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Does Herding Matter in the Chinese Stock Markets?

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This paper examines the herd behavior in six segmented markets on the Chinese stock markets. Using the OLS, GARCH, Quantile Regression, and State Space Models to examine the daily returns from 2003 to 2018, we find that herd behavior exists widely in all the segmented markets examined in China, particularly in the two B-share markets. The two B-share markets also show stronger (weaker) asymmetric herd effects when market returns are rising (falling) and when trading volumes are higher (lower). Further evidence suggests that the herd effect in China became stronger during the period of the Chinese stock market turbulence. The results can provide enlightenment for the Chinese policymakers to stabilize and to improve the efficiency of stock markets, and also help investors to identify their markets of interest and control financial risks.

Keywords: herd behavior; Chinese stock markets; asymmetric behavior

JEL Classification: G10; G41

1 Introduction

Unlike traditional finance, behavioral finance considers people's psychological factors in order to explore how so-called irrational humans will make decisions in the financial market. In financial markets, herd behavior describes individuals' tendency to act as a group without planned direction. Individual investors always follow the actions of other similar investors: they buy when others buy and sell when others sell. Some investors always think that others in the same market have informational advantages. The current huge enthusiasm for investing in stocks means the energy of individual investors rapidly accumulates and it is easy to form a homogenous herd effect. The effects brought by herding may have a significant influence on the credibility of collective information and, therefore, such irrational behavior can result in the

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deviation of stock prices from their fundamental values and prevent investors from taking advantage of profitable trading opportunities.

In order to test whether the herd effect exists, a lot of research has been conducted, such as those carried out by Christie and Huang (1995) and Chang et al. (2000). Their research mostly focuses on the international market or developed markets, and their findings are not completely consistent, but in general show herd effects do exist in various markets.

As the world's second largest economy and a rapidly growing market, the Chinese market is attracting much attention. The Chinese stock market is an emerging market with an investor structure dominated by retail investors who are quite actively trading in the market. Such features are in line with the conditions under which the herd effect is formed. The degree of government intervention during its establishment and initial development has made the stock market distinct from other those of other countries. In Mainland China, the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) were established in 1990 and 1999 respectively. The SSE has only a main board, with mainly large companies listed and a relatively small number of newly listed companies. The SZSE has a mainboard, a Small- and Medium-sized Enterprise (SME) board, and a Growth Enterprise Market (GEM) board. Compared with the SSE, companies listed on the SZSE are smaller but there are more of them. On these two exchanges, two classes of stocks, A shares (SSE A-share (SHA), SZSE A-share (SZA)) and B shares (SSE B-share (SHB), SZSE B-share (SZB)), are offered. A shares could only be traded by domestic investors and B shares could only be traded by foreign investors before February 2001. Since then, B shares have been traded by both domestic and foreign investors. In summary, the SSE and SZSE, as well as A shares and B shares, have different characteristics that may result in different levels of herding.

In this paper, we attempt to investigate and compare the herd behaviors in the six segmented Chinese markets: the SSE, SZSE, SHA, SZA, SHB, and SZB. The stock return dispersions are always found to be significantly high during periods of large changes in the market index. To explore the return dispersions for upside and downside movements of the market, we use the Cross-Sectional Standard Deviations (CSSD) and Cross-Sectional Absolute Deviations (CSAD) as return dispersions indicators in order to detect any possible relationships between herd effects and stock market movements. To better understand the feature of herd behavior in each market, we further investigate any potential asymmetries in herd behavior under different market conditions that are described by different states of market return, trading volume, and volatility. In addition to the traditional Ordinary Least Squares (OLS) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) regression models, the quantile regression model and the state space model are also employed. Lastly, a robustness test is conducted to see if financial crisis is capable of stimulating herd effects. We find evidence that herd behavior appears widely in all the segmented markets examined, particularly in the two B-share markets. Furthermore, the herd effect in China became stronger during the period of

Chinese stock market turbulence. The results shed light on herd behavior in the context of emerging Chinese stock markets. Our findings provide important implications for Chinese policymakers to stabilize and to improve the efficiency of the markets and help investors develop effective risk management and portfolio diversification.

To our knowledge, this study is one of the few that analyze six segmented markets in a single research. Most past studies have only analyzed the Shenzhen and/or Shanghai markets (Demirer and Kutan, 2006; Li et al., 2018) or A-share and/or B-share markets (Lao and Singh, 2011; Li et al., 2019), while some analyzed four segmented markets (Tan et al., 2008; Yao et al., 2014). Our research can provide a better understanding of the Chinese markets by analyzing more segmented markets. Investors can search for their market of interest accordingly. In addition, existing literature typically focuses on one or two types of econometric tools to examine herd behavior. By using a more variety of econometric tools in our analysis, the present empirical results are expected to be more robust and convincing.

The rest of this paper is organized as follows. Section 2 discusses related previous research work on herding. Section 3 introduces the sample data and methodologies employed in the study. Section 4 presents empirical results and findings. Section 5 gives a robustness test, and Section 6 concludes.

2 Literature Review

According to Bikhchandani and Sharma (2000), herd behavior means investors intentionally duplicating other investors' behavior when investing in stock markets, and is mostly caused by lack of information, reputation concerns, and compensation plans. Past researchers believe that it is in people's nature to be consistent with others (Devenow & Welch, 1996).

Many researchers have studied herd behavior in different markets, but their findings have not been consistent. Christie and Huang (1995) (hereafter CH) introduce the CSSD to detect herd effects. In the CH method, the investment decisions of individuals are assumed to be based on overall market conditions. When the absolute value of the market returns increases during a normal period, the dispersion in returns should move in the same direction because investors are trading rationally and variously. However, when the market is experiencing huge movements, individuals are more likely to act in a group, driving the individual stock returns to cluster around the market returns. As a result, the herd effect can be quite significant during the times extreme returns occur. Using daily and monthly returns to examine the herd effect in the U.S. stock markets, the authors suggest that herding is not an important factor in determining equity returns during periods of market stress.

Gleason et al. (2004) report that there are no herd effects in ETF*s* during extreme market movements, and no symmetry exists for up and down markets after news are fully reflected. Boyer et al. (2006) state that the herd effect is indeed present when market volatility is high.

Chiang et al. (2007) focus on herd effects during extreme periods, such as the financial crisis. They find that herd behavior dominates market movements during the later stages of financial crisis. BenSaïda (2017) takes the industry into consideration and examines all the listed companies on the U.S. market. The author reports that herding exists in almost every sector of the U.S. market during turmoil periods and that, furthermore, herding can affect the volatility of some stocks. Litimi (2017) also finds herding in the French market during turmoil periods and only in certain sectors throughout the whole sample period.

Instead of the CH method, an alternative and less stringent method is proposed by Chang et al. (2000) (hereafter CCK). The authors use the CSAD to examine different markets including several Asian markets. On one hand, they find no evidence or only partial evidence of herding in Hong Kong and Japan while, on the other hand, strong herd behavior exists in Taiwan and South Korea during periods of extreme market movement. Consistent with CCK's findings, Blasco and Ferreruela (2008) find that no evidence of herding occurs in Japan by using the CSSD method to test the data in seven countries from January 1998 to April 2004.

Chiang and Zheng (2010) examine if herding exists in Asian markets including Indonesia, Malaysia, Singapore, South Korea, Taiwan, and Thailand. They find that the herd effect is widespread on these Asian markets. Lao and Singh (2011) test the top 300 firms listed on the Bombay Stock Exchange index (BSE) over the period from 1st July 1999 to 30th June 2009. The authors find the herd effect exists on the Indian market, especially during up markets. According to their study, the herding in India is weaker than that found in the Chinese market. Munkh-Ulzii et al. (2018) show evidence of herd behavior regardless of market conditions in the stock markets of Mainland China and Taiwan during the sample period from 1999 to 2014.

With the development of the Chinese stock markets, more and more researchers have begun to study herd behavior in the Chinese markets, and the impacts of other financial and economic factors on the herd effect. As yet, there is no unified conclusion. Demirer and Kutan (2006) find that there are no herd effects in Chinese markets by using both individual-level and sector-level data of 375 listed firms from January 1999 to December 2002, and May 1993 to November 2001, on the Shanghai Stock Exchange and the Shenzhen Stock Exchange respectively. Their results imply that the asset pricing models and efficient market hypothesis still apply to the Chinese stock markets. On the contrary, Tan et al. (2008) report that there is evidence of herding in both A-share and B-share markets on the Shanghai and Shenzhen stock exchanges. They also report herding to be stronger in A-share markets than in B-share markets, and that the herd effect is stronger in up markets, periods of high trading volume, and periods of high trading volatility on the Shanghai A-share market. In the Shenzhen A-share market, herding is only stronger during periods of high trading volatility. Chiang et al. (2010) find evidence of herding within both the Shanghai and Shenzhen A-share markets but not within B-share markets. By applying quantile regression analysis, they find significant herd behavior in both A-share and B-share markets in the lower quantile region. In addition to other selected Asian markets previously mentioned, Chiang and Zheng (2010) find herd effects in both up and down markets in China by using the daily data from 12th August 1996 to 24th April 2009. Yao et al. (2014) investigate the Chinese stock markets under different market conditions. They find significant evidence of herding in the B-share markets but not in the A-share markets, and the herd effect is more pronounced in a down market. Luo and Schinckus (2015) investigate herd behavior under asymmetric and extreme market conditions using daily data from the Shanghai and Shenzhen markets. They report that a bullish scenario would generate herd behavior for B-shares while a bearish scenario would favor a crowd movement for A-shares. Ju (2019) applies the CSAD model to A-share and B-share markets to examine whether the herd effect is fundamentally driven. The author reports that herding is prevalent throughout the sample period for both markets and investors tend to herd more frequently in response to non-fundamental information during financial crises.

3 Data and Methodology

3.1 Data

Our sample consists of individual stock prices for the firms listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), market composite indexes of both markets, and trading volume of the SSE, SHA, SHB, SZSE, SZA and SZB over the period of 1st January 2003 to 31st December 2018. This study uses the variable of return to investigate the herd behaviors in the Shanghai and Shenzhen markets. In total, 1,548 listed firms in SSE and 2,231 listed firms in SZSE are employed. A-share firms and B-share firms listed in the two markets are examined separately. There are 1,493 and 55 listed firms on the Shanghai A-share (SHA) and B-share (SHB) markets respectively, and 2,172 and 59 listed firms in Shenzhen A-share (SZA) and B-share (SZB) markets respectively.

The sample data have been obtained mainly from the CSMAR database. The return variable is defined as follows:

$$\mathrm{R_t} = 100 \times (\log(\mathrm{P_t}) - \log(\mathrm{P_{t-1}})) \tag{1}$$

where the time *t* is recorded daily and *P* is either individual stock price or market index.

3.2 Methodology

In the study, we employ both the CH and CCK methods to examine the herd behavior in the Chinese stock markets by using individual stock returns and market returns. In the CH method, the herd behaviors can be examined with the following specification:

$$\mathrm{CSSD_t} = \alpha_0 + \beta_1 \mathrm{D_{U,t}} + \beta_2 \mathrm{D_{L,t}} + \varepsilon_t \tag{2}$$

where $D_{L,t}$ is a dummy variable that has the value of l when the market return at time t falls in the extreme lower tail (1%, 5%, and 10%) of the distribution, 0 otherwise. $D_{U,t}$ is a dummy variable that has the value of 1 when the market return at time t rises in the extreme higher tail (1%, 5%, and 10%) of the distribution, 0 otherwise. The variable $CSSD_t$ describes the cross-sectional standard deviation:

$$CSSD_t = \sqrt{\sum_{i=1}^{N} \frac{(R_{i,t} - R_{m,t})^2}{N-1}} \tag{3}$$

where $R_{i,t}$ is the individual stock return of i at time t, $R_{m,t}$ is the return of specific market where the selected stocks listed at time t, and N is the total number of selected stocks. According to the CH method, when investors behave similarly and herding occurs, the return dispersions should be low, which means both β_1 and β_2 in Eq.(2) are statistically significant and negative.

Since $CSSD_t$ is calculated by squaring return-deviations, which may lead to the results that can be sensitive to outliers, the CCK method, which implies a linear relationship between the dispersion of individual stock returns and market returns, is developed to detect the herding using the following equation:

$$\mathrm{CSAD_t} = \alpha_0 + \delta_1 |\mathrm{R_{m,t}}| + \delta_2 (\mathrm{R_{m,t}})^2 + \varepsilon_t \tag{4}$$

where $CSAD_t$ is measured by the cross-sectional absolute deviation:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \tag{5}$$

The CCK method includes two new terms, $|R_{m,t}|$ and $(R_{m,t})^2$, in Eq.(4). In a rational world, it is noted that the dispersion in individual asset returns is linearly related to the market returns. Therefore, during normal periods, the dispersion in returns is expected to increase when the absolute value of the market return increases. While during the large market movement periods, as investors tend to act in the same way, the corresponding dispersion may decrease or only increase by an insignificant amount. Thus, if the coefficient δ_2 of the non-linear market return, $(R_{m,t})^2$ is statistically significant and negative, herd behavior occurs. Both the OLS and GARCH regression models are adopted in the CCK method.

We then further investigate whether herd effect in the six markets varies with market conditions. To examine the asymmetric effect in herd behaviors, we follow the model of Tan et al. (2008) to test the potential asymmetries in herd behavior under different trading environments described by different states of market return, trading volume, and volatility.

Firstly, we examine the asymmetric effect of market returns when they are rising and falling. The model is specified as follows:

$$\mathrm{CSAD_t} = \gamma_0 + \gamma_1 \mathrm{D_t^{UP}} \mathrm{R_{m,t}} + \gamma_2 \mathrm{D_t^{DOWN}} \mathrm{R_{m,t}} + \gamma_3 \mathrm{D_t^{UP}} (\mathrm{R_{m,t}})^2 + \gamma_4 \mathrm{D_t^{DOWN}} (\mathrm{R_{m,t}})^2 + \varepsilon_t \quad (6)$$

where $D_t^{UP} = 1$ if $R_{m,t} > 0$, $D_t^{UP} = 0$ otherwise; $D_t^{DOWN} = 1$ if $R_{m,t} < 0$, $D_t^{DOWN} = 0$ otherwise.

Aside from market returns, trading volumes and volatilities may also be related to the levels of herd behavior in stock markets. The asymmetric effect of trading volumes can be examined with the following model:

$$CSAD_t = \gamma_0 + \gamma_1 D_t^{V-HIGH} R_{m,t} + \gamma_2 D_t^{V-LOW} R_{m,t} + \gamma_3 D_t^{V-HIGH} (R_{m,t})^2$$

$$+ \gamma_4 D_t^{V-LOW} (R_{m,t})^2 + \varepsilon_t \quad (7)$$

where $D_t^{V-HIGH} = 1$ if trading volume > MA (30 days), $D_t^{V-HIGH} = 0$ otherwise. $D_t^{V-LOW} = 1$ if trading volume < MA (30 days), $D_t^{V-LOW} = 0$ otherwise. The trading volume (V) is high if V_t is greater than the previous 30-day moving average (MA). The trading volume is low if V_t is lower than the previous 30-day moving average. Similarly, the asymmetric effect of volatilities can be examined with the following model:

$$CSAD_t = \gamma_0 + \gamma_1 D_t^{\hat{\sigma}^2-HIGH} R_{m,t} + \gamma_2 D_t^{\hat{\sigma}^2-LOW} R_{m,t} + \gamma_3 D_t^{\hat{\sigma}^2-HIGH} (R_{m,t})^2$$

$$+ \gamma_4 D_t^{\hat{\sigma}^2-LOW} (R_{m,t})^2 + \varepsilon_t \quad (8)$$

where $D_t^{\hat{\sigma}^2-HIGH} = 1$ if volatility > MA (30 days), $D_t^{\hat{\sigma}^2-HIGH} = 0$ otherwise. $D_t^{\hat{\sigma}^2-LOW} = 1$ if volatility < MA (30 days), $D_t^{\hat{\sigma}^2-LOW} = 0$ otherwise. The volatility $\hat{\sigma}_t^2$ is calculated by squaring the standard deviation of market return at time t. The volatility is high if $\hat{\sigma}_t^2$ is greater than the previous 30-day moving average. The volatility is low if $\hat{\sigma}_t^2$ is lower than the previous 30-day moving average. In order to test the asymmetric herd effect of market returns in Eq.6, trading volumes in Eq.7, and volatilities in Eq.8, F and Chi-square tests are used to check the significance of $\gamma_3 - \gamma_4$ for OLS and GARCH regression models respectively.

In addition, we employ quantile regression analysis to examine whether different quantiles of stock return dispersions affect the asymmetric herd behavior in Chinese stock markets. The general model of quantile regression, $y_i = x_i' \beta_\theta + u_{\theta i}$, is developed by Buchinsky (1998), where x_i is a vector of independent variables and β_θ is a vector of regression parameters with θ

percentile. Then, the quantile regression estimators can be achieved by minimizing the weighted sum of the absolute errors as follows:

$$estimated\ \beta_\theta = \arg\ \min\left(\sum_{i:y_i>x_i'\beta}\theta\left|y_i - x_i'\beta\right| + \sum_{i:y_i>x_i'\beta}(1-\theta)\left|y_i - x_i'\beta\right|\right) \tag{9}$$

Our quantile regression models for estimating $CSAD_t$ with j percentile are characterized as follows:

$$Q_r(\theta|X_t) = \gamma_0 + \gamma_1 D_t^{UP} R_{m,t} + \gamma_2 D_t^{DOWN} R_{m,t} + \gamma_3 D_t^{UP}(R_{m,t})^2 + \gamma_4 D_t^{DOWN}(R_{m,t})^2 + \varepsilon_t \tag{10}$$

where X_t represents the vector of the independent variables.

Lastly, we employ the state-space model proposed by Hwang and Salmon (2004) to focus on the cross-sectional variability of factor sensitivities. The standard state-space model can be estimated by the Kalman filter:

$$\log[Std_c(\beta_{i,m,t}^b)] = \mu_m + H_{m,t} + v_{m,t} \tag{11}$$

$$H_{m,t} = \phi_m H_{m,t\text{-}1} + \eta_{m,t} \tag{12}$$

where $Std_c\left(\beta_{i,m,t}^b\right)$ is the cross-sectional standard deviation of the betas on the market portfolio, H_{mt} is the latent state variable with dynamic pattern of movements, and $\eta_{m,t}\sim iid(0, \sigma_{m,\eta}^2)$. A significant $\sigma_{m,\eta}^2$ can be considered as the existence of herd behavior.

Our robustness analysis investigates if financial crises affect the cross-sectional dispersion of Chinese stock returns. Within our sample period, the Chinese stock market experienced two major financial crises. They are the global financial crisis of 2007-2008 and the Chinese stock market turbulence of 2015-2016. The global financial crisis started in August 2007 and, with the U.S. subprime mortgage crisis, soon affected the Chinese markets. The Shanghai Composite Index fell abruptly in just a few months to its lowest point on 31st October 2008. The A-share markets fell more than 20% during the crisis. The Chinese stock market turbulence began with the popping of the stock market bubble in June 2015. Starting on 15th June 2015, the Shenzhen Composite Index plunged by nearly a half within three months and the Shanghai stock market fell more than one-third as more than half of listed firms filed for a trading halt in an attempt to prevent further losses. In this paper, two specific periods, the two financial crises, are formed and we apply the CCK method to examine the herd behavior during the periods of extreme economic environment. The first period is from 15th October 2007 to 31st October 2008 and the second is from 15th June 2015 to 31st December 2015. These two sub-sample periods consist of 258 and 136 daily data, respectively.

4 Empirical Results and Findings

4.1 Descriptive Statistics

Table 1 shows the descriptive statistics for the six segmented markets including both the CSSD (CH method) and CSAD (CCK method). As discussed before, the mean values of CSSD and CSAD represent the consistency between the stock return and the market return. The lower the mean value is, the more consistent the stock return is with the market return; when the mean value equals 0, the stock return should perfectly fit the market return. In contrast, when the mean value is large, the stock returns should be significantly different from market returns. In Panel A, the mean values of CSSD in the SSE, SHA, SZSE and SZA are roughly the same while the mean values of CSSD in the B-share markets, SHB and SZB, are relatively lower. The results show significant variations across individual stock returns in the markets except in the two B-share markets. In Panel B, the results of the six CSAD means can be seen to be consistent with those of the CSSD means. Both the CH and CCK methods generate higher market variations among the stock returns in the SSE, SZSE, SHA, and SZA but lower market variations in both the SHB and SZB.

Table 1: Descriptive Statistics for the Six Segmented Markets

Panel A: CSSD (CH Method)						
	SSE	SHA	SHB	SZSE	SZA	SZB
N	3885	3885	3885	3885	3885	3885
Mean	2.6307	2.6600	1.5975	2.8860	2.9097	1.9004
Std. Dev.	0.9690	0.9796	0.9882	1.1587	1.1820	1.1409
Std. Err.	0.0155	0.0157	0.0159	0.0186	0.0190	0.0183
Skewness	1.6692	1.6955	4.5278	1.6759	1.6975	7.7315
Kurtosis	8.2989	8.4847	39.6420	8.0457	8.3322	127.1604
Panel B: CSAD (CCK Method)						
	SSE	SHA	SHB	SZSE	SZA	SZB
N	3885	3885	3885	3885	3885	3885
Mean	1.7373	1.7608	1.0906	1.7826	1.7953	1.3235
Std. Dev.	0.7355	0.7440	0.5523	0.6300	0.6397	0.6034
Std. Err.	0.0118	0.0119	0.0089	0.0101	0.0103	0.0097
Skewness	2.3982	2.3901	1.9582	1.9529	1.9218	1.9565
Kurtosis	13.4532	13.2643	9.7132	10.3105	10.0704	9.6475

4.2 Herding in the Six Segmented Markets

In Table 2, $\beta_1 s$ are positive in all six markets and statistically significant in only the two B-share markets. Although all $\beta_2 s$ are statistically significant at the 1% level, they are also all positive. As a result, the CH method implies that there are no herd behaviors in every segmented Chinese stock market examined. However, the small values of R^2 means the explanatory power in the CH method is very weak. We doubt if the CH method suffices to measure the herd behavior in the Chinese markets.

In Table 3, both the OLS and GARCH models give significant and negative d_2 in all six markets, and thus the Chinese markets exhibit herd effects when examined using the CCK method. Furthermore, the SSE has larger absolute estimates of d_2 than the SZSE's in both Panels A and B and therefore herding in the Shanghai market is stronger than in the Shenzhen market. This may be due to the smaller number of stocks traded on the Shanghai Stock Exchange. The fewer firms listed, the easier the market is driven by individual stocks. Comparing A-share markets with B-share markets, both the SHA and SZA have larger absolute estimates of d_2 than SHB's and SZB's. The result indicates that domestic investors, who trade only in A-share markets, are more irrational than foreign investors, who are only allowed to

Table 2: Herding in the Six Segmented Markets Using the CH Method

Market	Extreme Level	α_0	β_1	β_2	R^2
SSE	1% tail	2.4504***	0.0662	0.1092***	0.0085
	5% tail	2.0755***	0.1654	0.5369***	0.0083
	10% tail	2.4766***	0.3921	0.5369***	0.0042
SHA	1% tail	2.8881***	0.0073	0.4140***	0.0072
	5% tail	2.5417***	0.2211	0.2121***	0.0018
	10% tail	2.3432***	0.2806	0.3482***	0.0030
SHB	1% tail	2.9084***	0.8808	0.9924***	0.0148
	5% tail	1.4725***	0.3332***	0.5451***	0.0556
	10% tail	1.0093***	0.8864***	0.5809***	0.0490
SZSE	1% tail	2.6241***	0.2801	0.0408***	0.0023
	5% tail	2.4777***	0.9360	0.7040***	0.0094
	10% tail	2.6161***	0.6658	0.7391***	0.0016
SZA	1% tail	2.8797***	0.0067	0.0835***	0.0048
	5% tail	2.3754***	0.9179	0.1411***	0.0090
	10% tail	2.8523***	0.0702	0.7107***	0.0011
SZB	1% tail	1.0733***	0.9433***	0.6076***	0.0489
	5% tail	1.5608***	0.5327***	0.4661***	0.0789
	10% tail	1.6451***	0.5908***	0.2476***	0.0912

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

Table 3: Herding in the Six Segmented Markets Using the CCK Method

Panel A: OLS						
Market	α_0	d_1	d_2	R^2		
SSE	1.9788***	0.2256***	-0.2715***	0.1219		
SHA	1.7986***	0.2780***	-0.2473***	0.1237		
SHB	1.5323***	0.2652***	-0.2105***	0.1614		
SZSE	1.6503***	0.2424***	-0.1883***	0.1182		
SZA	1.0437***	0.2373***	-0.1155***	0.1165		
SZB	1.6192***	0.2777***	-0.0745***	0.1339		
Panel B: GARCH						
Market	α_0	d_1	d_2	ARCH(1,1)	GARCH(1,1)	R^2
SSE	1.6936***	0.1845***	-0.1115***	0.3541***	0.6423***	0.0187
SHA	1.5958***	0.1834***	-0.1159***	0.4139***	0.6386***	0.0132
SHB	1.1602***	0.1184***	-0.0702***	0.3397***	0.6320***	0.0744
SZSE	1.5337***	0.1796***	-0.0804***	0.3794***	0.6956***	0.0604
SZA	1.5426***	0.1522***	-0.0721***	0.3196***	0.6969***	0.0588
SZB	1.0095***	0.1191***	-0.0640***	0.3694***	0.6194***	0.0412

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

trade in B-share markets. This may be due to the dominance of retail investors in the Chinese A-share markets. These retail investors are often unwilling or unable to process costly financial information and display intrinsic preferences that conform to the government-guided market consensus. In B-share markets, using both OLS and GARCH, the SHB always has larger absolute estimates of d_2 than does the SZB. One possible explanation could be that HK dollar investors are more rational than US dollar investors in China. Most of the foreign investors in the SZB are from Hong Kong and are familiar with the Shenzhen market, while the foreign investors in the SHB are mainly from international countries and are less familiar with the Shanghai market.

4.3 Asymmetric Herd Behavior

We further investigate if the herd effect in the six segmented markets varies with market conditions. As mentioned above, the CCK method is preferred to the CH method, which may not suffice to measure herd behavior in the Chinese markets. From now on, we only report the results of the CCK method.

4.3.1 Effects of Market Return

First of all, we examine the asymmetric herd effect of market returns when they are rising and falling. In Table 4, using the OLS model, all six markets have significantly negative estimates of γ_3 and γ_4. There are also significant herd effects in both rising and falling markets. Taking the correlation of variance over time into account, the GARCH model shows that only the SSE, SHB, and SZB have both significant and negative γ_3 and γ_4, while the SHA, SZSE, and SZA have neither significant nor negative γ_3 and γ_4. We further use F and Chi-square tests to determine the asymmetric herd effect of market returns. In Panel C, significant asymmetric herd effects are found in both the B-share markets, SHB and SZB. Whether using the OLS or GARCH model, the herd effect is stronger when the market is rising and weaker when the market is falling.

4.3.2 Effects of Trading Volume

In addition to the different states of market returns, different trading volumes of markets are also used to examine the asymmetric herd effect. Panel A of Table 5 shows that all six markets have significant and negative estimates of γ_3. γ_4s for both the SZSE and SZA are negative but

Table 4: Asymmetric Herd Effect of Market Returns in the Six Segmented Markets

Panel A: OLS								
Market	γ_0	γ_1	γ_2	γ_3	γ_4	R^2		
SSE	1.6095***	0.2697***	-0.2841***	-0.2690***	-0.1621***	0.1596		
SHA	1.6854***	0.2678***	-0.2814***	-0.2152***	-0.1650***	0.1534		
SHB	1.7168***	0.2698***	-0.2567***	-0.2690***	-0.1621***	0.1882		
SZSE	1.3689***	0.2101***	-0.2884***	-0.2041***	-0.1396***	0.1902		
SZA	1.7752***	0.2175***	-0.2034***	-0.2402***	-0.1865***	0.1565		
SZB	1.3295***	0.2270***	-0.2665***	-0.2946***	-0.1879***	0.1568		
Panel B: GARCH								
Market	γ_0	γ_1	γ_2	γ_3	γ_4	ARCH(1,1)	GARCH(1,1)	R^2
SSE	1.4678***	0.0789***	-0.0277***	-0.0377***	-0.0172***	0.4869***	0.5466***	0.0398
SHA	1.4992***	0.0367***	-0.0269***	0.0477**	-0.0369	0.4057***	0.5568***	0.0384
SHB	1.8198***	0.1542***	-0.0144***	-0.0995***	-0.0460**	0.3487***	0.6936***	0.0944
SZSE	1.3991***	0.0124**	-0.0201***	0.0385	-0.0111	0.4832***	0.6988***	0.0999
SZA	1.8676***	0.1125***	-0.0230***	0.0387	-0.0246	0.4333***	0.6160***	0.0897
SZB	1.4703***	0.1724***	-0.0165***	-0.0699***	-0.0287***	0.3514***	0.6279***	0.0930
Panel C: H_0: $\gamma_3 - \gamma_4 = 0$								
Market	OLS	F	GARCH	Chi-square				
SSE	-0.1069	3.7266*	-0.0107	5.8626*				
SHA	-0.0502	3.1166*	-0.0050	4.2522				
SHB	-0.1069	5.9854**	-0.0107	18.8789***				
SZSE	-0.0645	2.6750	-0.0065	3.7601				
SZA	-0.0537	2.6264	-0.0054	3.7167				
SZB	-0.1067	10.3336***	-0.0107	15.4193***				

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

not significant at the 5% level and the SSE, SHA, SHB, and SZB have significantly negative γ_4. In other words, only the SZSE and SZA do not exhibit herd effects when trading volumes are low. Panel B shows that all six markets show herd effects when trading volumes are high, as their $\gamma_3 s$ are significant and negative. However, when trading volumes are low, only the SHB and SZB have significantly negative γ_4. Although the other four markets have highly significant γ_4, their estimates are positive. As a result, only the two B-share markets display herd effects regardless of whether trading volumes are high or low. In Panel C, asymmetric herd effects in all the markets are highly statistically significant whether using the OLS or GARCH models. The herd effect is stronger when the trading volume is higher and weaker when the trading volume is lower. Based on results given in Table 5, it is reasonable to expect that significant asymmetric herd effects appear in the two B-share markets in China when trading volumes are taken into consideration.

Table 5: Asymmetric Herd Effect of Trading Volumes in the Six Segmented Markets

Panel A: OLS								
Market	γ_0	γ_1	γ_2	γ_3	γ_4	R^2		
SSE	1.8083***	0.0529***	-0.0514***	-0.2761***	-0.1347**	0.1571		
SHA	1.5285***	0.0284***	-0.0420***	-0.2654***	-0.1557**	0.1645		
SHB	0.4599***	0.0885**	-0.0999***	-0.2804***	-0.1168***	0.1992		
SZSE	1.0022***	0.0544***	-0.0402***	-0.1909***	-0.0515*	0.1796		
SZA	1.3955***	0.0843***	-0.0993***	-0.1892***	-0.0267	0.1527		
SZB	0.9958***	0.0741***	-0.0529***	-0.2994***	-0.1112***	0.1924		
Panel B: GARCH								
Market	γ_0	γ_1	γ_2	γ_3	γ_4	ARCH(1,1)	GARCH(1,1)	R^2
SSE	1.6276***	0.0845***	-0.1929***	-0.1672***	0.2907***	0.4781***	0.5492***	0.0413
SHA	1.6939***	0.0898***	-0.1561***	-0.1747***	0.2921***	0.4915***	0.5596***	0.0384
SHB	0.9126***	0.0262***	-0.1339***	-0.1969***	-0.0679***	0.4968***	0.6954***	0.1344
SZSE	1.2456***	0.1947***	-0.1195***	-0.0914***	0.1908***	0.3563***	0.5376***	0.0980
SZA	1.0689***	0.0581***	-0.1531***	-0.0967***	0.1942***	0.4574***	0.5785***	0.0752
SZB	1.3400***	0.0815*	-0.6669***	-0.1951***	-0.0969***	0.3761***	0.6084***	0.1297
Panel C: H_0: $\gamma_3 - \gamma_4 = 0$								
Market	OLS	F	GARCH	Chi-square				
SSE	-0.1415	20.1153***	-0.4579	249.1163***				
SHA	-0.1097	18.2103***	-0.4668	244.6550***				
SHB	-0.1636	45.3826***	-0.1290	123.0154***				
SZSE	-0.1394	26.0309***	-0.2823	97.5682***				
SZA	-0.1626	14.5819***	-0.2909	62.8391***				
SZB	-0.1882	15.1419***	-0.0982	32.6854***				

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

4.3.3 Effects of Volatility

Using the OLS model, Panel A of Table 6 shows that only the SHB and SZB have both significantly negative γ_3 and γ_4, and that the SSE and SHA have significant and negative γ_3 but not γ_4. The rest are not significant or even positive. The results in Panel B, generated using the GARCH model, are consistent with those in Panel A, except for the positive coefficients becoming significant. Overall, again, only the two B-share markets, SHB and SZB, show asymmetric herd effects, which are marginally significant at the 10% level. It implies that the herd effect is weaker when volatility is higher and stronger when volatility is lower in these two markets.

Table 6: Asymmetric Herd Effect of Volatilities in the Six Segmented Markets

Panel A: OLS								
Market	γ_0	γ_1	γ_2	γ_3	γ_4	R^2		
SSE	1.9305***	0.0161***	-0.0825***	-0.2494***	0.2669	0.1531		
SHA	1.7356***	0.0563***	-0.0833***	-0.2674***	0.2728	0.1763		
SHB	1.1040***	0.0698***	-0.0196**	-0.2870***	-0.7499***	0.1973		
SZSE	1.8491***	0.0261***	-0.0834***	0.1285	0.2439	0.1501		
SZA	1.8965***	0.0974***	-0.0882***	0.1584	0.2483	0.1507		
SZB	1.2105***	0.0349***	-0.0141**	-0.2832***	-0.6251***	0.1698		
Panel B: GARCH								
Market	γ_0	γ_1	γ_2	γ_3	γ_4	ARCH(1,1)	GARCH(1,1)	R^2
SSE	1.6319***	-0.0972***	-0.1969***	-0.0829***	0.7172***	0.3466***	0.5457***	0.0580
SHA	1.8328***	-0.0619***	-0.1515***	-0.0883***	0.6909***	0.3857***	0.6685***	0.0692
SHB	0.8241***	-0.1065***	0.5437**	-0.1678***	-0.3344***	0.4241***	0.6833***	0.1244
SZSE	1.5246***	-0.0722***	-0.6837***	0.0273**	0.3220**	0.3564***	0.5925***	0.1092
SZA	1.6849***	-0.0553***	-0.6109***	0.0395***	0.3319**	0.3288***	0.5428***	0.1003
SZB	1.3429***	-0.1064***	0.0108**	-0.1466***	-0.3141***	0.4241***	0.6532***	0.1107
Panel C: H_0: $\gamma_3 - \gamma_4 = 0$								
Market	OLS	F	GARCH	Chi-square				
SSE	-0.5164	3.7264*	-0.8001	24.1751***				
SHA	-0.5402	2.6183	-0.7792	22.5634***				
SHB	0.4629	14.9812***	0.1666	4.8834*				
SZSE	-0.1154	2.6725	-0.2947	8.7673**				
SZA	-0.0899	2.2991	-0.2925	8.7126**				
SZB	0.3419	3.3315*	0.1676	4.6125*				

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

4.4 Quantile Regression Model

In this part, we again apply the CCK method to examine whether different quantiles of stock return dispersions affect the asymmetric herd behavior in different stock markets. Compared with the traditional OLS model, the quantile regression model can consider more information about extreme outliers. In addition, to further validate our previous findings, this model can provide more robust results and efficient estimates.

The results of the quantile regression model applied to the six segmented Chinese markets with 10%, 30%, 50%, 70%, and 90% quantiles are shown in Table 7. The two regression coefficients, γ_3 and γ_4, in Eq.(10) are always negative across the quantiles, and nearly all coefficient estimates are statistically significant at the 5% level and even the 1% level. The few exceptional cases are the marginally significant γ_3 when $\theta = 50\%$ and γ_4 when $\theta = 90\%$ in the SHA, the insignificant γ_3 when $\theta = 50\%$ and 70% in the SZSE, and the marginally significant γ_3 when $\theta = 50\%$ in the SZA. In summary, the SSE, SHB, and SZB have persistent herd effect across all quantiles regardless of whether the market is rising or falling. The results are quite consistent with our pervious findings.

Table 7: Herding in the Six Segmented Markets Using Quantile Regression Model

Market	Quantile	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	Chi-square
SSE	θ=10%	1.0411	0.2187	-0.1415	-0.1482	-0.1041	0.1100	23.8016***
		(70.1452)***	(2.7618)***	(-11.2872)***	(-3.2273)***	(-4.2709)***		
	θ=30%	1.9322	0.2190	-0.2059	-0.1787	-0.1508	0.1141	23.9354***
		(78.9978)***	(2.9188)***	(-14.7326)***	(-6.8923)***	(-5.2458)***		
	θ=50%	2.1373	0.2782	-0.2407	-0.2254	-0.1667	0.1308	-
		(80.1502)***	(3.9385)***	(-17.8237)***	(-8.4925)***	(-5.9461)***		
	θ=70%	2.1506	0.2837	-0.2935	-0.2285	-0.1906	0.1293	12.6246***
		(65.4376)***	(5.1267)***	(-4.7431)***	(-5.8721)***	(-3.2211)***		
	θ=90%	2.3728	0.3681	-0.3610	-0.2729	-0.1927	0.1150	12.9249***
		(33.2361)***	(2.3369)**	(-4.0491)***	(-4.2769)***	(-2.9509)***		
SHA	θ=10%	1.1373	0.1838	-0.1940	-0.2206	-0.0932	0.1156	27.3786***
		(69.6655)***	(2.3633)**	(-8.9864)***	(-5.3234)***	(-5.3103)***		
	θ=30%	1.3545	0.2319	-0.2794	-0.2267	-0.1073	0.1162	24.7405***
		(73.8508)***	(3.6737)***	(-9.7238)***	(-7.1272)***	(-7.4467)***		
	θ=50%	1.4189	0.2819	-0.2829	-0.2451	-0.1130	0.1283	-
		(66.9771)***	(3.9844)***	(-14.2301)***	(-1.6811)*	(-9.2927)***		
	θ=70%	1.4344	0.2899	-0.2876	-0.2696	-0.1158	0.1552	20.2539***
		(50.1468)***	(2.7698)***	(-8.1146)***	(-9.1625)***	(-2.3450)**		
	θ=90%	1.7266	0.3479	-0.3176	-0.2810	-0.1929	0.1154	20.3745***
		(44.6596)***	(2.4667)**	(-7.1249)***	(-6.7347)***	(-1.7334)*		
SHB	θ=10%	1.0953	0.1829	-0.1933	-0.1598	-0.1183	0.0931	21.3539***
		(65.2533)***	(3.7601)***	(-5.3165)***	(-6.9428)***	(-6.3779)***		

Market	Quantile	γ_0	γ_1	γ_2	γ_3	γ_4	Pseudo R^2	Chi-square
	θ=30%	1.6429	0.1994	-0.1982	-0.1760	-0.1214	0.1394	26.9857***
		(67.3136)***	(4.6725)***	(-8.9187)***	(-8.1691)***	(-11.5846)***		
	θ=50%	1.8498	0.2065	-0.2480	-0.2120	-0.1507	0.1477	-
		(72.8367)***	(7.2129)***	(-9.6716)***	(-5.9122)***	(-14.2349)***		
	θ=70%	1.8767	0.2253	-0.2928	-0.2163	-0.1528	0.1299	25.7020***
		(64.2199)***	(2.3170)**	(-13.2166)***	(-3.8824)***	(-11.2635)***		
	θ=90%	2.0057	0.3097	-0.3241	-0.2212	-0.1615	0.0987	22.8986***
		(49.6888)***	(2.1112)**	(-7.3256)***	(-3.2361)***	(-7.3751)***		
SZSE	θ=10%	1.5576	0.1885	-0.1542	-0.1632	-0.1253	0.1176	38.2021***
		(57.9842)***	(3.8787)***	(-9.2331)***	(-4.7466)***	(-7.7336)***		
	θ=30%	1.6436	0.1983	-0.1611	-0.1847	-0.1393	0.1137	12.7714***
		(69.9232)***	(3.9818)***	(-12.7635)***	(-8.9132)***	(-8.4648)***		
	θ=50%	1.9741	0.2147	-0.2802	-0.2281	-0.1549	0.1377	-
		(73.6216)***	(5.1122)***	(-15.2221)***	(-0.9675)	(-9.8153)***		
	θ=70%	1.9992	0.2303	-0.2880	-0.2462	-0.1598	0.1172	15.3711***
		(56.7723)***	(7.2136)***	(-7.3341)***	(-0.9008)	(-9.2312)***		
	θ=90%	2.0156	0.2924	-0.3255	-0.2577	-0.1684	0.1002	28.5285***
		(39.1122)***	(4.3124)***	(-8.6181)***	(-14.2824)***	(-5.7764)***		
SZA	θ=10%	1.3519	0.1801	-0.1585	-0.1834	-0.1440	0.1160	14.2895***
		(56.2565)***	(3.2127)***	(-4.8938)***	(-7.8762)***	(-5.6267)***		
	θ=30%	1.4143	0.1912	-0.1844	-0.1840	-0.1547	0.1189	18.1522***
		(76.2239)***	(5.3643)***	(-6.2431)***	(-2.1571)**	(-6.9213)***		
	θ=50%	1.9645	0.2049	-0.2789	-0.2199	-0.1877	0.1249	-
		(89.2346)***	(5.7318)***	(-9.7821)***	(-1.7109)**	(-7.4211)***		
	θ=70%	2.3865	0.2251	-0.2820	-0.2201	-0.1966	0.1258	24.9041***
		(46.8481)***	(4.2136)***	(-14.5434)***	(-4.2217)***	(-2.2945)**		
	θ=90%	2.4544	0.2277	-0.3111	-0.2310	-0.2043	0.0968	35.0475***
		(37.7834)***	(2.9988)***	(-7.7634)***	(-3.9867)***	(-3.1284)***		
SZB	θ=10%	1.1945	0.1019	-0.1951	-0.2271	-0.1759	0.0834	29.2355***
		(65.1212)***	(3.2312)***	(-6.3877)***	(-7.1743)***	(-6.2649)***		
	θ=30%	1.5718	0.1324	-0.2010	-0.2482	-0.1900	0.0915	23.9082***
		(73.2429)***	(3.8957)***	(-12.4652)***	(-6.3557)***	(-10.2963)***		
	θ=50%	1.6603	0.1490	-0.2125	-0.2584	-0.2025	0.1426	-
		(79.9561)***	(7.9264)***	(-25.6576)***	(-9.2536)***	(-14.2325)***		
	θ=70%	1.9253	0.1661	-0.2314	-0.2845	-0.2030	0.1347	16.8386***
		(69.3761)***	(5.3166)***	(-11.0733)***	(-4.4764)***	(-7.4132)***		
	θ=90%	2.1544	0.1811	-0.2868	-0.3031	-0.2072	0.1128	28.8663***
		(57.2132)***	(4.2987)***	(-6.7424)***	(-4.6542)***	(-4.9153)***		

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

4.5 State Space Model

Lastly, we employ the state-space model proposed by Hwang and Salmon (2004) to focus on the cross-sectional variability of factor sensitivities. For the beta estimation, two intervals of 20 days for short term and 60 days for median term are used. According to Hwang and Salmon (2004), a significant $\sigma^2_{m,\eta}$ can be regarded as evidence that supports herd behavior. In any case, this paper adopts the natural logarithmic form of σ^2 in order to avoid any singular matrix problem in our tests.

The results using the State Space Model are given in Table 8. Regardless of short term or median term of beta estimation interval, all six markets have significant and positive ϕ_m. The AR(1) process of $H_{m,t}$ is supported. The estimates of $\ln(\sigma^2_{m,\eta})$ are highly significant at the 1% level regardless of markets. The results indicate that strong herd behavior appears across all the segmented markets examined.

Table 8: Herding in the Six Segmented Markets Using State Space Model

Markets	Beta interval	μ_m	ϕ_m	$\ln(\sigma^2)$
SSE	20 days	-0.7240***	0.9992***	-5.2213***
	60 days	-1.1507***	0.9983***	-6.6518***
SHA	20 days	-0.7464***	0.9905***	-4.6811***
	60 days	-1.1947***	0.9986***	-6.3454***
SHB	20 days	-1.2679***	0.9960***	-5.9859***
	60 days	-0.0307	0.9918***	-7.2075***
SZSE	20 days	-0.8898***	0.9982***	-4.8843***
	60 days	-1.2625***	0.9964***	-6.5018***
SZA	20 days	-0.6203***	0.9929***	-5.3143***
	60 days	-1.2513***	0.9951***	-6.6249***
SZB	20 days	-0.9401***	0.9985***	-5.7907***
	60 days	-1.5166***	0.9964***	-7.4078***

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

5 Robustness Test

In this section, we apply the CCK method to examine whether the herd effect in Chinese markets persists under extreme economic conditions. Table 9 shows the results of the CCK method during the two sub-sample periods: the global financial crisis of 15th October 2007 to 31st October 2008 and the Chinese stock market turbulence of 15th June 2015 to 31st December 2015.

Table 9: Herding in the Six Segmented Markets during Two Financial Crises

Panel A: Global Financial Crisis, 15th October 2007 - 31st October 2008					
Market	N	α_0	d_1	d_2	R^2
SSE	258	1.2939***	0.3498***	-0.2045***	0.1164
SHA	258	1.8405***	0.3836***	-0.3428***	0.1219
SHB	258	1.8371***	0.2686**	-0.1045*	0.1037
SZSE	258	1.1448***	0.2801***	-0.2073***	0.1165
SZA	258	1.1439***	0.3241***	-0.3088***	0.1182
SZB	258	1.9229***	0.2641**	-0.1034*	0.1039
Panel B: Chinese Stock Market Turbulence, 15th June 2015 - 31st December 2015					
Market	N	α_0	d_1	d_2	R^2
SSE	136	1.3313***	0.2241***	-0.2907***	0.1116
SHA	136	1.6743***	0.3630***	-0.3166***	0.2192
SHB	136	1.7983***	0.2085***	-0.2566***	0.1137
SZSE	136	1.3174***	0.3029***	-0.3616***	0.1416
SZA	136	1.7866***	0.2204***	-0.3589***	0.1357
SZB	136	1.5268***	0.3245***	-0.1588***	0.1014

*, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively

In Panel A of the first sub-sample period, the SSE, SHA, SZSE, and SZA have highly significant and negative d_2s, while the SHB and SZB have marginally significant and negative d_2s. The result is beyond our expectations. In the previous findings, both B-share markets, the SHB and SZB, are considered to show strong herd behavior persistently. However, the herd effect in the B-share markets weakened during the global financial crisis. Generally, financial crises should augment herding. As suggested by Naoui et al. (2010), one possible reason is the weak dynamic conditional correlations between the Chinese and U.S. markets. China seemed unaffected by the U.S. subprime mortgage crisis during 2007-2008. In Panel B, the second sub-sample period, all six markets have highly significant and negative d_2s. The absolute estimates of the coefficient during the Chinese stock market turbulence are larger than those of the whole sample period. The herd effect was even stronger during the market turbulence.

6 Conclusions

This paper empirically examines the herd effects of six segmented markets on the Chinese stock markets during the sample period from 1st January 2003 to 31st December 2018. Both CH and CCK methods and both OLS and GARCH models are used to examine herd effects as well as asymmetries in herd behaviors. We further employ quantile regression and state space models in our analysis. Lastly, our robustness test takes into account two financial crises, the global financial crisis and Chinese stock market turbulence.

This study finds that the CCK method has stronger explanatory power than the CH method. Regardless of the econometric models used, our analysis provides evidence that strong herd effects appear widely in all six segmented Chinese markets. In particular, the Shanghai market and the two B-share markets are found to have persistent herd effects across all quantiles, whether the market is up or down. Among these three markets, the two B-share markets have significant asymmetric herd effects of market return and the effects of up markets are stronger than down markets. The B-share markets are also found to have herd effects no matter whether trading volumes are high or low, and both markets show stronger (weaker) asymmetric herd effects when trading volumes are higher (lower). Again, the two B-share markets display herd effects regardless of whether volatility is high or low, but their asymmetric effects are relatively less significant. Lastly, our results show that the herd behaviors existed in all the examined Chinese markets during the two periods of financial crises. We find that the herd effect during the period of Chinese stock market turbulence is even stronger than during the whole sample period used in the study. In any case, the herd effect in the two B-share markets was weakened during the global financial crisis.

Our findings can provide insights for the policymakers in China. The evidence of herding in all segmented markets suggests that traditional asset price models may not be applied to the Chinese markets. Although China is the second largest economy in the world, its stock markets are relatively young and emerging only. There is still huge room for improvement in the investment awareness of the dominant domestic retail investors, and the efficiency of market information transmission is not high. Therefore, it is not surprising that the evidence of the herd effect in the Chinese stock markets implies, to some extent, the inefficiency of the markets. Investors can form zero-investment portfolios to gain abnormal return from price-disparities that are driven by herding.

There is also supportive evidence that the persistent herd effect found in the two B-share markets is more significant, although there is little literature reporting herding in the Chinese B-share markets (Tan et al. 2008; Yao at al. 2014). The B-share markets are dominated by foreign investors and are smaller compared to the A-share markets. The markets are understandably affected by the volatility of large FDI. Generally, foreign investors from developed countries are seen as more rational and having less herd behavior. However, when these investors invest in foreign markets, they become more prudent and loss averse. They avoid selling assets that have decreased in value and herd on other market participants (Ali, 2018). In any case, this irrational behavior may be explained by information asymmetry between the A-share and B-share markets. In China, the B-share market is less liquid than the A-share market, and low liquidity often leads to high information asymmetry in emerging markets (He et al., 2003; Yao et al., 2014). While domestic and foreign investors have access to the same publicly available information, it is more difficult or restricted for foreign investors to acquire primary information in China. When less information is available for foreign investors, they have to bear higher information costs and incline to follow the trend of other main market participants. As a result, the B-share markets are less efficient to adjust to information than the A-share markets, and these make the B-share markets more prone to herd effects.

To upgrade to developed markets, the Chinese regulatory authority should continue to make the markets more open to foreign investors, reduce the excessive intervention in the markets, cultivate more institutional investors, improve the transparency of corporate governance, and disclose more timely financial information to the public. Furthermore, the asymmetric herd effect found in this study can help regulators easily stabilize the markets by focusing on specific market conditions.

It should be noted that this study assumes that the segmented markets in China do not affect each other, but it is probably not the case in real life. Because of H-shares, there could be a cross-market effect between the A-share and the B-share markets as well as between the Shanghai and the Shenzhen markets. Besides, the existence of Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect may also generate cross-market effects. These cross-market effects, if any, should first be eliminated in order to measure the real or actual herd effect in the Chinese markets. Future research is advised to address this potential limitation.

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