^U	*F-value*
Shanghai A Shares (1/2/96-12/31/02)												
CSSD	0.0202	0.0044	0.0062	0.47	0.0201	0.0060	0.0075	0.76	0.0198	0.0062	0.0057	0.19
	(112.681)***	(2.436)**	(3.406)***		(111.886)***	(4.726)***	(5.949)***		(108.049)***	(7.772)***	(7.158)***	
RCSDI	1.2655	-0.4313	-0.2076	1.69	1.2672	-0.1925	-0.2059	0.01	1.2738	-0.1076	-0.1807	0.95
	(106.080)***	(-3.534)***	(-1.701)*		(104.988)***	(-2.251)**	(-2.407)**		(102.273)***	(-1.975)**	(-3.317)***	
Shenzhen A Shares (1/2/96-12/31/02)												
CSSD	0.0211	-0.0003	0.0176	33.01***	0.0209	0.0063	0.0140	12.72***	0.0203	0.0083	0.0123	9.25***
	(97.309)***	(-0.145)	(7.941)***		(96.206)***	(4.131)***	(9.126)***		(93.735)***	(8.819)***	(13.007)***	
RCSDI	1.2442	-0.5673	-0.1374	5.92**	1.2455	-0.2530	-0.1574	0.60	1.2497	-0.1044	-0.1400	0.21
	(101.456)***	(-4.522)***	(-1.095)		(100.215)***	(-2.873)***	(-1.787)*		(97.283)***	(-1.859)*	(-2.493)**	
Shanghai B Shares (1/2/96-12/31/02)												
CSSD	0.0237	-0.0028	0.0026	1.65	0.0236	0.0020	0.0019	0.0007	0.0233	0.0036	0.0051	0.62
	(80.076)***	(-0.951)	(0.859)		(78.977)***	(0.972)	(0.934)		(75.716)***	(2.716)***	(3.800)***	
RCSDI	1.1300	-0.5863	-0.4953	0.13	1.1365	-0.3886	-0.4677	0.20	1.1468	-0.3245	-0.2184	0.92
	(64.106)***	(-3.258)***	(-2.752)***		(63.900)***	(-3.089)***	(-3.718)***		(62.409)***	(-4.046)***	(-2.723)***	
Shenzhen B Shares (1/2/96-12/31/02)												
CSSD	0.0241	0.0055	0.0148	4.77**	0.0240	0.0074	0.0082	0.07	0.0237	0.0053	0.0080	2.15
	(80.703)***	(1.848)*	(4.922)***		(79.518)***	(3.488)***	(3.861)***		(76.300)***	(3.909)***	(5.928)***	
RCSDI	1.0557	-0.4786	-0.0154	4.79**	1.0597	-0.2713	-0.1812	0.36	1.0676	-0.2030	-0.1315	0.58
	(70.819)***	(-3.185)***	(-0.103)		(70.356)***	(-2.540)**	(-1.697)*		(68.659)***	(-2.994)***	(-1.939)*	
Whole market (24/02/92-12/31/02)												
RCSDCR	1.5826	-0.5593	-0.3897	0.30	1.5868	-0.3687	-0.3051	0.09	1.6069	-0.3416	-0.3251	0.02
	(74.363)***	(-2.573)**	(-1.793)*		(73.788)***	(-2.424)**	(-2.005)**		(72.604)***	(-3.536)***	(-3.365)***	

Table 4. Testing Herding for the Four China Markets using Trading Volume

This table reports the GMM estimated coefficients of the following regression model:

$$\ln(RCSDI_t) = \alpha_0 + \alpha_1 \ln(RCSDI_{t-1}) + \alpha_2 \ln(V_{t-1}) + \alpha_3 \Delta \ln(V_t) + e_t \,,$$

where V_t is the average trading volume ratio for A or B shares at time t. For the $RCSDCR_t$ measures of cross-sectional dispersion, the following model is applied instead,

$$\ln(RCSDCR_t) = \alpha_0 + \alpha_1 \ln(RCSDCR_{t-1}) + \alpha_2 \ln(V_{t-1}) + e_t \,,$$

where V_t is the sum of average trading volume between A and B shares. $RCSDI_t$ and $RCSDCR_t$ are relative cross-sectional dispersion of idiosyncratic returns and controlled residuals defined in Section 2.1, respectively. "***", "**", "*" stand for significance at the 1%, 5%, and 10% levels, respectively.

Markets/ Measures	α_0	α_1	α_2	α_3	Adj R^2
Shanghai A Shares (1/2/96-12/31/02)					
$\ln(RCSDI_t)$	0.1220	0.8000	0.0160	0.3146	0.6910
	(2.546)**	(56.238)***	(1.957)*	(15.311)***	
Shenzhen A Shares (1/2/96-12/31/02)					
$\ln(RCSDI_t)$	0.0690	0.8533	0.0092	0.3424	0.7537
	(2.037)**	(68.931)***	(1.513)	(17.704)***	
Shanghai B Shares (1/2/96-12/31/02)					
$\ln(RCSDI_t)$	-0.4923	0.8290	-0.0700	0.1231	0.7700
	(-7.779)***	(65.689)***	(-7.616)***	(7.486)***	
Shenzhen B Shares (1/2/96-12/31/02)					
$\ln(RCSDI_t)$	-0.6394	0.7124	-0.0856	0.1028	0.6507
	(-10.139)***	(44.006)***	(-9.856)***	(6.494)***	
Whole market(1/2/96-12/31/02)					
$\ln(RCSDCR_t)$	-0.1682	0.8383	-0.0381		0.7058
	(-2.852)***	(63.398)***	(-3.733)***		

Table 5. Testing Herding for Size-Ranked Portfolios using Trading Volume

This table reports the GMM estimated coefficients of the following regression models:

$$\ln(RCSDI_t) = \alpha_0 + \alpha_1 \ln(RCSDI_{t-1}) + \alpha_2 \ln(V_{t-1}) + \alpha_3 \Delta \ln(V_t) + e_t ,$$

where V_t is the average trading volume ratio for A or B shares at time t and $RCSDI_t$ is relative cross-sectional dispersion of idiosyncratic returns defined in Section 2.1. "***", "**", "*" stand for significance at the 1%, 5%, and 10% levels, respectively.

Markets/Measures	α_0	α_1	α_2	α_3	Adj R^2
A Shares					
Portfolio 1	0.1738	0.7850	0.0253	0.3484	0.6674
(smallest)	(3.959)***	(53.126)***	(2.943)***	(14.213)***	
Portfolio 2	0.1344	0.7991	0.0203	0.2909	0.6810
	(3.318)***	(55.517)***	(2.640)***	(12.854)***	
Portfolio 3	0.1640	0.7716	0.0259	0.3180	0.6528
	(3.856)***	(50.853)***	(3.299)***	(13.889)***	
Portfolio 4	0.1797	0.7491	0.0285	0.3533	0.6298
	(4.080)***	(47.713)***	(3.621)***	(15.963)***	
Portfolio 5	0.1502	0.7412	0.0224	0.3481	0.6217
	(2.976)***	(47.040)***	(2.768)***	(16.715)***	
B Shares					
Portfolio 1	-0.6862	0.6414	-0.1009	0.0868	0.5656
(smallest)	(-9.832)***	(35.395)***	(-10.247)***	(4.672)***	
Portfolio 2	-0.5987	0.7125	-0.0857	0.0831	0.6484
	(-9.684)***	(43.552)***	(-9.632)***	(5.170)***	
Portfolio 3	-0.5446	0.7484	-0.0740	0.1017	0.6624
	(-8.584)***	(48.912)***	(-8.264)***	(6.174)***	
Portfolio 4	-0.6149	0.7344	-0.0814	0.1049	0.6342
	(-8.522)***	(46.877)***	(-8.037)***	(6.154)***	
Portfolio 5	-0.6964	0.7053	-0.0883	0.1022	0.6023
	(-8.934)***	(42.682)***	(-8.274)***	(5.564)***	

Table 6. Testing Herding for Industry-Ranked Portfolios using Trading Volume

This table reports the GMM estimated coefficients of the following regression models:

$$\ln(RCSDI_t) = \alpha_0 + \alpha_1 \ln(RCSDI_{t-1}) + \alpha_2 \ln(V_{t-1}) + \alpha_3 \Delta \ln(V_t) + e_t ,$$

where V_t is the average trading volume ratio for A or B shares at time t and $RCSDI_t$ is relative cross-sectional dispersion of idiosyncratic returns defined in Section 2.1. "***", "**", "*" stand for significance at the 1%, 5%, and 10% levels, respectively.

Markets/Measures	α_0	α_1	α_2	α_3	Adj R^2
A Shares					
Agriculture	0.1941	0.5212	0.0290	0.4778	0.3599
	(3.091)***	(26.214)***	(2.398)**	(16.415)***	
Mining	-0.1256	0.4653	-0.0053	0.4304	0.2525
	(-1.768)*	(21.133)***	(-0.460)	(11.194)***	
Manufacturing	0.1828	0.7741	0.0263	0.3198	0.6561
	(3.793)***	(51.275)***	(3.133)***	(14.596)***	
Utilities	0.3859	0.6503	0.0641	0.3582	0.5329
	(6.141)***	(35.667)***	(6.251)***	(14.854)***	
Construction	0.4033	0.5008	0.0753	0.4945	0.3703
	(5.610)***	(24.524)***	(5.881)***	(16.442)***	
Transportation	0.2920	0.6116	0.0486	0.4271	0.4648
	(5.029)***	(32.595)***	(4.914)***	(17.045)***	
Information Technology	0.2196	0.6520	0.0314	0.3976	0.5089
	(3.840)***	(36.667)***	(2.988)***	(16.580)***	
Wholesale and Retail	0.2127	0.7368	0.0340	0.3703	0.6107
	(4.366)***	(45.789)***	(3.761)***	(15.528)***	
Finance and Insurance	0.0565	0.3483	0.0501	0.4195	0.2064
	(0.795)	(15.697)***	(3.868)***	(14.603)***	
Real Estate	0.1924	0.6493	0.0292	0.3727	0.4932
	(3.221)***	(36.207)***	(2.800)***	(15.463)***	
Services	0.3785	0.6410	0.0615	0.3837	0.5048
	(5.644)***	(34.880)***	(5.334)***	(15.262)***	
Telecommunications	0.3589	0.5368	0.0552	0.4694	0.3820
	(4.273)***	(26.991)***	(3.693)***	(16.448)***	
Conglomerates	0.2058	0.7344	0.0306	0.3781	0.6120
	(4.511)***	(45.772)***	(3.602)***	(16.173)***	
B shares					
Manufacturing	-0.4893	0.7980	-0.0709	0.0736	0.7478
	(-8.721)***	(59.583)***	(-8.718)***	(5.032)***	
Utilities	-0.5528	0.4031	-0.0257	0.1671	0.1778
	(-3.964)***	(17.884)***	(-1.281)	(5.635)***	
Construction	-1.3275	0.1284	0.0448	0.1276	0.0162
	(-5.683)***	(3.014)***	(1.244)	(1.842)*	
Transportation	-0.7928	0.4338	-0.0841	0.0160	0.2437
	(-8.078)***	(20.195)***	(-6.422)***	(0.732)	
Information Technology	-0.7728	0.4772	-0.0987	0.0743	0.2632
	(-6.043)***	(22.175)***	(-5.371)***	(2.814)***	
Wholesale and Retail	-1.4916	0.3042	-0.1657	-0.0037	0.2104
	(-12.463)***	(13.005)***	(-10.772)***	(-0.156)	
Real Estate	-1.1062	0.5444	-0.1262	0.1161	0.4162
	(-10.488)***	(27.469)***	(-9.360)***	(4.844)***	
Services	-0.9350	0.5530	-0.1162	0.0727	0.3710
	(-8.061)***	(27.774)***	(-7.013)***	(2.938)***	
Conglomerates	-1.7772	0.3141	-0.1814	0.0320	0.2080
	(-11.655)***	(13.387)***	(-10.100)***	(1.121)	

Table 7. GARCH model (size ranked portfolios)

Test the herd behavior based on the following GARCH model

$$\begin{cases} \tilde{r}_{m,t+1} = \sigma_{m,t}\xi_{m,t+1} \\ \sigma^2_{m,t} = \omega_m + \gamma_m \sigma^2_{m,t-1} + \alpha_m \xi^2_{m,t} \\ \tilde{r}_{i,t+1} = \sigma_{i,t}\xi_{i,t+1} \\ \sigma^2_{i,t} = \sigma^2_{I,i,t} + \sigma^2_{m,t} \\ \sigma^2_{I,i,t} = \omega_{I,i} + \gamma_{I,i}\sigma^2_{I,i,t-1} + \alpha_i \xi^2_{i,t} + \lambda_{I,i}[|\xi_{m,t}| - c_{I,i}\xi_{m,t}] \end{cases}$$

where $\tilde{r}_{m,t}$ and $\tilde{r}_{i,t}$ are demeaned market return and the *i*-th size portfolio return, respectively.

Markets/Measures	$\omega_{I,i}$	$\gamma_{I,i}$	α_i	$\lambda_{I,i}$	$c_{I,i}$	Log-likelihood
A Shares						
Portfolio 1 (smallest)	0.00003	0.1603	0.1214	-0.0001	-0.0896	4793
	(10.9341)***	(25.1402)***	(5.2136)***	(-18.4011)***	(-2.0136)**	
Portfolio 2	0.00001	0.0903	0.0491	0.0003	0.2107	5006
	(0.2886)	(4.9457)***	(0.1515)	(21.1904)***	(4.9908)***	
Portfolio 3	0.00002	0.0854	0.0397	0.0003	0.0669	5062
	(0.5951)	(6.0207)***	(0.7830)	(22.6403)***	(1.7115)*	
Portfolio 4	0.00004	0.1117	0.0461	0.0002	0.0443	5043
	(1.1133)	(6.0992)***	(1.3367)	(22.1934)***	(1.1318)	
Portfolio 5	0.00002	0.1131	0.0259	0.0003	0.0566	5087
	(0.8429)	(5.8261)***	(1.4504)	(20.9573)***	(1.3217)	
B Shares						
Portfolio 1 (smallest)	0.00003	0.0834	0.0179	-0.0006	-0.2542	4311
	(8.7716)***	(6.0502)***	(0.3788)	(-25.7062)***	(-6.9054)***	
Portfolio 2	0.00001	0.0923	0.0209	-0.0005	-0.1230	4448
	(6.8529)***	(5.8815)***	(1.4276)	(-18.3749)***	(-2.478)**	
Portfolio 3	0.00001	0.1024	0.0229	-0.0006	-0.1350	4411
	(3.7913)***	(4.9992)***	(1.0392)	(-17.0698)***	(-2.7362)***	
Portfolio 4	0.00005	0.0486	0.0218	-0.0005	-0.1828	4539
	(2.6530)**	(4.4989)***	(0.2286)	(-21.6239)***	(-4.4886)***	
Portfolio 5	0.0002	0.1013	0.0979	-0.0005	-0.1231	4650
	(2.5927)**	(6.1081)***	(1.0168)	(-20.3718)***	(-2.4209)**	

Table 8. GARCH model (industry portfolios)

Test the herd behavior based on the following GARCH model

$$\begin{cases} \tilde{r}_{m,t+1} = \sigma_{m,t}\xi_{m,t+1} \\ \sigma^2_{m,t} = \omega_m + \gamma_m \sigma^2_{m,t-1} + \alpha_m \xi^2_{m,t} \\ \tilde{r}_{i,t+1} = \sigma_{i,t}\xi_{i,t+1} \\ \sigma^2_{i,t} = \sigma^2_{I,i,t} + \sigma^2_{m,t} \\ \sigma^2_{I,i,t} = \omega_{I,i} + \gamma_{I,i}\sigma^2_{I,i,t-1} + \alpha_i \xi^2_{i,t} + \lambda_{I,i}[|\xi_{m,t}| - c_{I,i}\xi_{m,t}] \end{cases}$$

where $\tilde{r}_{m,t}$ and $\tilde{r}_{i,t}$ are demeaned market return and the *i*-th industry portfolio return, respectively.

Markets/Measures	$\omega_{I,i}$	$\gamma_{I,i}$	α_i	$\lambda_{I,i}$	$c_{I,i}$	Log-likelihood
A Shares						
Agriculture	0.00001	0.1252	0.0125	0.0003	-0.0582	4792
	(0.0914)	(8.1313)***	(1.0959)	(23.9865)***	(-1.6007)	
Mining	0.00003	0.5414	0.2054	0.0002	-0.1695	4155
	(11.9962)***	(18.0560)***	(9.4286)***	(15.2986)***	(-4.1125)***	
Manufacturing	0.0001	0.1328	0.0559	0.0002	-0.2627	5086
	(0.7357)	(6.3415)***	(1.2375)	(18.9635)***	(-5.4809)***	
Utilities	0.00001	0.0984	0.0173	0.0003	0.0775	4920
	(0.4809)	(6.4792)***	(1.8941)*	(21.2819)***	(1.8371)*	
Construction	0.00004	0.1255	0.0464	0.0003	-0.1210	4778
	(0.4943)	(7.0810)***	(3.1294)***	(23.9475)***	(-3.2377)***	
Transportation	0.00005	0.0973	0.0178	0.0003	-0.1495	4892
	(7.4925)***	(6.4081)***	(1.1526)	(22.1239)***	(-3.5857)***	
Information Technology	0.00003	0.0899	0.0444	0.0003	0.0315	4792
	(2.4450)**	(6.8798)***	(1.1740)	(20.1539)***	(0.7445)	
Wholesale and Retail	0.00001	0.1106	0.0645	0.0003	-0.1701	5027
	(0.7441)	(7.0146)***	(0.9600)	(21.1156)***	(-3.8785)***	
Finance and Insurance	0.00003	0.4698	0.2021	0.0002	-0.1106	4298
	(7.4554)***	(9.2971)***	(6.7241)***	(17.3628)***	(-2.4689)**	
Real Estate	0.0001	0.1102	0.0166	0.0003	0.0890	4763
	(0.3462)	(6.1681)***	(1.6381)	(20.2601)***	(1.9669)*	
Services	0.00001	0.1088	0.0391	0.0003	-0.1063	4947
	(0.1866)	(5.8839)***	(1.3759)	(20.4587)***	(-2.5769)***	
Telecommunications	0.00000	0.2028	0.1534	0.0003	-0.0249	4584
	(0.3706)	(7.4593)***	(6.5607)***	(16.3890)***	(0.4994)	
Conglomerates	0.00001	0.0531	0.0192	0.0003	-0.1316	4997
	(0.5870)	(5.2617)***	(1.0761)	(22.8077)***	(-3.3498)***	
B shares						
Manufacturing	0.00001	0.0523	0.0183	-0.0005	-0.1835	4689
	(0.6212)	(5.9423)***	(0.9105)	(-22.6209)***	(-4.7902)***	
Utilities	0.00001	0.1268	0.0268	-0.0007	0.0316	4181
	(1.5094)	(8.4105)***	(1.5083)	(-28.6484)***	(0.9731)	
Construction	0.00006	0.6591	0.2083	-0.0004	-0.2640	2838
	(14.0759)***	(17.8919)***	(13.0955)***	(-13.8418)***	(-6.1020)***	
Transportation	0.00001	0.147	0.0474	-0.0006	-0.0456	4218
	(1.6790)*	(8.8316)***	(3.4108)***	(-22.0356)***	(-1.0698)	
Information Technology	0.00008	0.1586	0.0174	-0.0006	-0.0421	3964
	(7.1017)***	(8.1167)***	(0.7632)	(-17.0368)***	(-1.7592)*	
Wholesale and Retail	0.00001	0.1545	0.0335	-0.0007	-0.0620	3885
	(10.2325)***	(6.6279)***	(1.4258)	(-16.4888)***	(-1.1928)	
Real Estate	0.00003	0.0979	0.0167	-0.0007	-0.0182	4195
	(9.8224)***	(5.3490)***	(1.1009)	(-18.9673)***	(-3.7541)***	
Services	0.00003	0.0703	0.0211	-0.0006	-0.0971	4202
	(4.8584)***	(4.1837)***	(1.3501)	(-17.5406)***	(-1.9720)**	
Conglomerates	0.00002	0.2647	0.0639	-0.0006	-0.1053	3560
	(2.2408)**	(7.7487)***	(3.2983)***	(-14.6185)***	(-1.7070)*	