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Empirical investigation of herding behavior in Chinese stock markets: Evidence from quantile regression analysis

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ABSTRACT

This study examines the herding behavior of investors in Chinese stock markets. Using a least squares method, we find evidence of herding within both the Shanghai and Shenzhen A-share markets and no evidence of herding within both B-share markets. A-share investors display herding formation in both up and down markets. However, we cannot find herding activity for B-share investors in the up market. By applying quantile regression analysis to estimate the herding equation, we find supporting evidence of herding behavior in both A-share and B-share investors conditional on the dispersions of returns in the lower quantile region.

1. Introduction

In the recent finance literature, empirical analysis of herding behavior has received considerable attention in studies examining the grouping behavior of investors. The importance of investigating herding behavior stems from the fact that investors, following the actions of others, tend to form a collective decision that, in turn, drives stock prices away from their underlying fundamental values. The resulting divergence between market price and fundamental value offers arbitragers an opportunity to reap excess profits. A long-run consequence of this herding behavior may lead to greater instability and inefficiency if the market correction fails to make the market price and the fundamental value converge.

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Numerous papers have been devoted to the study of herding activities in global markets.[1] For instance, by applying firm-level data to examine whether investors in global markets have a tendency to exhibit herd behavior, Chang, Cheng, and Khorana (2000) find significant evidence of herding in South Korea and Taiwan and partial evidence of herding in Japan. However, there is no evidence of herding for market participants in the U.S. and Hong Kong. The evidence indicates that herding behavior is more likely taking place in emerging markets. Following the same approach, Demirer and Kutan (2006) test whether investors in Chinese markets, in making their investment decisions, are following market consensus during periods of market stress rather than private information. Their test results find no evidence of herd formation, suggesting that market participants in Chinese stock markets make investment choices rationally. However, a recent study of Chinese stock markets by Tan, Chiang, Mason, and Nelling (2008) reports that herding occurs under both rising and falling market conditions. This herding phenomenon is more profound in A-share investors.[2] Thus, the evidence on herding behavior in the Chinese markets is inconclusive.

This paper attempts to provide new empirical evidence that helps to resolve the mixed findings of herding behavior in Chinese markets. Our study is also motivated by the inadequacy of using aggregate data in analyzing herding behavior. In particular, previous studies of Chinese stock market behavior customarily follow the classifications A-share vs. B-share markets or Shanghai stock exchange vs. Shenzhen stock exchange. While this conventional approach offers a general direction for herding activity in terms of market classification, its drawback is that it fails to provide precise information that explains behavioral changes conditional on a particular market condition.

The approach used by Christie and Huang (1995), Chang et al. (2000), and Gleason, Mathur and Peterson (2004) attempts to argue that the formation of herds is more likely to be present during periods of market stress, since investors are more likely to suppress their own beliefs and use market consensus during large changes in price. The testing methodology thus suggests that equity return dispersions are sensitive to aggregate market returns squared, especially during periods of market stress. If applying least squares estimators produces a negative coefficient on the market return squared term, it would suggest the existence of herding behavior.

It is generally recognized that least squares estimators are based on the *mean* of the conditional distribution of stock return dispersions. Such a model specification is inconsistent with behavior involving stressful environments, since the tail information has not been addressed. The innovation of this paper is to examine the data conditional on different quantiles and test the behavioral relation between stock return dispersions and aggregate market movements with different quantile distributions. An additional benefit from using quantile regression is that some of the statistical problems, such as errors in variables, sensitivity to outliers, and non-Gaussian error distribution, can be alleviated (Barnes & Hughes, 2002).

The remainder of this paper is organized as follows. Section 2 presents the methodology used to detect herding behavior. Section 3 describes the data. Section 4 reports evidence of herding behavior based on a least squares estimator by organizing Chinese stock data into aggregate level, A-share and B-share groups, and four sub-markets. Section 5 presents a quantile regression method and applies it to estimate the herding equation. Section 6 concludes the paper.

2. Detecting herding behavior by investors

Two studies that have proposed methods of detecting herding behavior using stock return data are Christie and Huang (1995) (hereafter CH) and Chang et al. (2000) (hereafter CCK). CH suggest that the investment decision-making process used by market participants depends on overall market conditions. They contend that during normal periods, rational asset pricing models predict that the dispersion in returns will increase with the absolute value of the market return, since individual investors are trading based on their own private information, which is diverse. However, during periods of extreme market movements, individuals tend to suppress their own beliefs, and their investment decisions are more likely

[1] Herding behavior has been studied for various groups, including mutual fund managers (Lakonishok, Shleifer, & Vishny, 1992; Wermers, 1999); financial analysts (Trueman, 1994; Graham, 1999; Welch, 2000; Hong, Kubik, & Solomon, 2000; Clement & Tse, 2005), and market participants (Chang et al., 2000).

[2] Hwang and Salmon (2006) examine herding behavior in the U.S., U.K., and South Korean stock markets, and they find beta herding when investors believe that they know where the market is heading rather than when the market is in crisis.

based on the collective actions in the market. Individual stock returns under these conditions tend to cluster around the overall market return. Thus, CH argue that herding will be more prevalent during periods of market stress, which is defined as the occurrence of extreme returns on the market portfolio. Christie and Huang (1995) use the following equation in their empirical specification:

$$RD_t = \alpha + \beta^L I_t^L + \beta^U I_t^U + \varepsilon_t \tag{1}$$

where RD_t is the return dispersion at time t. I_t^L is an indicator variable at time t taking on the value of unity when the market return at time t lies in the extreme lower tail of the distribution, and 0 otherwise. Similarly, I_t^U is an indicator variable with a value of unity when the market return at time t lies in the extreme upper tail of the distribution, and 0 otherwise. To measure the return dispersion, CH propose the cross-sectional standard deviation (CSSD) method, which is expressed as:

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

where N is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm i at time t, and $R_{m,t}$ is the cross-sectional average stock of N returns in the portfolio at time t. CH's model suggests that if herding occurs, investors will make similar decisions, leading to lower return dispersions. Thus, statistically significant negative values for β^L and β^U in Eq. (1) would indicate the presence of herding.

Demirer and Kutan (2006) apply the CH method to examine herding in Chinese equity markets. They use daily stock return data from 1999 to 2002 for 375 Chinese stocks and find no evidence of herding. One of the challenges associated with the approach described above is that it requires the definition of extreme returns. CH note that this approach is rather arbitrary by using a value of 1% or 5% as the cutoff point to identify the upper and lower tails of the return distribution. In practice, investors may differ in their opinions as to what constitutes an extreme return, and the characteristics of the return distribution may change over time. In addition, herding behavior may occur to some extent over the entire return distribution but may become more pronounced during periods of market stress. In fact, the CH method captures herding only during periods of extreme returns. Additional challenges arise when applying this method to Chinese stock market data, since the relatively short history of these markets makes it difficult for investors to identify when extreme returns occur.

Chang et al. (2000) propose an alternative approach to test for herding. CCK note that the CH approach is a more stringent test, which requires "a far greater magnitude of non-linearity" in order to find evidence of herding. CCK's herding test facilitates the detection of herding over the entire distribution of market returns. They construct $CSAD_t$ as a measure of return dispersion, which is derived by calculating the cross-sectional absolute deviation:

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

With the measure of stock return dispersions, we can set up the herding equation as:

$$CSAD_t = \gamma_0 + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4}$$

where $R_{m,t}$ is the equally weighted average stock return in the dual-listed portfolio.[3] Note that both $|R_{m,t}|$ and $R_{m,t}^2$ terms appear in the right-hand side of Eq. (4). This is based on the rationale that under normal conditions, a linear relationship between the return dispersion and market volatility is anticipated. However, during periods of relatively large price swings, in which market participants are more likely to herd around indicators such as the average consensus of all market opinions, the relation between CSAD and the average market return is more likely to be nonlinear. For this reason, a nonlinear market return, $R_{m,t}^2$, is

[3] We also construct a $CSAD_t$ measure from a value-weighted portfolio using two different weighting methods: one based on total market value, and another based on the market value of shares in circulation (sometimes referred to as "the float"). We test all empirical results for robustness using these alternatives. The results obtained using these alternatives are very similar; so in the interest of brevity, we report only the results for the equally weighted portfolio.

included in the test equation. Thus, a significantly negative coefficient γ_2 in the empirical test will indicate the occurrence of herding behavior, since it reflects the phenomenon that during periods of market stress, a negative, nonlinear relationship between return dispersion and $R^2_{m,t}$ exists.

Note that the model specification in Eq. (4) restricts γ_1 to be the same for both up and down markets; no consideration is given to asymmetric effects arising from market risings or falls. To capture this asymmetry, Eq. (4) can be alternatively written as:

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 D\ R_{m,t} + \gamma_3 R^2_{m,t} + \varepsilon_t \tag{5}$$

where D is a dummy variable. In Eq. (5), we can investigate asymmetry in linear terms of market return by setting $D=1$ if $R_{m,t}<0$, and $D=0$ otherwise.[4] As we stated earlier, if herding exists, we expect γ_3 to be negative and statistically significant.

3. Data

We collect data on stock prices and turnover ratios for all firms listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) over the period January 1, 1996, to April 30, 2007. There are 861 Shanghai A-share firms (SHA), 55 Shanghai B-share firms (SHB), 639 Shenzhen A-share firms (SZA), and 59 Shenzhen B-share firms (SZB). Each firm's industry code is also collected from the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The industry distribution for all firms is listed in the Appendix. We also collect the Shanghai Composite Index, Shanghai A-share Index, the Shanghai B-share Index, the Shenzhen Composite Index, the Shenzhen A-share Index, and the Shenzhen B-share Index. The returns for individual stocks and the market are calculated as $R_t = 100 \times (\ln(P_t) - \ln(P_{t-1}))$. Because B-shares are denominated in U.S. dollars or Hong Kong dollars for Shanghai B- and Shenzhen B-shares, respectively, the returns on B-shares are computed after adjusting for exchange rate effects.[5] We use daily stock return data in our herding tests. The sample consists of 2736 daily return observations for Shanghai A and Shenzhen A-shares, 2730 observations for Shanghai B-shares, and 2690 observations for Shenzhen B shares.[6]

4. Empirical results

4.1. Descriptive statistics

Table 1 contains a summary of statistics for cross-sectional absolute deviations. Panel A reports the statistics for the aggregate Chinese market, which includes all listed firms; Panel B reports those for A- and B-share markets; and Panel C contains statistics separately for Shanghai A- and B- and Shenzhen A- and B-share markets. The statistics show that the mean values of *CSAD* for A-shares are consistently higher than those of B shares, accompanied by lower standard deviations. This holds true for both the Shanghai and the Shenzhen exchanges and for A- and B-share markets as a whole. The statistical results are interesting. Even though the A-share market lists more than 90% of the stocks offered on the Chinese stock market and the B-share market lists less than 10%, the A-share return dispersion has a smaller standard deviation than that of the B-share market. This statistic is consistent with the behavior that investors in B-share markets are more likely to react to news and diverse shocks.

4.2. Evidence on herding

In the empirical estimations, we shall present the estimates of the herding equation in the following order. First, we report the aggregate market, and then we examine A-share and B-share market portfolios, which

[4] Duffee (2000) adds the $R_{m,t}$ to the equation as: $CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2|R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$. It can be shown that $\gamma_2 + \gamma_1$ captures the relation between return dispersion and market return when $R_{m,t}>0$, while $\gamma_2 - \gamma_1$ shows the relation when $R_{m,t} \leq 0$.

[5] The B-share returns in either currency are very similar.

[6] Slight differences in non-trading days arise between A-share and B-share markets. For instance, on February 11, 2001, when the China Securities Regulatory Commission (CSRC) announced that A-share investors may purchase B-shares, B-shares stopped trading between the 20th and 23rd of February 2001.

Table 1
Descriptive statistics of cross-sectional absolute deviations.

Statistic	Observations	Minimum	Maximum	Mean	Standard deviation
Panel A: Statistics for Chinese aggregate market $CSAD_t$					
China	2736	0.762	7.594	2.523	0.952
Panel B: Statistics for A-share and B-share market $CSAD_t$					
A-share	2736	0.785	7.908	2.441	0.953
B-share	2730	0.217	10.633	2.350	1.208
Panel C: Statistics for four Chinese market $CSAD_t$					
SHA	2736	0.738	9.759	2.369	0.979
SHB	2730	0.266	11.239	2.107	1.235
SZA	2736	0.022	11.023	2.416	1.046
SZB	2690	0.059	12.851	2.271	1.213

This table lists descriptive statistics of daily equally weighted cross-sectional absolute deviations ($CSAD_t$) for Shanghai A (*SHA*), Shanghai B (*SHB*), Shenzhen A (*SZA*), and Shenzhen B (*SZB*) stock markets. The data range is from 1/1/1996 to 4/30/2007.

allows us to compare the difference in performance between A-share and B-share markets. Afterwards, we examine four sub-markets sorted by stock exchange locations and A- or B-share markets: Shanghai A-shares (SHA), Shanghai B-shares (SHB), Shenzhen A-shares (SZA), and Shenzhen B-shares (SZB). Grouping the data by different classifications will help us to allocate the source of variations in the empirical analysis.

Table 2 reports the results of estimating the herding regression represented by Eq. (4), which is in the spirit of CCK's specification. As suggested in the literature, a negative value on the coefficient γ_2 is consistent with herding.[7] The statistics reported in Panel A are based on the data of the entire market, which includes all listed stocks.[8] The test result shows that the coefficient on the market return square, γ_2, is negative and statistically significant, suggesting that herding behavior exists in the Chinese market.

By dividing the entire market into A-shares and B-shares on the two exchanges, we re-estimate the test equation and the results are contained in Panel B. The evidence indicates that the A-share market presents herding behavior, while there is no supporting evidence for the B-share market.

Further analyzing the data by separating the sample into A-share and B-share markets with the stocks listed on the Shanghai and Shenzhen stock exchanges, respectively, we find that the estimated coefficient of γ_2 reported in Part I of Panel C to be significantly negative for both A-share markets, while the coefficient for B-share markets is insignificant, suggesting that both A-share markets display herding behavior. No evidence is found in both B-share markets. Since the A-share markets are dominated by individual Chinese investors, and B-share markets are dominated by institutional investors from developed countries, the findings can be interpreted as being consistent with those of CCK, who find evidence of herding in emerging markets and no evidence of herding in developed markets.

We also test the herding equation by restricting it to data on the dual-listed firms. The evidence in Part II of Panel C indicates no qualitative difference in the test result. The finding for B-share markets does not agree with that documented by Tan et al. (2008), who find that dual-listed B-shares display herding behavior. The difference in the sample length of the two studies accounts for the discrepancy in the finding.[9] These four-market results are consistent with those reported in Panel B. This finding is in contrast

[7] We also estimated Eq. (3) separately on sub-periods before and after February 11, 2001, when A-share investors were allowed to invest in B-share markets. The results are very similar to those for the entire sample period. These tables are available upon request.

[8] Schwert and Seguin (1990) conclude that measures that use squared deviations tend to be sensitive to outliers. However, we do not find much different in our experiment using squared deviations for the measure of stock return dispersions. The estimated results are available upon request.

[9] Tan et al. (2008) report the testing results for dual-listed Shanghai B and Shenzhen B-share market separately using a sample range from 7/12/1994 to12/31/2003 (see their Table 2, Panel A). They find that herding behavior is present in both B-share markets. The current study in Table 2, Panel B reports that there is no herding behavior for combined dual-listed B-share markets using a sample range from 1/1/1996 to 4/30/2007. By adjusting the sample period used by Tan et al. (2008) to the current study, we re-estimate the model by using separate market data and cannot find supportive evidence for herding. Thus, we obtain consistent evidence of no herding behavior for the period of 1/1/1996 to 4/30/2007, whether it is examined in the combined Shanghai B- and Shenzhen B-share markets or in the separate Shanghai B- and Shenzhen B-share markets.

Table 2
Analysis of herding behavior in Chinese stock markets.

Market (No. of observation)	γ_0	γ_1	γ_2	$\overline{R^2}$
Panel A: Regression results for the aggregate Chinese market				
Aggregate China Market (2736)	2.165	0.338	−0.021	0.09
	(68.11)***	(9.42)***	(−3.17)***	
Panel B: Regression results for A-share and B-share markets				
A-share (2736)	2.088	0.337	−0.023	0.08
	(67.95)***	(10.20)***	(−4.12)***	
B-share (2736)	1.977	0.285	−0.012	0.08
	(49.45)***	(6.45)***	(−1.57)	
Panel C — Part I: Regression results for all listed Chinese firms				
SHA (2736)	2.099	0.268	−0.020	0.05
	(63.84)***	(7.92)***	(−3.71)***	
SHB (2730)	1.769	0.255	−0.011	0.06
	(34.84)***	(4.26)***	(−1.21)	
SZA (2736)	2.012	0.354	−0.020	0.10
	(58.55)***	(9.45)***	(−3.02)***	
SZB (2690)	1.993	0.182	−0.003	0.06
	(51.89)***	(4.60)***	(−0.49)	
Panel C — Part II: Regression results for dual-listed Chinese firms				
SHA (2736)	1.654	0.370	−0.021	0.09
	(45.88)***	(8.16)***	(−2.19)**	
SHB (2730)	1.752	0.265	−0.012	0.06
	(34.68)***	(4.43)***	(−1.23)	
SZA (2736)	1.738	0.358	−0.031	0.07
	(51.03)***	(10.04)***	(−5.29)***	
SZB (2690)	1.935	0.210	−0.005	0.07
	(48.32)***	(4.79)***	(−0.75)	

This table reports results of the following regression for Chinese markets: $CSAD_t = \gamma_0 + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$, where $R_{m,t}$ is the equally weighted market portfolio return at time t. $CSAD_t$ is the equally weighted cross-sectional absolute deviation. $\overline{R^2}$ is the adjusted R^2. The sample period is from 1/1/1996 to 4/30/2007. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. *** and ** represent statistical significance at the 1% and 5% levels, respectively.

to the report provided by Demirer and Kutan (2006), who find no evidence of herding when they apply daily data for 375 Chinese stocks from 1999 to 2002. Since our data contain the complete list of firms that include the dual-listed firms, our statistical results are able to reduce the biasedness due to sampling.

4.3. Herding under up and down markets

Recent empirical research (Conrad, Gultekin, & Kaul, 1991; Bekaert & Wu, 2000; Hong, Tu, & Zhou, 2007) highlights the asymmetric characteristics of asset returns. Duffee (2000), Longin and Solnik (2001), and Tan et al. (2008) provide more concrete evidence to substantiate the asymmetric investor behavior under different market conditions. In our context, it is of interest to examine whether herding behavior presents an asymmetric reaction on days when the market is up vis-à-vis days when the market is down. Therefore, we generalize Eq. (5) in the following expression:

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 D\ R_{m,t} + \gamma_3(1-D)R^2_{m,t} + \gamma_4 DR^2_{m,t} + \varepsilon_t \tag{6}$$

where D is a dummy variable. In Eq. (6), we consider asymmetry in both linear and nonlinear terms by setting $D=1$ if $R_{m,t}<0$ and $D=0$ otherwise.

Table 3 contains regression estimates for testing asymmetric herding behavior under market ups and downs. The estimated results in Panel A clearly indicate that herding is present in the Chinese stock market. However, when the market data are divided into A- and B-shares, the statistics in Panel B suggest that only investors in the A-share market reveal herding behavior and fail to find such comparable behavior in the B-share market.

Table 3
Analysis of herding behavior in up and down Chinese stock markets.

Market (No. of Observation)	γ_0	γ_1	γ_2	γ_3	γ_4	$\overline{R^2}$	Wald coefficient test H_0: $\gamma_3=\gamma_4$	
							$\gamma_3-\gamma_4=0$	χ^2
Panel A: Regression results for aggregate Chinese stock								
Aggregate China Market	2.157	0.359	−0.348	−0.032	−0.019	0.09	−0.013	(2.73)*
(2736)	(66.96)***	(7.88)***	(−8.43)***	(−2.95)***	(−2.40)**			
Panel B: Regression results for A-share and B-share markets								
A-share (2690)	2.081	0.345	−0.359	−0.032	−0.022	0.09	−0.010	(1.69)
	(66.23)***	(7.89)***	(−9.34)***	(−3.25)***	(−3.40)***			
B-share (2690)	1.974	0.243	−0.327	−0.010	−0.013	0.09	0.003	(0.06)
	(48.68)***	(3.94)***	(−7.45)***	(−0.85)	(−1.60)			
Panel C — Part I: Regression results for four all listed Chinese stocks								
SHA (2736)	2.096	0.239	−0.315	−0.023	−0.022	0.05	−0.001	(0.02)
	(66.28)***	(6.40)***	(−8.89)***	(−3.40)***	(−3.92)***			
SHB (2730)	1.753	0.156	−0.381	−0.001	−0.025	0.08	0.024	(16.08)***
	(46.42)***	(4.66)***	(−10.25)***	(−0.30)	(−4.79)***			
SZA (2736)	2.015	0.303	−0.401	−0.014	−0.026	0.10	0.012	(2.62)
	(59.94)***	(7.88)***	(−11.47)***	(−1.94)**	(−5.12)***			
SZB (2690)	1.995	0.102	−0.248	0.005	−0.007	0.07	0.012	(7.05)***
	(55.73)***	(3.13)***	(−8.50)***	(1.19)	(−2.35)**			
Panel C — Part II: Regression results for four dual-listed Chinese stocks								
SHA (2690)	1.656	0.319	−0.419	−0.013	−0.028	0.09	0.015	(2.78)*
	(42.57)***	(7.42)***	(−9.97)***	(−1.68)*	(−4.01)***			
SHB (2690)	1.739	0.158	−0.389	−0.001	−0.024	0.08	0.022	(13.24)***
	(44.41)***	(4.53)***	(−10.11)***	(−0.32)	(−4.40)***			
SZA (2690)	1.751	0.258	−0.424	−0.012	−0.042	0.07	0.030	(13.91)***
	(50.03)***	(6.55)***	(−11.96)***	(−1.67)*	(−7.84)***			
SZB (2690)	1.941	0.108	−0.290	0.005	−0.011	0.08	0.016	(11.85)***
	(52.69)***	(3.19)***	(−9.63)***	(1.32)	(−3.32)***			

This table reports results of the following regression for Chinese markets: $CSAD_t=\gamma_0+\gamma_1(1-D)\,R_{m,t}+\gamma_2 DR_{m,t}+\gamma_3\,(1-D)\,R^2_{m,t}+\gamma_4 DR^2_{m,t}+\varepsilon_t$ where $D=1$ *if* $R_{m,t}<0$, $R_{m,t}$ is the equally weighted market portfolio return at time t. $CSAD_t$ is the equally weighted cross-sectional absolute deviation. $\overline{R^2}$ is the adjusted R^2. χ^2 is the Chi-squared statistic with one degree of freedom for the Wald test. The sample period is from 1/1/1996 to 4/30/2007. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel C reports regression results for four Chinese markets based on all-firm data. In terms of Eq. (6), if the estimated coefficient of γ_3 is negative and statistically significant, we would conclude that investors herd in the up market. Likewise, if the estimated coefficient of γ_4 is negative and statistically significant, investors herd in the down market. The evidence in Part I of Panel C indicates that both A-share markets (SHA and SZA) display herding behavior in up and down markets. However, for the B-share markets, evidence to support herding can be found only in a downside market, rather than in an upside market. When we test the model by using data from dual-listed firms, the estimated statistics shown in Part II achieve the same conclusion for the four markets. By comparing the results from Panel B, we find that on days when the market is down, investors in B-share markets are more likely to display herding behavior.

The finding of parallel herding behavior in both up and down markets for A-share investors may be driven by Chinese investors' over-enthusiastic/over-reacting behavior. Numerous practitioners have observed that Chinese A-share investors tend to actively engage in purchasing activities when the market goes up and selling stocks when the market goes down (in Chinese: “Zhui Zhang Sha Die”).[10] This reaction

[10] See the Asian Times' website: http://www.atimes.com/atimes/China_Business/IG13Cb01.html.

is similar to the feedback trader's behavior as noted by Sentana and Wadhwani (1992). From an information perspective, the A-share investors appear to be more homogeneous, since their investment strategies/decisions are mainly based on the information available from the Chinese market. Thus, limited information leads to homogeneous investors and the merit from foreign market signaling becomes less significant. It is not surprising that herding behavior in the A-share markets is more consistent.[11]

B-share investors, composed of foreign or institutional investors, are more rational and have diverse information to assess, enabling them to compare stock performance in the Chinese market and with that in global markets. Apparently, their investment decisions to some extent are correlated with the information available in the world market. As a result, B-investors are less likely to herd with the Chinese market when the global investment perspective is seen to be bullish (an up market), since they can alternatively invest in their home or global markets.

Moreover, the Chinese market is known to be guided by government policy; that is, the government's frequent interventions in financial markets, as seen by B-share investors, are likely to be interpreted as indicating market uncertainty.[12] Because of information asymmetry, B-share investors, who have less knowledge and experience with the Chinese government's policies, are more concerned about the risk triggered by government intervention in a down market. For this reason, B-share investors are likely to show herding formation in a down market.

We also test the equality of the herding coefficient between the up and down markets. The Chi-squared statistics, as shown in the last column of Table 3, indicate that the null hypothesis of $\gamma_3 = \gamma_4$ cannot be rejected for both A-share markets based on the all-firms data. However, the null is rejected for the B-share markets in Panel C. The latter result is consistent with the view that investors react significantly, and differently to up markets and down markets.

Next, looking at the Chi-squared statistics from the dual-listed data, the null is rejected in all of the markets, indicating that the magnitude of the estimated herding coefficients is somehow different even though the signs of herding are consistent with each other between the two sets of data. It is interesting to note that for the B-share market, the herding coefficient is much larger (in absolute terms) in the down market that shows herding compared with the up market without herding.

Although we have employed a much larger data set in this study and the data cover both all listed and dual-listed firms, our empirical results lie somewhere between the findings of Demirer and Kutan (2006) and Tan et al. (2008) in that the former find no herding activity in Chinese markets, and the latter report herding formation under both rising and falling market conditions. Our study shows that A-share investors tend to herd during both up and down markets, while B-share investors herd only during down markets. In their research, Demirer and Kutan (2006) provide reasons as to the cause of the difference between the Shanghai and Shenzhen markets. According to their paper, because firms in Shanghai are larger than those in Shenzhen, the two markets trade different types of firms, and because the Shanghai market is more informed than the Shenzhen market, they expect the Shenzhen market to be more likely to demonstrate herding behavior. However, our evidence does not agree with their expectations. Tan et al. (2008) show that the deviation of B-share investors from A-share investors may be attributed to the fact that B-share investors are mainly foreign investors who are better informed and more correlated with international financial news and economic activity; A-share investors are local investors who tend to trade according to market consensus and to herd due to a lack of fundamental and private information about firms. As we explained earlier, this information asymmetry and the difference in investor characteristics cause different herding formation. As we shall show in the following section, in addition to the differences in data among these studies, the main problem may also be a result of the methodology used to analyze the data.

[11] Ashiya and Doi (2001) find that Japanese economists who got useful information stopped herding to signal their ability when economists are heterogeneous. All economists herd when economists are homogeneous and the merit from signaling is small. The empirical results suggest that Japanese economists are more homogeneous than American economists.

[12] See Reuters' website: http://www.reuters.com/article/ousiv/idUSSHA6426620070529. For example, on May 30, 2007, to cool down the overheated market, the Chinese authorities raised the stock trading stamp duty to 0.3% from 0.1%. In the week afterward, realizing the market had rebounded quickly, the State Council said on June 13, 2007 that further policy initiatives, such as financial and tax measures, would be introduced.

5. Quantile regression analysis

5.1. The model

In the previous section (Panel C of Table 3), we found some variations in herding behavior when the data are divided into four subset observations under both up and down markets. This approach is useful, since it provides information conditional on certain groups of the data. This empirical result also motivates us to address the issue of whether herding behavior is sensitive to a different quantile of stock return dispersions. In addition, if the error distribution is unable to conform to a Gaussian setting, quantile estimators may be more efficient than the ordinary least squares method (Buchinsky, 1998). As noted by Koenker and Bassett (1978), Koenker (2005), and Barnes and Hughes (2002), one key source of lost efficiency is that the least squares estimators focus on the mean as a measure of location. Information about the tails of a distribution is lost. In financial markets, news in the form of extreme outliers can significantly affect tail values of a distribution, which in turn distorts the estimated results. To address these issues, we employ a quantile regression, which is more robust and consequently renders more efficient estimates, since it enables us to cover a full range of conditional quantile functions.[13]

Briefly defined, a quantile regression is a statistical procedure designed to estimate conditional quantile functions (Alexander, 2008; Koenker, 2005).[14] To elucidate, we write a linear conditional quantile function as:

$$QY_i(\tau IX = x) = x_i{}'\gamma \tag{7}$$

where y_i is a dependent variable and x_i is a vector of independent variables and γ is a vector of coefficients. By minimizing weighted deviations from the conditional quantile, we obtain:

$$\hat{\gamma}_{\text{quantile},\tau} = arg\ min \sum_{i=1}^{n} \rho_\tau(y_i - x_i'\gamma) \tag{8}$$

where the conditional distribution of the dependent variable y_i is characterized by different values of the τth quantile given x_i (Koenker, 2005), and ρ_τ is a weighting factor called a check function. For any $\tau \in (0,1)$, a check function is defined as:

$$\rho_\tau(u_i) = \begin{cases} \tau\ u_i & \text{if } u_i \geq 0 \\ (\tau - 1)u_i & \text{if } u_i < 0 \end{cases} \tag{9}$$

where $u_i = y_i - x_i'\gamma$. Eqs. (8) and (9) imply that

$$\hat{\gamma}_{\text{quantile},\tau} = arg\ min \left(\sum_{i:y_i > x_i'\gamma} \tau \left| y_i - x_i'\gamma \right| + \sum_{i:y_i < x_i'\gamma} (1-\tau) \left| y_i - x_i'\gamma \right| \right). \tag{10}$$

Expression (10) states that the quantile regression estimators can be achieved by minimizing a weighted sum of the absolute errors, where the weights are dependent on the quantile values. When $\tau = 0.5$, the quantile regression becomes the median regression. The quantile regression is not restrictive at the median level; it allows us to estimate the interrelationship between a dependent variable and its explanatory variables at any specific quantile. Thus, it provides a broader picture in helping us examine the relation between $CSAD_t$ and $R_{m,t}^2$.

[13] Note that quantile regression is different from quintile analysis, which uses a mean regression method. The following text will make the point clear.

[14] The τth quantile is that value of the target variable distribution below which the proportion of the population is τ. For example, the median is the 0.5th quantile, the value of a distribution where 50% of the observations are below the median. Other common quantiles are a quartile, which is the 0.25th quantile — the value of a distribution where 25% of the observations are below the quartile; a quintile is the 0.20th quantile — the value of a distribution where 20% of the observations are below the quintile; a decile is the 0.10th quantile — the value of a distribution where 10% of the observations are below the decile; a percentile is the 0.01th quantile — the value of a distribution where 1% of the observations are below the percentile (Koenker, 2005).

Table 4
Quantile regression results for four all listed Chinese stocks. Analysis of herding behavior in Chinese stock markets by quantile regression.

Panel A: Quantile regression results for aggregate Chinese stocks							
China Market Quantile	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	1.205	0.289	−0.300	−0.034	−0.023	0.05	14.588***
	(40.61)***	(9.09)***	(−7.77)***	(−7.56)***	(−4.17)***		
Quantile ($\tau=25\%$)	1.516	0.387	−0.308	−0.044	−0.015	0.05	3.493
	(45.74)***	(10.17)***	(−8.20)***	(−7.97)***	(−2.14)**		
Quantile ($\tau=50\%$)	2.035	0.351	−0.311	−0.033	−0.010	0.05	–
	(51.42)***	(6.23)***	(−6.73)***	(−2.64)***	(−1.04)		
Quantile ($\tau=75\%$)	2.705	0.320	−0.251	−0.023	0.001	0.04	1.188
	(50.62)***	(3.62)***	(−3.28)***	(−1.00)	(0.04)		
Quantile ($\tau=90\%$)	3.295	0.401	−0.371	−0.019	−0.015	0.06	3.591
	(41.56)***	(4.13)***	(−2.18)***	(−1.51)	(−0.32)		
Panel B — Part I: Quantile regression results for A-share stocks							
A-share Market Quantile	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	1.149	0.262	−0.307	−0.030	−0.024	0.05	15.912***
	(45.29)***	(7.54)***	(−7.17)***	(−5.28)***	(−2.65)***		
Quantile ($\tau=25\%$)	1.440	0.338	−0.313	−0.039	−0.018	0.04	5.396
	(44.28)***	(7.37)***	(−8.25)***	(−4.35)***	(−2.16)**		
Quantile ($\tau=50\%$)	1.939	0.331	−0.314	−0.033	−0.010	0.05	–
	(70.94)***	(6.39)***	(−7.90)***	(−2.81)***	(−1.02)		
Quantile ($\tau=75\%$)	2.612	0.324	−0.308	−0.034	−0.010	0.04	0.151
	(55.51)***	(3.82)***	(−5.16)***	(−1.59)	(−0.76)		
Quantile ($\tau=90\%$)	3.252	0.354	−0.357	−0.019	−0.014	0.05	1.499
	(42.39)***	(2.43)**	(−4.33)***	(−0.47)	(−0.75)		
Panel B — Part II: Quantile regression results for B-share stocks							
B-share Market Quantile	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	0.763	0.288	−0.280	−0.027	−0.018	0.04	9.296**
	(19.71)***	(6.41)***	(−6.03)***	(−3.41)***	(−1.72)*		
Quantile ($\tau=25\%$)	1.156	0.354	−0.303	−0.036	−0.017	0.04	9.97**
	(34.58)***	(9.79)***	(−6.92)***	(−8.93)***	(−2.30)**		
Quantile ($\tau=50\%$)	1.754	0.345	−0.415	−0.034	−0.028	0.04	–
	(32.93)***	(5.14)***	(−6.91)***	(−2.62)***	(−2.23)**		
Quantile ($\tau=75\%$)	2.544	0.158	−0.422	0.013	−0.020	0.05	21.224***
	(45.18)***	(1.72)*	(−6.05)***	(0.60)	(−1.20)		
Quantile ($\tau=90\%$)	3.401	0.070	−0.266	0.035	0.020	0.07	21.246***
	(36.96)***	(0.71)	(−2.28)**	(1.91)*	(0.77)		
Panel C: Quantile regression results for four all listed Chinese stocks Part I: SHA market							
SHA	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	1.117	0.222	−0.303	−0.024	−0.028	0.05	9.908**
	(40.77)***	(8.78)***	(−10.80)***	(−5.37)***	(−6.23)***		
Quantile ($\tau=25\%$)	1.414	0.291	−0.292	−0.034	−0.022	0.03	5.944
	(43.30)***	(7.10)***	(−6.56)***	(−4.56)***	(−2.39)**		
Quantile ($\tau=50\%$)	1.893	0.244	−0.298	−0.022	−0.015	0.03	–
	(56.74)***	(6.35)***	(−6.16)***	(−2.54)**	(−1.82)*		
Quantile ($\tau=75\%$)	2.570	0.255	−0.348	−0.020	−0.023	0.02	0.971
	(34.01)***	(3.23)***	(−4.94)***	(−1.18)	(−2.38)**		
Quantile ($\tau=90\%$)	3.403	0.131	−0.223	−0.004	−0.008	0.02	2.436
	(38.81)***	(1.41)	(−2.54)**	(−0.20)	(−0.46)		
Part II: SHB market							
SHB	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	0.498	0.245	−0.290	−0.021	−0.023	0.04	21.478***
	(24.70)***	(11.36)***	(−9.63)***	(−6.17)***	(−3.70)***		

Table 4 (*continued*)

Part II: SHB market							
SHB	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=25\%$)	0.841	0.341	−0.324	−0.034	−0.020	0.04	20.037***
	(23.62)***	(7.40)***	(−6.47)***	(−6.60)***	(−2.40)**		
Quantile ($\tau=50\%$)	1.471	0.364	−0.517	−0.039	−0.045	0.04	–
	(23.72)***	(5.36)***	(−8.23)***	(−3.97)***	(−5.15)***		
Quantile ($\tau=75\%$)	2.425	0.132	−0.373	0.001	−0.016	0.04	9.189*
	(28.88)***	(1.06)	(−4.17)***	(0.00)	(−0.88)		
Quantile ($\tau=90\%$)	3.121	0.135	−0.464	0.013	−0.024	0.06	15.037***
	(36.69)***	(1.62)	(−5.56)***	(1.02)	(−1.84)*		
Part III: SZA market							
SZA	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	1.087	0.282	−0.289	−0.031	−0.020	0.05	18.528***
	(45.60)***	(10.51)***	(−6.75)***	(−7.34)***	(−1.95)**		
Quantile ($\tau=25\%$)	1.377	0.326	−0.301	−0.038	−0.016	0.05	14.961***
	(44.03)***	(6.75)***	(−8.20)***	(−3.32)***	(−2.49)**		
Quantile ($\tau=50\%$)	1.793	0.341	−0.381	−0.024	−0.020	0.06	–
	(46.72)***	(5.12)***	(−8.41)***	(−1.42)	(−2.46)**		
Quantile ($\tau=75\%$)	2.534	0.178	−0.380	0.016	−0.015	0.05	7.564
	(40.77)***	(2.02)**	(−4.33)***	(0.76)	(−0.88)		
Quantile ($\tau=90\%$)	3.354	0.238	−0.491	0.014	−0.026	0.06	6.810
	(36.58)***	(1.54)	(−4.12)***	(0.30)	(−1.46)		
Part IV: SZB market							
SZB	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	χ^2 (4)
Quantile ($\tau=10\%$)	0.846	0.238	−0.226	−0.025	−0.017	0.03	16.733***
	(24.01)***	(6.24)***	(−4.82)***	(−3.16)***	(−1.86)*		
Quantile ($\tau=25\%$)	1.251	0.199	−0.170	−0.018	−0.004	0.03	16.112***
	(40.51)***	(5.00)***	(−3.56)***	(−4.26)***	(−0.49)		
Quantile ($\tau=50\%$)	1.777	0.237	−0.261	−0.024	−0.009	0.03	–
	(38.24)***	(3.30)***	(−4.35)***	(−1.73)**	(−0.88)		
Quantile ($\tau=75\%$)	2.430	0.183	−0.304	0.001	−0.005	0.05	12.242**
	(40.92)***	(2.31)**	(−4.58)***	(0.09)	(−0.43)		
Quantile ($\tau=90\%$)	3.199	0.076	−0.368	0.039	−0.010	0.07	9.857*
	(46.77)***	(1.08)	(−5.25)***	(1.63)	(−1.02)		

This table reports the quantile regression estimates for Chinese stock markets by different CSAD quantile groups. The estimated equation is given by: $Q_r(\tau|X_t)=\gamma_{0,\tau}+\gamma_{1,\tau}(1-D)R_{m,t}+\gamma_{2,\tau}D\cdot R_{m,t}+\gamma_{3,\tau}(1-D)R^2_{m,t}+\gamma_{4,t}D\cdot R^2_{m,t}+\varepsilon_{\tau,t}$ where $R_{m,t}$ is the equally weighted market portfolio return at time *t*. $CSAD_t$ is the equally weighted cross-sectional absolute deviation, which is the dependent variable. X_t represents a vector of the right-hand-side variables on the above equation. D is a dummy variable by setting $D=1$ if $R_{m,t}<0$, and $D=0$ otherwise. $\gamma_{k,\tau}$ refers to the kth coefficient conditional on τth quantile distribution in the estimated equation. $\chi^2(4)$ is the Chi-squared distribution with four degrees of freedom for the Wald test. The sample period is from 1/1/1996 to 4/30/2007. Numbers in parentheses are *t*-statistics. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

In the spirit of our test equation, quantile regressions for estimating $CSAD_t$ and a set of explanatory variables, X_t, for τ quantiles are characterized as:

$$Q_r(\tau|X_t) = \gamma_{0,\tau} + \gamma_{1,\tau}(1-D)R_{m,t} + \gamma_{2,\tau}D\cdot R_{m,t} + \gamma_{3,\tau}(1-D)R^2_{m,t} + \gamma_{4,t}D\cdot R^2_{m,t} + \varepsilon_{\tau,t} \tag{11}$$

where X_t represents a vector of the right-hand-side variables of Eq. (11); D is a dummy variable by setting $D=1$ if $R_{m,t}<0$, and $D=0$ otherwise.

The quantile regression is solvable if the quantile is expressed as linear functions of the parameters.[15] It is useful to compare Eq. (11), which is in the form of a quantile regression, with the regression in Eq. (6). The coefficients in Eq. (6) are obtained by minimizing the squares of deviations from the conditional mean of the sample, while the quantile regression estimators are achieved by minimizing a weighted sum of the

[15] We estimate the quantile regression by using EViews® (Version 6, 2007).

absolute errors, where the weights are dependent on the quantile values. The estimation using quantile regression is based on the distributions of the dependent variable and the estimations use *the sample points* conditional on a specific quantile. Thus, the quantile regression is more efficient and appropriate when extreme values are present, since it can be used in various distributions. This is especially true for stock return dispersions that present fat tails and/or a skewed distribution. Thus, unlike the least squares regression, quantile regressions help to alleviate some of the statistical problems due to fat tails or outliers (Barnes & Hughes, 2002).

5.2. Empirical evidence from quantile regressions

Table 4 presents the estimated results for market aggregate (Panel A), A-share and B-share groups (Panel B), and four individual sub-markets, SHA, SHB, SZA, and SZB (Panel C) using the quantile regression method.[16] Looking at Panels A and B, the estimated statistics suggest that both coefficients on γ_3 and γ_4 are negative and statistically significant at the 5% level in the quantiles ($\tau=10\%$ and 25%) up to the median level ($\tau=50\%$). Beyond the median level, we do not find the herding coefficient to be statistically significant. If we look at Panel C, the estimated statistics from the four sub-markets produce a similar pattern, with an exception in the SZB market, where we find less significance in the downside market. In general, we observe that herding tends to display in quantiles at and below the median levels and is less likely to occur when the quantile is above the median level. The phenomenon of herding behavior to be more significant for cases in lower quantiles reflects the fact that herding activity is more likely to occur for the return dispersions at the lower tail of the distribution, which reveals that investors display more homogeneous trading behavior. Thus, we observe market consensus in lower quantiles for periods of market stress.

Evidence in Table 4 clearly indicates that the estimated coefficients vary with the quantile levels. It would be more compelling if we conduct a formal test for examining the equality of slopes. Since the median quantile is close to the mean value of the least squares estimation that has been conventionally used in testing herding equations, we shall address the equality test of the coefficients at various quantiles conditional on $\tau\neq0.5$ against the median quantile coefficients ($\tau=0.5$).

The Wald test is designed to examine the null hypothesis of the equality of slopes. As we inspect the χ^2 (4) statistics in the last column, the null is uniformly rejected at lower quantile distributions associated with A-share investors, suggesting that the estimated coefficients for the quantiles of 0.10 and 0.25 are significantly different from that of the median distribution.

However, turning to the B-share investors, the test results are somewhat different. In all of the cases, the null is rejected across different quantiles. This indicates that the B-share markets appear to be more variable as we test the herding equation conditional on different quantiles, suggesting that using a mean or median level of the data to examine herding behavior may produce a deceptive statistical inference.

It would be interesting to compare the quantile regression results with those we derived from Table 3, where the conventional least squares method was used. To recall, in the earlier empirical analysis, we concluded that the coefficients on γ_3 and γ_4 are significantly negative for A-share markets, while they are less significant for B-share markets on days when the market is up, indicating that herding behavior is displayed in A-share markets but there is no strong support for such behavior in B-share markets. Now we find consistent evidence for herding formation in both A-share and B-share markets in the lower quantiles and no supporting evidence in the higher quantiles. The divergence in the statistics between the two approaches is due to the fact that the least squares method focuses on the mean as a measure of location, while the quantile regression allows us to compute a family of regression curves, each corresponding to a different quantile of the conditional distribution of the dependent variable. Thus, the quantile regression provides a much more complete picture of the conditional distribution between return dispersions and independent variables (Alexander, 2008). For this reason, we are able to spot that herding behavior is more prevalent at the quantile distributions of the return dispersions from the low to the median quantiles. This holds true for both up market and down market conditions. Therefore, this study provides some insights

[16] The quantile regression analysis for dual-listed shares is also conducted. Due to space limitations, they are not reported in the text but are available upon request.

into herding behavior in Chinese markets by using the distributional information from the quantile regression analysis.

6. Conclusions

This study examines the herding behavior of investors in the Chinese stock markets. Estimations are based on daily data classified into aggregate market, A-share and B-share groups, and four sub-markets: SHA, SHB, SZA, and SZB. The test results consistently show that investors in the aggregate market display herding behavior. Dividing the data into A-share and B-share markets offers evidence that A-share investors consistently display herding behavior, but B-share investors do not reveal such a phenomenon.

We examine possible behavioral changes by using different market conditions. The statistical results on A-share investors indicate that herding is present in both up and down markets. However, we are unable to find evidence of herding for B-share investors on days when the market is up.

We further test the herding equation by employing a quantile regression model, which is based on the distributions of the dependent variable (return dispersions) and the estimations are made by using the sample points conditional on a specific quantile. The evidence shows that herding behavior is more prevalent at the median and lower tails of the quantile distributions of the return dispersions. This behavior holds true for the evidence derived from the Chinese aggregate stock market, the A-share markets group (SHA and SZA) and the B-share markets group (SZB and SZB), and individual sub-markets (SHA, SZA, SHB, and SZB), although the evidence for the SZB is less significant compared with the other cases. This finding casts some doubt on the empirical conclusion that A-share market investors display herding activity, while B-share market investors do not. By using a quantile regression procedure, this study finds that B-share investors consistently exhibit herding behavior in the quantiles from the 10% to 50% levels on days when stock market returns are up. Thus, the mixed results in the literature are mainly due to the fact that in empirical estimations, the model fails to capture the asymmetric responses of market returns and ignores the distributional information from the quantile regression approach.

Appendix A. Chinese stock market industry distribution as of April 30, 2007

Industry count	Industry name	Number of firms in industry
1	Agriculture	39
2	Mining	31
3	Manufacturing	939
4	Utilities	65
5	Construction	33
6	Transportation	72
7	Technology	96
8	Trade	86
9	Finance	15
10	Real Estate	67
11	Service	47
12	Media	11
13	Other	113

Data source: Shenying Wanguo Securities Company Limited.

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