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Herding behavior in Chinese stock markets: An examination of A and B shares

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Abstract

This study examines herding behavior in dual-listed Chinese A-share and B-share stocks. We find evidence of herding within both the Shanghai and Shenzhen A-share markets that are dominated by domestic individual investors, and also within both B-share markets, in which foreign institutional investors are the main participants. Herding occurs in both rising and falling market conditions. Herding behavior by A-share investors in the Shanghai market is more pronounced under conditions of rising markets, high trading volume, and high volatility, while no asymmetry is apparent in the B-share market.

JEL classification: G15; G14
Keywords: Herding behavior; Chinese stock market; Asymmetric behavior; A and B shares

1. Introduction

Herding in financial markets has been typically described as a behavioral tendency for an investor to follow the actions of others. Practitioners are interested in whether herding exists, because the reliance on collective information rather than private information may cause prices to deviate from fundamental value and present profitable trading opportunities. Herding has also attracted the

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attention of academic researchers, because the associated behavioral effects on stock price movements may affect their risk and return characteristics and thus have implications for asset pricing models.

Theoretical models of herding behavior have been developed by Bikhchandani et al. (1992), Scharfstein and Stein (1990), and Devenow and Welch (1996). Empirical studies have mainly focused on detecting the existence of herding behavior among mutual fund managers (Lakonishok et al., 1992; Wermers, 1999) or financial analysts (Trueman, 1994; Graham, 1999; Welch, 2000; Hong et al., 2000; Gleason and Lee, 2003; Clement and Tse, 2005).

The Chinese stock market provides an interesting setting for the analysis of investor herding behavior. Since the establishment of the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) in December 1990, two classes of shares have been issued. *A shares* can be purchased and traded only by domestic (Chinese) investors and are denominated in the local currency, the Renminbi (RMB). *B shares* were sold only to foreign investors before February 2001, and have been sold to both foreign and domestic investors since then. A shares and B shares are traded simultaneously on the Shanghai and Shenzhen stock markets. However, the characteristics of their investors are very different. The A-share market is dominated by domestic individual investors (China Securities and Futures Statistical Yearbook, 2004), who typically lack significant knowledge and experience in investments. In contrast, the B-share market is dominated by foreign institutional investors, who tend to be more knowledgeable and sophisticated than A-share investors. The different characteristics of A-share and B-share investors may result in differences in the level of herding in each market.

In this study, we examine whether herding behavior exists *within* each of the Chinese stock markets, whether it exists *across* A-share and B-share markets, and whether it exists *across* the Shanghai and Shenzhen markets. For markets characterized by herding behavior, we further examine whether herding exhibits asymmetric effects associated with market returns, trading volume, and return volatility. Our results indicate that dual-listed Chinese A and B shares exhibit significant herding behavior. Herding by A-share investors in the Shanghai market displays strong asymmetric characteristics: it is higher during periods of rising stock markets, high trading volume, and high market volatility. We find no evidence of asymmetric effects in the herding behavior of B-share investors. Although herding occurs *within* each of the markets examined, we find no evidence of information *across* markets affects the dispersion in returns.

The remainder of this paper is organized as follows. Section 2 presents the methodology used to detect herding behavior. Section 3 describes data. Section 4 reports evidence of herding behavior within each market. Section 5 studies the asymmetric effects of herding in response to market conditions, trading volume, and return volatility. Section 6 examines the effects of cross-market information on herding. Section 7 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 referred to as CH) and Chang et al. (2000) (hereafter referred to as 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 based on the collective actions in the market. Individual stock returns under these conditions should tend to cluster around the overall market return. Thus, they 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. They use the following equation in their empirical specification:

$$S_t = \alpha + \beta^{\mathrm{L}} D_t^{\mathrm{L}} + \beta^{\mathrm{U}} D_t^{\mathrm{U}} + \varepsilon_t \tag{1}$$

where S_t is the return dispersion at time t. D_t^{L} is a dummy 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, D_t^{U} is a dummy 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:

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

where N is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm i at time t, $R_{m,t}$ is the cross-sectional average stock of N returns in the portfolio at time t. This 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 definition is arbitrary, and they use values of one percent and five percent as the cutoff points to identify the upper and lower tails of the return distribution. In practice, investors may differ in their opinion 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 become more pronounced during periods of market stress, and the CH method captures herding only during periods of extreme returns. Additional challenges arise when applying this method to Chinese stock market data because the relatively short history of these markets makes it difficult for investors to identify when extreme returns occur.

An alternative to the CH test for herding is that of Chang et al. (2000) (CCK). They examine several international stock markets, and find no evidence of herding in developed markets, such as the U.S. and Hong Kong. However, they do find evidence of herding in the emerging markets of South Korea and Taiwan. 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.

The herding test of CCK facilitates the detection of herding over the entire distribution of market return with the following specification:

$$\mathrm{CSAD}_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3}$$

The left-hand-side variable, CSAD_t, is a measure of return dispersion, which is measured by the cross-sectional absolute deviation:

$$\mathrm{CSAD}_t = \frac{1}{N} \sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \tag{4}$$

where $R_{m,t}$ is the equal-weighted average stock return in the dual-listed portfolio.[4] Note that both $|R_{m,t}|$ and $R^2_{m,t}$ terms appear in the right-hand-side of Eq. (3). CCK note that rational asset pricing models imply a linear relation between the dispersion in individual asset returns and the return on the market portfolio. As the absolute value of the market return increases, so should the dispersion in individual asset returns. During periods of relatively large market price movements, investors may react in a more uniform manner, exhibiting herding behavior. This behavior is likely to increase the correlation among asset returns, and the corresponding dispersion among returns will decrease, or at least increase at a less-than-proportional rate with the market return. For this reason, a nonlinear market return, $R^2_{m,t}$, is included in the test equation, and a significantly negative coefficient γ_2 in the empirical test would be consistent with the occurrence of herding behavior.[5]

Four portfolios of dual-listed stocks are examined: Shanghai A shares, Shanghai B shares, Shenzhen A shares, and Shenzhen B shares. Empirical testing of herd behavior can be conducted by performing a significance test in terms of Eq. (3). A significantly negative coefficient on $(R_{m,t})^2$ would indicate the existence of herding behavior. As the market experiences large price swings, market participants tend to suppress their private information and herd around the information emerging from the consensus of all market constituents. Stock returns under these conditions tend to converge, causing the return dispersion to either decrease or increase at a decreasing rate. Thus, if herding exists, we expect the coefficient γ_2 to be negative and statistically significant.

Our measure of the return dispersion, $CSAD_t$, differs from that of CCK for two reasons. First, their measure relies on the accuracy of the specification of a single market factor of the CAPM, which may be questionable. Ours follows the method used by Christie and Huang (1995) and Gleason et al. (2004), which does not require the estimation of beta. Second, the CCK measure assumes that risk does not vary over time, and the characterization of time-varying risk requires the specification of an appropriate time window over which to measure risk. In practice, the length of this time window is arbitrary.

3. Data

We collect data on stock prices, trading volume, and earnings per share for all firms listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) over the period from July 12, 1994 to December 31, 2003. There are 746 Shanghai A-share firms (SHA), 54 Shanghai B-share firms (SHB), 489 Shenzhen A-share firms (SZA), and 57 Shenzhen B-share firms (SZB). Within this sample, there are 44 firms that are dual-list A and B shares on the Shanghai exchange, and 43 firms that dual-list A and B shares on the Shenzhen exchange. Our analysis focuses only on these 87 dual-listed firms.[6]

In addition to the above data for individual firms, we collect stock prices on the Shanghai A (SHA) composite index, Shanghai B (SHB) composite index, Shenzhen A (SZA) composite index, and Shenzhen B (SZB) composite index. The stock return for A shares is calculated as $R_t = 100 \times (\log(P_t) - \log(P_{t-1}))$. Because B shares are denominated in US dollars or Hong Kong

[4] 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.

[5] A negative coefficient on the squared market return could also be consistent with other interpretations, such as market-timing behavior by investors, or deviations from a linear asset pricing model.

[6] The industry distribution for dual-listed firms is available upon request.

dollars for Shanghai B- and Shenzhen B shares, respectively, the returns on B shares are computed after adjusting for exchange rate effects.[7] We use daily, weekly, and monthly stock return data in our herding tests. The data are provided by Shenying Wanguo Securities Company Limited, the largest investment firm in China.

Our daily data are from July 1, 1997 to December 31, 2003. We have 1569 daily return observations for Shanghai A and Shenzhen A shares, and 1534 observations for both B shares.[8] Weekly and monthly data are available from January 1, 1996 to December 31, 2003. The Chinese demand deposit rate is used to measure the risk-free rate, since it is the only readily available risk-free rate in Chinese markets. Interest rate data are obtained from the IFS database.

4. Empirical results

4.1. Descriptive statistics

Table 1 contains summary statistics for cross-sectional absolute deviations. Panel A reports the daily statistics, while Panels B and C report weekly and monthly statistics. As expected, the dispersion measure increases with the return interval: the average $CSAD_t$ based on monthly returns is greater than that based on weekly returns, which in turn is greater than that based on daily returns. The statistics also show that for both daily and weekly data the mean values of CSAD for B shares are consistently higher than that of A shares, accompanied by higher standard deviations. This holds true for both Shanghai and Shenzhen exchanges. This evidence is consistent with that of CCK, in which developed markets such as the U.S. and Hong Kong have larger mean values of return deviations than emerging markets such as South Korea and Taiwan. One possible explanation is that the sophisticated investors in developed markets have more information and analytical tools that allow them to assess and reallocate their investments, leading to higher means and standard deviations.

4.2. Evidence on herding

Table 2 reports the results of estimating the herding regression in Eq. (3), in which a negative value on the coefficient γ_2 is consistent with herding.[9] The results based on daily data in Panel A indicate that γ_2 is significantly negative for all four markets, suggesting that herding behavior exists in both the A- and B-share markets on the Shanghai and Shenzhen stock exchanges. Since the A-share markets are dominated by Chinese individual investors, the findings here can be interpreted as being consistent with those of CCK, who find evidence of herding in emerging markets. It is of interest to note that the B-share markets, which are dominated by institutional investors from developed countries, also demonstrate herding behavior. These results differ from those of CCK, who find no evidence of herding in U.S. and Hong Kong markets. It may be the

[7] Since exchange rates fluctuate very little in the sample period, the B-share returns in either currency are quite similar (the US to Chinese RMB exchange rate ranges between RMB8.2275 to RMB8.5103 per US dollar, while the exchange rates for Hong Kong dollar range from 7.7085 to 7.7996 per US dollar).

[8] Slight differences in non-trading days arise between A-share and B-share markets. For instance, on February 11, 2001, when 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.

[9] 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 indicate that the coefficient γ_2 is consistently negative and statistically significant. We do not find significant differences between the entire time period and the two sub-periods, indicating that herding was present over the entire time period.

Table 1
Descriptive statistics of cross-sectional absolute deviations

Statistic	SHA	SHB	SZA	SZB
Panel A: Statistics for daily $CSAD_t$				
Observations	1569	1534	1569	1534
Minimum	0.380	0.189	0.415	0.113
Maximum	5.067	6.117	5.148	5.454
Mean	1.345	1.866	1.387	1.609
Standard deviation	0.553	1.150	0.540	0.804
Panel B: Statistics for weekly $CSAD_t$				
Observations	389	387	389	387
Minimum	0.993	0.665	0.899	0.820
Maximum	8.258	13.735	15.141	11.799
Mean	3.109	3.596	3.154	3.435
Standard deviation	1.288	1.948	1.503	1.794
Panel C: Statistics for monthly $CSAD_t$				
Observations	96	96	96	96
Minimum	2.682	1.009	2.562	1.636
Maximum	12.534	12.809	16.321	15.291
Mean	6.354	6.154	6.728	6.638
Standard deviation	2.174	2.858	2.722	3.175

Notes:
This table lists descriptive statistics of daily, weekly and monthly 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 daily data range is from 7/1/1997 to 12/31/2003, and the weekly and monthly data range is from 1/1/1996 to 12/31/2003.

case that the typical U.S. or Hong Kong participant in their own domestic market exhibits different behavioral tendencies than the typical participant in the Chinese B-share markets.

Our results using daily data differ from those of Demirer and Kutan (2006), who find no evidence of herding using the Christie and Huang (1995) method on daily data from 1999 to 2002 for 375 Chinese stocks. Since our attention is restricted only to the 87 firms with dual-listed shares, it is likely that the difference in the sample of firms accounts for the difference in results.

Panel B reports the results of the herding tests using weekly data. We find that the magnitude of the coefficient γ_2 with weekly data is smaller than that found using daily data. The sign of the coefficient is negative in three of the four markets examined, but is statistically significant only for the Shanghai A-share and Shenzhen B-share markets. We rerun the herding tests using monthly data in Panel C. Similar to the results from weekly data, the coefficients are small in magnitude, and the only significantly negative coefficient is for the Shanghai B-share market. The weaker evidence of herding behavior displayed in weekly and monthly data is consistent with the observation by Christie and Huang (1995) that "herd behavior is a very short-lived phenomenon". We therefore restrict our attention in subsequent analyses to daily data.

As a robustness test, we examine the possible effect of the Asian financial crisis on our results. By adding a dummy variable to highlight the Asian crisis, we estimate the following equation:

$$\mathrm{CSAD}_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 (R_{m,t})^2 * \mathrm{DM}_t + \varepsilon_t \tag{5}$$

where the dummy variable DM_t takes value of unity during the Asian Crisis from July 2, 1997 to November 17, 1997, and zero otherwise. Results indicate that γ_3 is statistically insignificant for

Table 2
Analysis of herding behavior in Chinese stock markets

Panel A: regression results for daily data				
Market (no. of observation)	SHA (1569)	SHB (1534)	SZA (1569)	SZB (1534)
α	1.075	1.078	1.147	1.141
	(45.93)***	(24.65)***	(46.02)***	(30.27)***
γ_1	0.278	0.762	0.235	0.444
	(10.26)***	(16.87)***	(8.98)***	(13.19)***
γ_2	−0.023	−0.073	−0.017	−0.044
	(−4.76)***	(−12.68)***	(−3.71)***	(−10.77)***
Adjusted R^2	0.14	0.25	0.20	0.16
Panel B: regression results for weekly data				
Market (no. of observation)	SHA (389)	SHB (389)	SZA (389)	SZB (389)
α	2.389	2.697	2.384	2.307
	(21.78)***	(16.65)***	(16.97)***	(17.71)***
γ_1	0.287	0.233	0.205	0.3
	(6.15)***	(4.82)***	(2.73)***	(6.93)***
γ_2	−0.008	−0.002	0.004	−0.004
	(−2.43)**	(−0.73)	(0.54)	(−2.41)***
Adjusted R^2	0.15	0.35	0.27	0.30
Panel C: regression results for monthly data				
Market (no. of observation)	SHA (109)	SHB (109)	SZA (109)	SZB (109)
α	4.926	4.368	5.46	4.421
	(10.87)***	(8.11)***	(12.10)***	(10.13)***
γ_1	0.254	0.236	0.123	0.267
	(2.32)**	(3.83)***	(1.53)	(6.22)***
γ_2	−0.002	−0.002	0.0042	−0.008
	(−0.40)	(−2.22)**	(1.62)*	(−1.34)
Adjusted R^2	0.22	0.23	0.41	0.38

Notes:
This table reports results of the following regression for dual-listed Shanghai A and B and Shenzhen A and B shares: $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t$, where $R_{m,t}$ is the equally weighted portfolio return at time t. $CSAD_t$ is the equally weighted cross sectional absolute deviation. The sample period is from 7/1/1997 to 12/31/2003. 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.

all four markets examined, suggesting that the herding behavior was not significantly influenced by the Asian crisis.

Hwang and Salmon (2006) note that stock returns and herding are likely to be affected by fundamentals, at the level of the market or the individual firm. They use variables such as the dividend-price ratio, the Treasury bill rate, the term spread, and the default spread in their analysis of herding in the US, UK, and South Korean equity markets. To control for these fundamentals, we add the demand deposit rate and each firm's earnings yield (calculated as earnings per share divided by share price) to the herding regression.[10] In these expanded models as reported in Appendix A, the estimated coefficient γ_2 is still significantly negative for all markets. In

[10] Our choice of variables is driven by data limitations.

summary, even after controlling for the effect of market and firm fundamentals, we still find evidence of herd behavior in Chinese stock markets.

A potential concern is whether the herding coefficient γ_2 is capturing the relation between idiosyncratic risk and market returns, which is documented by Goyal and Santa-Clara (2003). Unlike CCK, our measure of CSAD_t does not rely on the accuracy of the market-based model of the CAPM. However, in order to control directly for the impact of volatility, a conditional variance is placed into the mean equation to serve as a control variable. We specify a GARCH (1,1)-in-mean model as:

$$\begin{aligned} \mathrm{CSAD}_t &= \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \theta_1(\mathrm{RF}_t) + \theta_2(\mathrm{EPS}_t^*) + \theta_3\sigma_t^2 + \varepsilon_t , \\ \sigma_t^2 &= \omega_0 + \omega_1\varepsilon_{t-1}^2 + \omega_2\sigma_{t-1}^2 \end{aligned} \tag{6}$$

where σ_t^2 is the conditional variance of the residual of CSAD_t. Equivalently, the variance equation can be expressed as

$$\varepsilon_t^2 = \omega_0 + (\omega_1 + \omega_2)\varepsilon_{t-1}^2 - \omega_2(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\varepsilon_t^2 - \sigma_t^2).$$

As shown in Appendix B, although both macro and firm fundamental variables as well as the conditional variance are statistically significant, the coefficient γ_2 remains negative and significant, providing further evidence of herd behavior. For this reason, we keep the model specification as in Eq. (3) for further analysis.

5. Asymmetric herding behavior

In this section, we investigate whether the herding behavior documented above varies with market conditions. Specifically, we examine potential asymmetries in herding behavior as the trading environment is characterized by different states of market returns, trading volume, and volatility. Christie and Huang (1995) and Chang et al. (2000) note that herding behavior may be more pronounced during periods of market stress. Return volatility and trading volume may help characterize such periods, so we use them to gain additional insight regarding the level of herding behavior under different market conditions.

5.1. Asymmetric effects of market return

Since the direction of the market return may affect investor behavior we examine possible asymmetries in herd behavior conditional on whether the market is rising or falling. The herding regression is estimated separately for positive and negative market returns. Specifically, the system can be written as:

$$\mathrm{CSAD}_t^{\mathrm{UP}} = \alpha + \gamma_1^{\mathrm{UP}}|R_{m,t}^{\mathrm{UP}}| + \gamma_2^{\mathrm{UP}}(R_{m,t}^{\mathrm{UP}})^2 + \varepsilon_t, \text{ if } R_{m,t}>0. \tag{7}$$

$$\mathrm{CSAD}_t^{\mathrm{DOWN}} = \alpha + \gamma_1^{\mathrm{DOWN}}|R_{m,t}^{\mathrm{DOWN}}| + \gamma_2^{\mathrm{DOWN}}(R_{m,t}^{\mathrm{DOWN}})^2 + \varepsilon_t, \text{ if } R_{m,t}<0 \tag{8}$$

where $R_{m,t}^{\mathrm{UP}}$ is the equal-weighted portfolio return at time t when the market rises, and $(R_{m,t}^{\mathrm{UP}})^2$ is the squared value of this term. $\mathrm{CSAD}_t^{\mathrm{UP}}$ is the CSAD at time t corresponding to $R_{m,t}^{\mathrm{UP}}$. Similarly, the variables with superscript "down" refer to the scenario in which the market declines.

Table 3 reports the herding regression results under asymmetric market conditions. In all four markets examined, the coefficient γ_2 is significantly negative in both rising and falling markets. We also test the equality of the herding coefficient in both market conditions. The results suggest that herding is stronger in Shanghai A shares during rising markets, but no asymmetry exists in the other markets examined.

5.2. Asymmetric effects of trading volume

The level of herding behavior may be associated with trading volume, so we examine possible asymmetric effects during periods of high or low volume. We characterize trading volume V_t as high if on day t it is greater than the previous 30-day moving average.[11] Trading volume is regarded as low if it is less than the previous 30-day moving average. The possible asymmetric effects are examined by using the following empirical specifications:

$$\mathrm{CSAD}_t^{\mathrm{V-HIGH}} = \alpha + \gamma_1^{\mathrm{V-HIGH}} |R_{m,t}^{\mathrm{V-HIGH}}| + \gamma_2^{\mathrm{V-HIGH}} (R_{m,t}^{\mathrm{V-HIGH}})^2 + \varepsilon_t \tag{9}$$

$$\mathrm{CSAD}_t^{\mathrm{V-LOW}} = \alpha + \gamma_1^{\mathrm{V-LOW}} |R_{m,t}^{\mathrm{V-LOW}}| + \gamma_2^{\mathrm{V-LOW}} (R_{m,t}^{\mathrm{V-LOW}})^2 + \varepsilon_t \tag{10}$$

where the superscripts V-HIGH and V-LOW refer to high and low trading volume.

Panels A and B of Table 4 report the results of the asymmetric volume herding regressions. The evidence from Panel A indicates that in the high volume state, the coefficient γ_2 for all of the Shanghai and Shenzhen A- and B-share markets is significantly negative, suggesting herding in these markets. In the low volume state, the coefficient γ_2 is negative for all four markets, but is significant only in the B-share markets. The results indicate that herding by B-share investors is unrelated to trading volume. Since these B-share markets tend to be dominated by foreign institutions, perhaps they typically rely on common sources of information regardless of the level of market activity. In contrast, the tendency for herding by A-share investors to occur only in the high volume state suggests that the information driving their behavior may be more diverse during relatively “quiet” periods of low volume.

5.3. Asymmetric effects of volatility

We further examine potential asymmetric effects of herding behavior with respect to market volatility. Similar to our analysis of trading volume, we define volatility to be high when the observed volatility exceeds the moving average of volatility over the previous 30 days.[12] Volatility is characterized as low when it is below the 30-day moving average. The asymmetric effects are examined using the following empirical specifications:

$$\mathrm{CSAD}_t^{\hat{\sigma}^2,\mathrm{HIGH}} = \alpha + \gamma_1^{\hat{\sigma}^2,\mathrm{HIGH}} |R_{m,t}^{\hat{\sigma}^2,\mathrm{HIGH}}| + \gamma_2^{\hat{\sigma}^2,\mathrm{HIGH}} (R_{m,t}^{\hat{\sigma}^2,\mathrm{HIGH}})^2 + \varepsilon_t \tag{11}$$

$$\mathrm{CSAD}_t^{\hat{\sigma}^2,\mathrm{LOW}} = \alpha + \gamma_1^{\hat{\sigma}^2,\mathrm{LOW}} |R_{m,t}^{\hat{\sigma}^2,\mathrm{LOW}}| + \gamma_2^{\hat{\sigma}^2,\mathrm{LOW}} (R_{m,t}^{\hat{\sigma}^2,\mathrm{LOW}})^2 + \varepsilon_t \tag{12}$$

where the superscripts $(\hat{\sigma}^2,^{\mathrm{HIGH}})$ and $(\hat{\sigma}^2,^{\mathrm{LOW}})$ refer to high return volatility and low return volatility, and $\hat{\sigma}_t^2$ is calculated as the square of the portfolio return in period t.

Table 5 reports the estimation results of the asymmetric volatility models. Panel A reports the regression results for Shanghai A, B and Shenzhen A, B markets when volatility is high. Consistent with previous findings, all of the estimated γ_2 coefficients are significantly negative,

[11] We also use 60-day, 90-day and 120-day moving averages to characterize volume as high or low, and obtain similar results.

[12] We also use 60-day, 90-day and 120-day moving averages to characterize volatility as high or low, and obtain similar results.

Table 3
Estimates of herding behavior in rising and declining Chinese stock markets

Panel A: Regression results when market rises ($R_{m,t}$>0)

Market (no. of observation)	SHA (798)	SHB (722)	SZA (797)	SZB (695)
α	1.076	1.087	1.141	1.249
	(34.43)***	(18.22)***	(34.40)***	(23.13)***
γ_1^{UP}	0.313	0.703	0.250	0.335
	(9.11)***	(11.51)***	(7.19)***	(7.27)***
γ_2^{UP}	−0.033	−0.067	−0.023	−0.036
	(−7.11)**	(−8.69)***	(−4.15)***	(−6.94)***
Adjusted R^2	0.13	0.23	0.11	0.09

Panel B: Regression results when market declines ($R_{m,t}$<0)

Market (no. of observation)	SHA (771)	SHB (806)	SZA (772)	SZB (803)
α	1.075	1.093	1.149	1.230
	(34.96)***	(18.57)***	(34.24)***	(26.56)***
γ_1^{DOWN}	0.241	0.796	0.229	0.386
	(6.87)***	(12.52)***	(6.26)***	(8.34)***
γ_2^{DOWN}	−0.012	−0.076	−0.014	−0.029
	(−1.77)*	(−9.07)***	(−2.08)***	(−4.49)***
Adjusted R^2	0.15	0.26	0.13	0.18

Panel C: Joint Wald Test H_0: $\gamma_2^{UP}-\gamma_2^{DOWN}=0$

$\gamma_2^{UP}-\gamma_2^{DOWN}$	−0.0220	0.0097	−0.0091	−0.0079
t-statistics Chi-square	(−2.50)***	(0.94)	(−1.13)	(0.98)
statistics	[6.25]***	[0.88]	[1.28]	[0.96]

Notes:
This table reports the regressions results for Chinese A-share and B-share stock markets:

$$\mathrm{CSAD}_t^{UP} = \alpha + \gamma_1^{UP}|R_{m,t}^{UP}| + \gamma_2^{UP}(R_{m,t}^{UP})^2 + \varepsilon_t, \qquad \text{if } R_{m,t}>0$$

$$\mathrm{CSAD}_t^{DOWN} = \alpha + \gamma_1^{DOWN}|R_{m,t}^{DOWN}| + \gamma_2^{DOWN}(R_{m,t}^{DOWN})^2 + \varepsilon_t, \qquad \text{if } R_{m,t}<0$$

where $R_{m,t}^{UP}$ ($R_{m,t}^{DOWN}$) is the equally weighted portfolio return during period t when the market is up (down). SHA refers to dual-listed A shares on the Shanghai stock exchange, SHB refers to dual-listed B shares on the Shanghai stock exchange, SZA refers to dual-listed A shares on the Shenzhen stock exchange, and SZB refers to dual-listed B shares on Shenzhen stock exchange. The sample period is from 7/1/1997 to 12/31/2003. 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.

providing evidence of herding. However, under conditions of low volatility, none of the coefficients γ_2 for the four markets displays a negative sign, suggesting that herding in Chinese equity markets occurs only during periods of high volatility.

5.4. Summary of asymmetric effects on herding

The sections above present an analysis of the possible asymmetric patterns in herding behavior based on the direction of the market return and the levels of trading volume and volatility. We examine the equality of herding coefficients in Panel C in Tables 3–5 using Wald tests. The evidence shows that for the Shanghai A-share market, the herding reaction is stronger when the market is rising, is characterized by higher trading volume, and is more volatile. In the Shenzhen

Table 4
Estimates of herding behavior during periods of high or low trading volume in Chinese stock markets

Panel A: Regression results when trading volume is high

Market (no. of observation)	SHA (649)	SHB (566)	SZA (630)	SZB (535)
α	1.271	1.378	1.364	1.39
	(34.74)***	(15.17)***	(30.92)***	(16.72)***
$\gamma_1^{\text{V-HIGH}}$	0.273	0.647	0.216	0.391
	(7.20)***	(9.39)***	(5.42)***	(6.88)***
$\gamma_2^{\text{V-HIGH}}$	−0.028	−0.063	−0.018	−0.04
	(−5.22)**	(−7.36)***	(−2.90)***	(−6.26)***
Adjusted R^2	0.11	0.16	0.08	0.10

Panel B: Regression results when trading volume is low

Market (no. of observation)	SHA (920)	SHB (960)	SZA (939)	SZB (963)
α	1.014	1.017	1.069	1.215
	(36.43)***	(20.96)***	(42.54)***	(30.58)***
$\gamma_1^{\text{V-LOW}}$	0.186	0.759	0.177	0.305
	(5.30)***	(13.1)***	(6.48)***	(8.04)***
$\gamma_2^{\text{V-HIGH}}$	−0.003	−0.075	−0.008	−0.03
	(−0.376)	(−9.72)***	(−1.60)	(−5.91)***
Adjusted R^2	0.12	0.25	0.10	0.09

Panel C: Joint Wald Test H_0: $\gamma_2^{\text{V-HIGH}} - \gamma_2^{\text{V-LOW}} = 0$

$\gamma_2^{\text{V-HIGH}} - \gamma_2^{\text{V-LOW}}$	−0.0254	0.0141	−0.0101	−0.0008
t-statistics Chi-square statistics	(−2.78)*** [7.73]***	(1.31) [1.72]	(−1.29) [1.67]	(−0.088) [0.007]

Notes:
This table reports the regressions results for Chinese A-share and B-share stock markets:

$$\mathrm{CSAD}_t^{\mathrm{V-HIGH}} = \alpha + \gamma_1^{\mathrm{V-HIGH}} |R_{m,t}^{\mathrm{V-HIGH}}| + \gamma_2^{\mathrm{V-HIGH}} (R_{m,t}^{\mathrm{V-HIGH}})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_t^{\mathrm{V-LOW}} = \alpha + \gamma_1^{\mathrm{V-LOW}} |R_{m,t}^{\mathrm{V-LOW}}| + \gamma_2^{\mathrm{V-LOW}} (R_{m,t}^{\mathrm{V-LOW}})^2 + \varepsilon_t$$

where V_t is the trading volume for A/B share dual-listed stock portfolio m at time t. Trading volume V_t is regarded as being high if it is larger than the previous 30-day moving average trading volume, and is considered to be low if it is below this average. SHA refers to dual-listed A shares on the Shanghai stock exchange, SHB refers to dual-listed B shares on the Shanghai stock exchange, SZA refers to dual-listed A shares on the Shenzhen stock exchange, and SZB refers to dual-listed B shares on Shenzhen stock exchange. The 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.

A-share market, herding is stronger when volatility is high. For the B-share market, no differences in the herding coefficients are statistically significant.

The finding of asymmetric herd behavior in A-share market returns may be driven by the effects of government intervention. Hu (1999) and Mei et al. (2004) document the role of the Chinese government in the stock market and the behavioral characteristics of Chinese investors. Our results suggest that Chinese investors, especially those in the Shanghai market, tend to be more optimistic and confident of government support in rising markets. The stronger effect in the Shanghai market compared to the Shenzhen market could be due to the Shanghai market being comprised mainly of larger companies, which were formerly owned by the state. These

Table 5
Estimates of herding behavior during periods of high or low volatility in Chinese stock markets

Panel A: Regression results when volatility is high				
Market (no. of observation)	SHA (560)	SHB (600)	SZA (586)	SZB (585)
α	0.786	1.000	0.863	0.782
	(9.21)***	(4.89)***	(11.22)***	(5.87)***
$\gamma_1^{\hat{\sigma}^2,\mathrm{HIGH}}$	0.447	0.782	−0.406	0.600
	(7.75)***	(7.23)***	(−7.94)***	(8.32)***
$\gamma_2^{\hat{\sigma}^2,\mathrm{HIGH}}$	−0.041	−0.075	−0.036	−0.058
	(−5.68)***	(−6.93)***	(−5.90)***	(−8.04)***
Adjusted R^2	0.13	0.08	0.13	0.11
Panel B: Regression results when volatility is low				
Market (no. of observation)	SHA (1001)	SHB (926)	SZA (975)	SZB (941)
α	1.161	1.076	1.258	1.153
	(29.84)***	(14.77)***	(28.98)***	(18.88)***
$\gamma_1^{\hat{\sigma}^2,\mathrm{LOW}}$	−0.076	0.72	−0.17	0.418
	(−0.50)**	(3.01)***	(−1.24)	(2.18)**
$\gamma_2^{\hat{\sigma}^2,\mathrm{LOW}}$	0.258	0.015	0.268	0.032
	(2.11)**	(0.09)	(2.63)***	(0.25)
Adjusted R^2	0.05	0.13	0.13	0.08
Panel C: Joint Wald Test H_0: $\gamma_2^{\hat{\sigma}^2,\mathrm{HIGH}} - \gamma_2^{\hat{\sigma}^2,\mathrm{LOW}} = 0$				
$\gamma_2^{\hat{\sigma}^2,\mathrm{HIGH}} - \gamma_2^{\hat{\sigma}^2,\mathrm{LOW}}$	−0.297	−0.1154	−0.3011	−0.1145
t-statistics Chi-square statistics	(2.98)*** [8.88]***	(−0.94) [0.89]	(−3.18)*** [10.13]***	(−1.11) [1.22]

Notes:
This table reports the daily regressions results for Shanghai A and B, and Shenzhen A and B stock markets:

$$\mathrm{CSAD}_t^{\sigma^2,\mathrm{HIGH}} = \alpha + \gamma_1^{\sigma^2,\mathrm{HIGH}} |R_{m,t}^{\sigma^2,\mathrm{HIGH}}| + \gamma_2^{\sigma^2,\mathrm{HIGH}} (R_{m,t}^{\sigma^2,\mathrm{HIGH}})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_t^{\sigma^2,\mathrm{LOW}} = \alpha + \gamma_1^{\sigma^2,\mathrm{LOW}} |R_{m,t}^{\sigma^2,\mathrm{LOW}}| + \gamma_2^{\sigma^2,\mathrm{LOW}} (R_{m,t}^{\sigma^2,\mathrm{LOW}})^2 + \varepsilon_t$$

where volatility, $\sigma_{m,t}^2$ is the stock return variance for A–B share dual-listed stock portfolio *m* at time *t*. Return volatility is defined as being in a high state if it is larger than the previous 30-day moving average trading volume, and is considered to be low if it is below this average. SHA refers to dual-listed A shares on the Shanghai stock exchange, SHB refers to dual-listed B shares on the Shanghai stock exchange, SZA refers to dual-listed A shares on the Shenzhen stock exchange, and SZB refers to dual-listed B shares on Shenzhen stock exchange. The 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.

companies traditionally rely on the government for financing, raw materials, and product distribution. In contrast, the Shenzhen market is composed mainly of smaller firms, which were less likely to be state-owned. When the market falls, investors tend to herd less, as they believe that the government will intervene and prevent the market from falling.

6. Herding behavior and cross-market information

Since Chen et al. (2001) find bilateral feedback between A-share and B-share returns, it is of interest to examine whether A-share investors make their investment decisions based on B-share investors' decisions, and vice versa. We test the relation between return dispersions and cross-

Table 6
Cross-market effects on herding behavior

Model	SHA	SHB	SZA	SZB
α	1.066	1.041	1.142	1.121
	(45.14)***	(24.28)***	(45.73)***	(30.56)***
γ_1	0.273	0.759	0.230	0.437
	(9.88)***	(17.03)*	(8.79)***	(12.91)***
γ_2	−0.024	−0.073	−0.017	−0.043
	(−4.86)***	(−12.60)***	(−3.85)***	(−10.66)***
γ_3	0.003	0.003	0.002	0.002
	(2.16)**	(0.53)	(1.97)**	(0.63)
Adjusted R^2	0.14	0.26	0.11	0.16

Notes:
This table reports daily regression results of the following models:

$$\mathrm{CSAD}_{\mathrm{SHA},t} = \alpha + \gamma_1 |R_{\mathrm{SHA},t}| + \gamma_2 (R_{\mathrm{SHA},t})^2 + \gamma_3 (R_{\mathrm{SHB},t})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_{\mathrm{SHB},t} = \alpha + \gamma_1 |R_{\mathrm{SHB},t}| + \gamma_2 (R_{\mathrm{SHB},t})^2 + \gamma_3 (R_{\mathrm{SHA},t})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_{\mathrm{SZA},t} = \alpha + \gamma_1 |R_{\mathrm{SZA},t}| + \gamma_2 (R_{\mathrm{SZA},t})^2 + \gamma_3 (R_{\mathrm{SZB},t})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_{\mathrm{SZB},t} = \alpha + \gamma_1 |R_{\mathrm{SZB},t}| + \gamma_2 (R_{\mathrm{SZB},t})^2 + \gamma_3 (R_{\mathrm{SZA},t})^2 + \varepsilon_t$$

The daily sample period is from 7/1/1997 to 12/31/2003. The 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.

market information by adding the squared cross-market return, which bears a coefficient of γ_3, in each of the regressions as follows:

$$\mathrm{CSAD}_{\mathrm{SHA},t} = \alpha + \gamma_1 |R_{\mathrm{SHA},t}| + \gamma_2 (R_{\mathrm{SHA},t})^2 + \gamma_3 (R_{\mathrm{SHB},t})^2 + \varepsilon_t \tag{13}$$

$$\mathrm{CSAD}_{\mathrm{SHB},t} = \alpha + \gamma_1 |R_{\mathrm{SHB},t}| + \gamma_2 (R_{\mathrm{SHB},t})^2 + \gamma_3 (R_{\mathrm{SHA},t})^2 + \varepsilon_t \tag{14}$$

$$\mathrm{CSAD}_{\mathrm{SZA},t} = \alpha + \gamma_1 |R_{\mathrm{SZA},t}| + \gamma_2 (R_{\mathrm{SZA},t})^2 + \gamma_3 (R_{\mathrm{SZB},t})^2 + \varepsilon_t \tag{15}$$

$$\mathrm{CSAD}_{\mathrm{SZB},t} = \alpha + \gamma_1 |R_{\mathrm{SZB},t}| + \gamma_2 (R_{\mathrm{SZB},t})^2 + \gamma_3 (R_{\mathrm{SZA},t})^2 + \varepsilon_t \tag{16}$$

Table 6 reports the estimation results of the cross-market effect. For all four markets, γ_2 is significantly negative, consistent with herding. However, the estimated γ_3 coefficients are positive, and in only the two A-share markets are they statistically significant. In summary, there is no evidence supporting the notion that the return dispersion decreases as investors receive cross-market information.

Although the Shanghai and Shenzhen stock exchanges are two separate markets, in different cities, with different listed firms and management teams, investment analysts often argue that one market follows the other. This motivates us to test whether return dispersions are

Table 7
Cross-exchange effects on herding behavior

Model	SHA	SHB	SZA	SZB
α	1.071	1.046	1.146	1.121
	(45.91)***	(24.62)***	(46.12)***	(30.11)***
γ_1	0.282	0.762	0.235	0.438
	(10.45)***	(17.11)***	(8.91)***	(13.04)***
γ_2	−0.028	−0.072	−0.019	−0.044
	(−4.32)***	(−10.80)***	(−3.78)***	(−9.69)**
γ_3	0.005	−0.002	0.003	0.002
	(1.17)	(−0.41)	(0.71)	(0.61)
Adjusted R^2	0.14	0.26	0.12	0.16

Notes:
This table reports daily regression results of the following models.

$$\mathrm{CSAD}_{\mathrm{SHA},t} = \alpha + \gamma_1|R_{\mathrm{SHA},t}| + \gamma_2(R_{\mathrm{SHA},t})^2 + \gamma_3(R_{\mathrm{SHA},t})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_{\mathrm{SHB},t} = \alpha + \gamma_1|R_{\mathrm{SHB},t}| + \gamma_2(R_{\mathrm{SHB},t})^2 + \gamma_3(R_{\mathrm{SHB},t})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_{\mathrm{SZA},t} = \alpha + \gamma_1|R_{\mathrm{SZA},t}| + \gamma_2(R_{\mathrm{SZA},t})^2 + \gamma_3(R_{\mathrm{SZA},t})^2 + \varepsilon_t$$

$$\mathrm{CSAD}_{\mathrm{SZB},t} = \alpha + \gamma_1|R_{\mathrm{SZB},t}| + \gamma_2(R_{\mathrm{SZB},t})^2 + \gamma_3(R_{\mathrm{SZB},t})^2 + \varepsilon_t$$

The daily sample period is from 7/1/1997 to 12/31/2003. The 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.

influenced by cross-exchange effects in the same class of security. To test this, we add an incremental variable of the squared cross-exchange return with a coefficient γ_3 in each of the equations as follows:

$$\mathrm{CSAD}_{\mathrm{SHA},t} = \alpha + \gamma_1|R_{\mathrm{SHA},t}| + \gamma_2(R_{\mathrm{SHA},t})^2 + \gamma_3(R_{\mathrm{SZA},t})^2 + \varepsilon_t \tag{17}$$

$$\mathrm{CSAD}_{\mathrm{SHB},t} = \alpha + \gamma_1|R_{\mathrm{SHB},t}| + \gamma_2(R_{\mathrm{SHB},t})^2 + \gamma_3(R_{\mathrm{SZB},t})^2 + \varepsilon_t \tag{18}$$

$$\mathrm{CSAD}_{\mathrm{SZA},t} = \alpha + \gamma_1|R_{\mathrm{SZA},t}| + \gamma_2(R_{\mathrm{SZA},t})^2 + \gamma_3(R_{\mathrm{SHA},t})^2 + \varepsilon_t \tag{19}$$

$$\mathrm{CSAD}_{\mathrm{SZB},t} = \alpha + \gamma_1|R_{\mathrm{SZB},t}| + \gamma_2(R_{\mathrm{SZB},t})^2 + \gamma_3(R_{\mathrm{SHB},t})^2 + \varepsilon_t \tag{20}$$

The estimates of the above set of equations are reported in Table 7. As before, γ_2 is negative and significant in all four markets. However, we find that none of the γ_3 coefficients is statistically significant, indicating that dispersions of return are independent of cross-exchange market movements.

7. Conclusions

This study examines the existence of herding behavior in dual-listed Chinese A- and B-share markets. Results based on daily data indicate that both the A-share and the B-share markets on the Shanghai and Shenzhen exchanges are characterized by investor herding. The evidence of herding over weekly and monthly time intervals is much weaker, suggesting that herding is a phenomenon confined to short time horizons.

We test for potential asymmetries in herd behavior related to market returns, trading volume, and volatility. Herding is present in all four markets examined when markets are rising, and when volume and volatility are high. The herding behavior of Shanghai A-share exhibits asymmetric tendencies, and is significantly stronger when markets are rising, experiencing higher trading volume, and more volatile. We find no such asymmetries for B-share investors. This apparent difference in investor behavior may be due to the different characteristics of A and B markets: the A-share market is dominated by domestic individual investors, whereas the B-share market is dominated by foreign institutional investors. In future research on Chinese equity markets, the consideration of investor characteristics and behavioral tendencies may yield interesting insights.

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Appendix A

A.1

Estimates of herding equation based on macroeconomic and firm fundamental variables

	SHA	SHB	SZA	SZB
α	1.412	−0.483	1.394	0.023
	(19.61)**	(−13.05)***	(18.68)***	(0.56)
γ_1	0.273	0.632	0.236	0.416
	(10.52)***	(20.21)***	(9.10)***	(15.51)***
γ_2	−0.022	−0.063	−0.017	−0.042
	(−4.82)***	(−16.45)***	(−3.75)***	(−11.63)***
θ_1	60.03	82.88	36.16	51.01
	(12.32)***	(16.80)***	(7.46)***	(17.91)***
θ_2	−65.64	5.25	−43.33	6.67
	(−9.29)**	(17.70)***	(−6.14)***	(10.90)***
Adjusted R^2	0.25	0.66	0.16	0.53

Notes:

This table reports the estimated results based on the following regression: $\text{CSAD}_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \theta_1 (RF_t) + \theta_2 (\text{EPS}_t^*) + \varepsilon_t$, where CSAD_t is the equally weighted cross sectional absolute deviation at time t. $R_{m,t}$ is the equally weighted portfolio return at time t. RF_t is the risk free rate represented by Chinese demand deposit rate. EPS_t^* is the earnings yield for each firm, calculated as earnings per share divided by share price. 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.

A.2

Estimates of herding equation based on macroeconomic and firm fundamental variables and GARCH(1,1)-in-Mean volatility process

	SHA	SHB	SZA	SZB
Mean equation				
α	0.973	−0.190	0.821	−0.006
	(18.09)***	(−5.00)***	(15.30)***	(−0.17)***

(continued on next page)

Appendix A.2 (*continued*)

	SHA	SHB	SZA	SZB
Mean equation				
γ_1	0.182	0.287	0.173	0.239
	(11.59)***	(22.89)***	(11.94)***	(16.67)***
γ_2	−0.014	−0.024	−0.173	−0.024
	(−6.70)***	(−12.97)***	(11.94)***	(−13.31)***
θ_1	35.762	69.407	21.220	12.346
	(10.86)***	(28.19)***	(7.58)***	(5.33)***
θ_2	−40.233	3.067	−5.834	7.609
	(−8.45)***	(9.13)***	(−1.75)*	(15.66)***
θ_3	1.135	1.318	0.948	1.655
	(8.19)***	(10.42)***	(11.25)***	(13.71)***
Variance equation				
ω_0	0.009	0.000	0.005	0.001
	(5.63)***	(0.94)	(4.11)***	(2.96)***
ω_1	0.105	0.042	0.106	0.053
	(9.40)***	(9.63)***	(10.10)***	(13.10)***
ω_2	0.856	0.959	0.875	0.947
	(68.56)***	(257.91)***	(70.84)***	(272.67)***
F-stat	108.53***	537.44***	81.700***	267.78***

Notes:

This table reports the results of the regression $\text{CSAD}_t = c + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \theta_1(\text{RF}_t) + \theta_2(\text{EPS}_t^*) + \theta_3\sigma_t^2 + \varepsilon_t$ where σ_t^2 is specified as a GARCH(1,1)-in-mean volatility process as $\sigma_t^2 = \omega_0 + \omega_1 e_{t-1}^2 + \sigma_{t-1}^2$ where CSAD_t is the equal-weighted cross sectional absolute deviation at time t. $R_{m,t}$ is the equal-weighted portfolio return at time t. RF_t is the risk free rate represented by Chinese demand deposit rate. EPS_t^* is the earnings yield for each firm, calculated as earnings per share divided by share price. 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.

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