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Does herding behavior exist in Chinese stock markets?

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Abstract

This paper examines the presence of herd formation in Chinese markets using both individual firm- and sector-level data. We analyze the behavior of return dispersions during periods of unusually large upward and downward changes in the market index. We also distinguish between the Shanghai and Shenzhen stock exchanges at the sector-level. Our findings indicate that herd formation does not exist in Chinese markets. We find that equity return dispersions are significantly higher during periods of large changes in the aggregate market index. However, comparing return dispersions for upside and downside movements of the market, we observe that return dispersions during extreme downside movements of the market are much lower than those for upside movements, indicating that stock returns behave more similarly during down markets. The findings support rational asset pricing models and market efficiency. Policy implications of the results for policymakers are discussed.

JEL classification: G14; G15

Keywords: Herd behavior; Equity return dispersion; Chinese financial markets

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1. Introduction

Understanding the decision making process of market participants has always been a major challenge to academics as well as practitioners. A number of papers have documented that the standard (efficient market) financial theory has major shortcomings in modeling real life stock returns (e.g. Summers, 1986; Shiller, 1981). This theory assumes that investors form rational expectations of future prices and also instantaneously discount all market information into expected prices in the same way. However, these assumptions form the basis for criticism of this theory in representing behavior of stock returns in practice. According to the theory of efficient markets, investors form homogeneous expectations based on all available information, know that others use this publicly available information exactly the same way they do, and are all perfect rational utility maximizers. Formation of investor herds has been proposed as an alternative explanation of how investors make investment choices. Such behavior presents a concern to policymakers as such behavior might aggravate volatility of returns, and hence destabilize financial markets, especially in crisis conditions.

Bikhchandani and Sharma (2000) define herd behavior as an obvious intent by investors to copy the behavior of other investors. Several views have been suggested on why profit or utility maximizing investors would tend to suppress their private information and mimic the actions of other investors. One line of research approaches the problem by focusing on the psychology of the investor who may have a preference for conformity with the market consensus (Devenow and Welch, 1996). A second view suggests that others may know something about the returns on the particular investment and their actions reveal this information (Chari and Kehoe, 1999, Calvo and Mendoza, 1998 and Avery and Zemsky, 1998). Finally, a third approach focuses on the principal–agent relationship where money managers might be drawn to imitating others as a result of the incentives provided by the compensation scheme, terms of employment or perhaps in order to maintain their reputation (Scharfstein and Stein, 1990, Rajan, 1994 and Maug and Naik, 1996). Bikhchandani and Sharma (2000) and Hirshleifer and Teoh (2001) provide a comprehensive survey of the literature.

In this paper, we examine the presence of herd formation in Chinese stock markets along the lines of Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2003, 2004). The testing methodology is based on the idea that investors are more likely to suppress their own beliefs in favor of the market consensus during large price changes, so herd behavior is most likely to emerge during such periods. Therefore, equity return dispersions around aggregate market return are used to test formation of herds during periods of market stress. Following this rationale, one would expect significantly lower dispersions in individual security returns as investors are drawn to the consensus of the market. Such a prediction contradicts rational asset pricing models that suggest that periods of market stress induce increased levels of dispersion as individual returns differ in their sensitivity to the market return. Notable applications of this methodology include Christie and Huang (1995) on US equities, Chang et al. (2000) on international equities, Gleason et al. (2003) on commodity futures traded on European exchanges and Gleason et al. (2004) on Exchange Traded Funds. In general, these studies provide results in favor of the rational asset pricing theories and conclude that herding is not an important factor in determining security returns during periods of market stress.

This paper extends the analysis to the Chinese stock market, including both Shanghai and Shenzhen Stock Exchanges and provides new insights into developing equity markets. Consistent with prior studies, we find no evidence of herd formation. Our analysis of firm-level data as well as sector-level data from the Shanghai and Shenzhen Stock Exchanges indicates that equity return dispersions increase during periods of large changes in the aggregate market index. This finding supports rational asset pricing models. However, comparing return dispersions for upside and downside movements of the market, we see that return dispersions during extreme downside movements of the market are much lower than those for upside movements indicating that stock returns behave more similar during down markets. This suggests that portfolio diversification strategies may not be as useful in bear markets, when benefits from diversification are most needed.

An outline of the remainder of the paper is as follows. Section 2 motivates the paper. Section 3 briefly summarizes the previous studies on Chinese stock markets. In Section 4, we provide the methodological details and data description. In Section 5, we present empirical results that we obtain using firm- and sector-level data. Finally, in Section 6 we provide concluding remarks and discuss further research.

2. Should we expect herding in Chinese stock markets?

Since they began their operations in early 1990s, the two official stock markets in China have expanded dramatically and became one of the leading equity markets. As of January 2003, it has more than 1200 listed firms and a market capitalization of about US$ 500 billion, making it the second largest market in Asia after Japan and the fastest growing market in the world in the last decade (Xu, in press). It is anticipated that China's stock market will continue to grow due to the nation's strong savings habits. For example, today more than 40% of China's gross domestic product is saved; but this figure for the US is only 17% (Xu, in press).

Despite its tremendous growth, the Chinese financial markets may not be characterized by the depth and maturity of a stock exchange observed in a developed country. Evidence of this is that China's market capitalization in 2001 as a proportion of GDP was about 45%, while the corresponding figure for the US was over 300% (Green, 2003). The legal framework and the rule of law are weak and there are few alternatives for investors. Interest rates are controlled and kept low for government enterprises to borrow loans at below market rates. The central government has a strong interest in the ability of the stock market to finance state-owned enterprises due to a thin corporate bond market. Investors facing only a few alternatives and heavy government involvement, such as regulation and central bank intervention, tend to speculate in the stock market, causing significant market volatility (Green, 2003).

Another distinct characteristic of the market is ownership (Huang and Fung, in press). About two-thirds of outstanding shares are not publicly tradable. In addition, there are only a few institutional investors in China's A markets (Green, 2003). One of the biggest problems facing traders is lack of transparency. Reporting requirements for listed companies in China are neither well developed nor extensive, and significantly less comprehensive than those in the stock markets of industrial countries.

As a result, trading behavior in China's financial markets may be different from those in other markets. Traders may base their actions on the decisions of others who may be more informed about market developments, by following the market consensus. Given the growing significance of China's stock market, along with its unique microstructure features and traders coping with a Communist (but increasingly market oriented) government, it is important to understand how traders in Chinese markets in this process of transition behave.

There are several intuitive reasons why investor behavior, and hence herd formation may be different between the Shanghai and Shenzhen Exchanges. First, it may be related to the size of the market. Second, the types of firms are different on the exchanges. For example, the Shanghai market makes up the bulk of the trading volume and consists of large, state-owned enterprises, while the Shenzhen market consists of mainly manufacturing and export companies doing business with Hong Kong. Third, Shanghai is presumably more informed as it is claimed the Chinese financial center, the Chinese government plans to invest more in development in the Shanghai market than the Shenzhen market. The Shenzhen market plans to develop a second board market for small and medium sized firms for listing on the exchanges. Herd behavior is then more likely to take place in the smaller Shenzhen market. However, export-oriented nature of the Shenzhen market may allow its traders to be more informed about global developments. In addition, firms in this market may have a closer relationship with institutional and foreign investors in market B because of their close connection with nearby Hong Kong companies. In fact, many foreign investors in China are from Hong Kong.

We also present evidence at the sector-level. It is anticipated that non-financial sectors with smaller capitalization rate and a large number of small retail investors than the financial sector that includes institutional investors, such as insurance companies, are more likely to be subject to herding. As a result of these factors, we hypothesize that investor behavior may be different in the stock exchanges and sectors, causing different herd formation. In particular, non-financial sectors in general and the smaller Shenzhen market populated by manufacturing and export companies may be more susceptible to herding. However, for the above reasons, this issue is not clear-cut. Therefore, herd behavior in China's stock markets can be best described as an empirical issue.

3. Previous studies on Chinese stock markets

Many aspects of the Chinese stock markets have been examined from different angles, including asset pricing in segmented Chinese markets (e.g. Poon et al., 1998; Sun and Tong, 2000; Fernald and Roger, 2002), the return and volatility link (e.g. Su and Fleisher, 1999), market efficiency, the price–volume relation (Long et al., 1999) and the significance of global information in Chinese markets (Bailey, 1994, Hu et al., 1997 and Huang et al., 2001). Chen et al. (2003) provide a review of the literature.

A number of recent studies have examined the information transmission patterns in Chinese stock markets. Chui and Kwok (1998) found that movements in the B-shares traded by foreign investors lead A-share returns traded by domestic investors. Fung et al. (2000) reported one-way causality of stock returns, running from Shenzhen to Shanghai. However, Song et al. (1998) found significant information feedback between the two markets. Yang

(2003) documented that the Shanghai B-share market leads both A-share markets in Shanghai and Shenzhen, and the Shenzhen B-share market. Poon and Fung (2000) presented evidence that red chips, compared to H-shares, play a stronger leading role in spreading the return and volatility information to the A and B markets in both Shanghai and Shenzhen. Contradictory to Poon and Fung (2000), Yang (2003) found that the Hong Kong H-share market more significantly explains the price variations of A- and B-share markets than red chip stocks. Further exploring the pattern of information flows of China-backed stocks that are cross-listed on exchanges in Hong Kong and New York, Xu and Fung (2002) found strong two-way information flows between the two markets. Finally, using daily and monthly sector returns, Wang et al. (in press) reported strong sector information flows, not only within each Shanghai and Shenzhen exchanges, but also across both markets.

Although the aforementioned studies provide evidence for particular types of information transmission patterns in Chinese stock markets, none provides evidence about another type of information transformation behavior, namely herd formation. We fill this gap in the literature by providing evidence about herding behavior, using both firm- and sector-level data. To our best knowledge, this is the initial study on this issue in Chinese stock markets.

4. Methodology and data

4.1. Methodology

We build on the methodology used in Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2003, 2004). Cross-sectional standard deviations (S.D.) are used as a measure of return dispersion as follows:

$$\mathrm{S.D.}_t = \sqrt{\frac{\sum_{j=1}^{n}(r_{jt} - \overline{r_t})^2}{n-1}} \tag{1}$$

where n is the number of firms in the aggregate market portfolio, r_{jt} the observed stock return on firm j for day t and $\bar{r}_t$ is the cross-sectional average of the n returns in the portfolio for day t. This measure can be regarded as a proxy to individual security return dispersion around the market average.

The main idea in this methodology is based on the argument that the presence of herd behavior would lead security returns not to deviate far from the overall market return. The rationale behind this argument is the assumption that individuals suppress their own beliefs and make investment decisions based solely on the collective actions of the market. On the other hand, rational asset pricing models offer a conflicting prediction suggesting that dispersions will increase with the absolute value of market return, since each asset differs in its sensitivity to the market return.

This methodology suggests that the presence of herd behavior is most likely to occur during periods of extreme market movements, as they would most likely tend to go with the market consensus during such periods. Hence, we examine the behavior of the dispersion measure in Eq. (1) during periods of market stress and estimate the following linear regression model:

$$\text{S.D.}_t = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \varepsilon_t \tag{2}$$

where $D_t^{\text{L}} = 1$, if the return on the aggregate market portfolio on day t lies in the *lower* tail of the return distribution; zero otherwise, and $D_t^{\text{U}} = 1$, if the return on the aggregate market portfolio on day t lies in the *upper* tail of the return distribution; zero otherwise. Although somewhat arbitrary, in the literature, an extreme market return is defined as one that lies in the one (and five) percent lower or upper tail of the return distribution.

The dummies in equation (2) aim to capture differences in return dispersions during periods of extreme market movements. As herd formation indicates conformity with market consensus, the presence of negative and statistically significant β_{D} (for down markets) and β_{U} (for up markets) coefficients would indicate herd formation by market participants.

It is important to emphasize that herding behavior does not necessarily indicate that traders are not rational. Under certain circumstances, such as investor compensation, it is entirely rational to follow others' trading decisions to avoid returns below an average market benchmark. In addition, when market participants face uncertainty regarding the accuracy of their information set, herd behavior may arise, even when investors act rational. Bikhchandani and Sharma (2000) provide detail discussions of this issue.

4.2. Data

We analyze individual firm-level returns as well as sector returns. The data set for individual firms contains daily stock returns for 375 Chinese stocks on the Shanghai and Shenzhen Stock Exchanges over the January 1999–December 2002 period. Data are obtained from Sinofin (www.sinofin.net). Bikhchandani and Sharma (2000) suggest that a group is more likely to herd if it is sufficiently homogeneous, i.e. each member faces a similar decision problem and each member can observe the trades of other members in the group. They argue "*such a group cannot be too large relative to the size of the market since in a large group, say a group that represents 80% of the market, both buyers and sellers would be adequately represented*". This leads to the conclusion that herd formation would be more likely to occur at the level of investments in a group of stocks (stocks of firms in an industry or in a country), of course, after the impact of fundamentals has been factored out. Therefore, we assign each firm to one of 18 industry groups including Agriculture, Fishery and Forestry, Food and Beverage, Textile and Clothing, Paper Printing and Publishing, Petroleum Products, Chemicals and Plastics, Electronics, Metals and Non-metals, Machinery, Medicine and Biomedical Products, Electricity, Gas and Water Supply, Transportation and Storage, Information Technology, Wholesale and Retail, Finance and Insurance, Real Estate, Social Services, Communications and Culture Products. We then calculate portfolio returns based on an equally weighted portfolio of all firms in each industry.

The second data set we analyze contains daily sector indexes of Shanghai and Shenzhen stock exchanges that are obtained from the Taiwan Economic Journal Financial Database. The dataset for Shanghai Stock Exchange consists of four sectors: Industry, Commerce, Realty and Utility. The sample period is from May 3, 1993 to November 16, 2001, totalling 1860 daily observations. The data set for Shenzhen Stock Exchange consists of five sectors:

Industry, Commerce, Realty, Finance and Utility. We note that there is no separate sector data published for the Finance sector in the Shenzhen market. The sample period for this market runs from July 20, 1994 to November 16, 2001, with a total of 1544 daily observations. Next section reports the empirical results.

5. Empirical results

5.1. Descriptive statistics

Table 1 provides summary statistics for average daily log returns, return dispersions and the average number of firms used to compute these statistics for each industry. Note that the number of stocks in an industry does not stay constant over time, so the number of returns used to calculate the daily dispersion measure varies over time. The average number of firms over the sample period is given in the second column of Table 1.

Average daily returns range between a low of −0.044% for Electronics and high of 0.01% for Metals. Over the 4-year sample period, majority of industries have had negative returns with the exception of Machinery, Communications and Metals/Non-metals. Volatility of daily returns, measured by standard deviation, ranges between a low of 0.97% for Machinery and a high of 2.26% for Finance and Insurance. Finance and Insurance and Agriculture have the most extreme daily changes with a minimum daily return of −13.87%, −14.219% and maximum daily return of 9.542%, 9.536% for Finance and Agriculture, respectively.

The level of return dispersion ranges from a low of 1.298% for Finance and Insurance to 2.444% to Information Technology. This indicates that, compared to stocks in other industries, financial stocks behave more similar as a group so that average cross-sectional standard deviation for this industry is the smallest. Even though this observation may seem counter-intuitive, it might be due to the regulated nature of this sector. As Wang et al. (in press) suggest, the Chinese government typically views the Finance sector as more sensitive and more critical to government planning, so it imposes more regulation and supervision on this sector. Next, we provide the dummy variable regression model results.

5.2. Regression results using individual firm returns

Table 2 provides the regression estimates for the regression

$$\text{S.D.}_t = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \varepsilon_t$$

across industries. Given the significant variation in dispersions and strong correlation, all estimations are done using the Newey–West heteroskedasticity and autocorrelation consistent standard errors. We construct two sets of dummy variables to identify days with extreme market movements. Following the methodology in Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2003), we use 1 and 5% criteria to restrict the variables D_t^{L} (D_t^{U}) to 1 and 5% of the lower (upper) tail of the market return distribution. We use the SSE Composite Index to represent the market. However, we also get consistent results when we use individual Shenzhen and Shanghai indexes separately to represent the market index. Our results are consistent with prior research in the sense that we do

Table 1
Summary statistics: average daily returns and cross-sectional standard deviations

Industry	# Firms	# Observations	Mean	Standard deviation	Minimum	Maximum
Average daily returns						
Agriculture, Fishery and Forestry	6	954	−0.031%	1.959%	−14.219%	9.536%
Food and Beverage	15	949	−0.008	1.030	−6.575	4.196
Textile and Clothing	14	950	−0.010	1.153	−5.882	4.985
Paper Printing and Publishing	7	941	−0.012	1.392	−11.242	6.040
Petroleum Products, Chemicals and Plastics	33	950	−0.023	0.996	−6.937	4.699
Electronics	10	950	−0.044	1.189	−7.079	5.246
Metals and Non-metals	30	950	0.010	1.023	−6.653	4.898
Machinery	52	951	0.000	0.970	−6.718	4.250
Medicine and Biomedical Products	20	951	−0.013	1.156	−6.594	5.456
Electricity, Gas and Water Supply	18	949	−0.028	1.079	−6.019	6.285
Transportation and Storage	13	951	−0.025	1.224	−7.167	5.465
Information Technology	26	950	−0.030	1.034	−5.949	5.197
Wholesale and Retail	50	950	−0.009	1.139	−8.117	6.813
Finance and Insurance	7	949	−0.027	2.261	−13.872	9.542
Real Estate	15	950	−0.027	1.196	−7.700	6.773
Social Services	11	950	−0.008	1.185	−7.796	6.902
Communications and Culture Products	7	949	0.001	1.342	−7.465	6.632
Miscellaneous	41	950	−0.036	1.055	−6.867	6.171
Cross-sectional standard deviations						
Agriculture, Fishery and Forestry			1.897%	1.743%	1.605%	0.015%
Food and Beverage			2.214	1.374	1.903	0.457
Textile and Clothing			2.199	1.573	1.831	0.384
Paper Printing and Publishing			2.260	1.656	1.917	0.385
Petroleum Products, Chemicals and Plastics			2.304	1.174	2.049	0.677
Electronics			2.199	1.390	1.867	0.366
Metals and Non-metals			2.325	1.129	2.071	0.645
Machinery			2.339	1.093	2.098	0.794
Medicine and Biomedical Products			2.107	1.235	1.807	0.561
Electricity, Gas and Water Supply			2.206	1.433	1.854	0.519
Transportation and Storage			2.029	1.601	1.690	0.379
Information Technology			2.444	1.391	2.126	0.751
Wholesale and Retail			2.260	1.119	1.988	0.672
Finance and Insurance			1.298	1.549	0.917	0.000
Real Estate			2.117	1.259	1.780	0.570
Social Services			2.167	1.173	1.865	0.526
Communications and Culture Products			2.313	1.400	2.013	0.267
Miscellaneous			2.423	1.375	2.052	0.735

Table 2
Regression coefficients for $\text{S.D.}_{\cdot t} = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \varepsilon_t$ using firm-level data

Return dispersions	Market return in the extreme upper/lower 1% of the return distribution			Market return in the extreme upper/lower 5% of the return distribution		
Industry	α	β_{D}	β_{U}	α	β_{D}	β_{U}
All firms	2.433%	1.038%*** (3.310)	1.619%*** (5.163)	2.367%	0.763%*** (5.337)	1.097%*** (7.670)
Agriculture, Fishery and Forestry	1.899%	0.387% (0.698)	−0.479% (−0.864)	1.814%	1.285%*** (5.030)	0.374% (1.464)
Food and Beverage	2.195	0.868** (1.995)	1.050** (2.412)	2.129	0.763*** (3.769)	0.939*** (4.682)
Textile and Clothing	2.181	0.817 (1.635)	0.852* (1.705)	2.107	1.022*** (4.394)	0.799*** (3.471)
Paper Printing and Publishing	2.246	0.667 (1.268)	0.707 (1.343)	2.157	1.299*** (5.325)	0.762*** (3.156)
Petroleum Products, Chemicals and Plastics	2.285	0.701*** (1.885)	0.937** (2.521)	2.216	0.795*** (4.632)	0.932*** (5.483)
Electronics	2.171	1.275*** (2.909)	1.440*** (3.285)	2.092	0.878*** (4.333)	1.261*** (6.279)
Metals and Non-metals	2.300	0.784** (2.206)	1.1407*** (3.957)	2.236	0.712*** (4.330)	1.032*** (6.334)
Machinery	2.312	1.634*** (4.766)	0.918*** (2.6678)	2.235	1.188*** (7.561)	0.886*** (5.711)
Medicine and Biomedical Products	2.091	0.587 (1.499)	0.841 (2.145)	2.022	0.692*** (3.815)	0.980*** (5.461)
Electricity, Gas and Water Supply	2.187	0.535 (1.179)	1.122** (2.469)	2.122	0.849*** (4.008)	0.784*** (3.737)
Transportation and Storage	2.009	0.838* (1.650)	1.030** (2.027)	1.932	0.612** (2.598)	1.308*** (5.601)
Information Technology	2.414	0.164*** (3.749)	1.174*** (2.679)	2.334	1.121*** (5.525)	1.077*** (5.359)
Wholesale and Retail	2.241	0.956*** (2.704)	0.975*** (2.759)	2.184	0.692*** (4.211)	0.841*** (5163)
Finance and Insurance	1.269	1.207** (2.470)	1.709*** (3.469)	1.214	0.649*** (2.837)	1.069*** (4.711)
Real Estate	2.098	0.722** (1.813)	1.090*** (2.733)	2.016	0.789*** (4.314)	1.229*** (6.779)
Social Services	2.151	0.712** (1.915)	0.753** (2.022)	2.081	0.954*** (5.558)	0.766*** (4.506)
Communications and Culture Products	2.297	0.481 (1.081)	1.060** (2.368)	2.239	0.681*** (3.283)	0.799*** (3.890)
Miscellaneous	2.408	0.654 (1.499)	0.889** (2.039)	2.335	0.629*** (3.114)	1.159*** (5.795)

t-Ratios in parentheses.
* Significance at 10%.
** Significance at 5%.
*** Significance at 1%.

not find any evidence in favor of herd formation during periods of large market swings. The regressions yield statistically significant and positive β_i (i = D, U) coefficients. Consistent with prior studies, almost all the coefficients are significantly positive indicating that equity return dispersions increase during periods of large price changes. This finding supports the rational asset pricing models that predict that periods of market stress induce increased levels of dispersion as individual returns differ in their sensitivity to the market return. However, comparing the coefficient values for upside and downside moves of the market, we see that return dispersions during extreme downside moves of the market are much lower than those for upside moves. This indicates a "flight to safety" of the market consensus in bad times. For some of the industries (e.g. Communications), we observe that return dispersions are as much as 50% smaller on the downside than on the upside. The only exception to this is Machinery where we observe higher downside return dispersions.

5.3. Regression results using sector index returns

Having found no evidence of herd formation using firm-level data, we next examine sector index returns reported for the Shanghai and Shenzhen markets to examine if the analysis yields different results when we distinguish between stock exchanges. Table 3 provides the summary statistics for daily sector index returns for the sectors in each stock exchange. Average daily returns in the Shanghai market ranges from a low of 0.01% for the Industry sector to a high of 0.045% for Utility sector. Note that the higher returns in the Utility sector correspond to relatively higher volatility as well. Returns in the Shenzhen market ranges from a low of 0.039% for Realty and a high of 0.134% for Finance. Volatilities range from a low of 2.735% for Industry and a high of 3.428% for Commerce.

Cross-sectional standard deviations of sector index returns for each market are reported in Table 4. We see that sector returns in the Shanghai market behave more uniformly, as indicated by a smaller average return dispersion for this market (0.746%). However, when we run the dummy regressions to analyze how return dispersions behave during extreme markets, we find consistent results to those obtained using firm-level data. Table 5 provides

Table 3
Average daily returns of sector indexes of Shanghai and Shenzhen stock exchanges

Sector	# Observations	Mean	Standard deviation	Minimum	Maximum
Shanghai Stock Exchange					
Industry	1859	0.010%	2.710%	−19.661%	27.451%
Commerce		0.020	2.852	−18.941	28.488
Utility		0.045	2.893	−19.075	33.714
Realty		0.030	2.892	−14.745	27.968
Shenzhen Stock Exchange					
Industry	1543	0.107%	2.735%	−20.031%	30.204%
Commerce		0.122	3.428	−22.599	32.737
Utility		0.098	3.000	−20.009	29.953
Realty		0.039	3.103	−20.825	29.797
Finance		0.134	2.863	−18.993	23.206

Table 4
Cross-sectional standard deviations of daily sector index returns of Shanghai and Shenzhen Stock Exchanges

	Mean	Standard deviation	Minimum	Maximum
Shanghai	0.746%	0.638%	0.038%	6.590%
Shenzhen	1.139	0.840	0.011	7.730

the regression estimates for

$$\mathrm{S.D.}_t = \alpha + \beta_{\mathrm{D}} D_t^{\mathrm{L}} + \beta_{\mathrm{U}} D_t^{\mathrm{U}} + \varepsilon_t.$$

However, this time we use sector index returns for each market separately. Again, the results are based on the Newey–West estimates. Once again, the regressions yield statistically significant and positive β_{i} (i = D, U) coefficients, indicating that herd formation does not take place in these markets. However, when we examine return dispersions for up versus down markets, once again, we see that return dispersions are much lower on the downside than on the upside indicating that sectors behave more similar during extreme downward moves of the market. Thus, using both firm and sector data based on two different sample periods, we find no evidence supporting herd behavior in Chinese markets. Our results are also robust to the market index used in the analysis.[1]

5.4. Robustness analysis

Tests of herd formation along the lines of Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2003) provide no evidence to herd behavior in Chinese markets. In this section, we extend the model to account for different periods of volatility, which may affect our inferences. In the first subsection, we analyze the impact of the Asian crisis that took place in 1997. Next, we examine the effect of regulation changes on test results.

5.4.1. The impact of the Asian financial crisis

The data set, which contains daily sector indexes of Shanghai and Shenzhen stock exchanges, include the period of the Asian crisis. Therefore, we ran similar regressions for these exchanges only; however, this time we include dummy variables to examine the potential effect of the crisis on test results. To model the impact of the crisis and to infer the dates of the crisis, we have referred to previous studies: in the first model, we followed Hatemi-J and Roca (2004) and broke the sample into two sub-periods. Hatemi-J and Roca use July 1, 1997 as the cut-off point and exclude the period from July 1, 1997 to January 1, 1998, so that the effect of the Asian crisis can be analyzed by comparing the results from two sub-periods. In our analysis, Shanghai data is split into two sub-periods in which the first

[1] Potential thin trading at the firm level may affect the results, however. We have no trading volume data at the firm-level to confirm this; however, because our results at the firm and sector (portfolio) level are consistent, we believe that thin trading is less likely affect our inferences. Moreover, the overall trading volume in the Chinese stock markets has been growing tremendously over time. For example, according to the Standard and Poor, China's stock market capitalization exceeded that of Hong Kong in 2001. It is possible that this issue might have been more important in the earlier years and/or for the B market in which many shares are well known not to trade for days.

Table 5
Regression coefficients for $\text{S.D.}_{\cdot t} = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \varepsilon_t$ using sector index returns (t-ratios in parentheses)

Return dispersions	Market return in the extreme upper/lower 1% of the return distribution			Market return in the extreme upper/lower 5% of the return distribution		
Industry	α	β_{D}	β_{U}	α	β_{D}	β_{U}
Shanghai Stock Exchange	0.738%	0.231% (1.497)	0.906%*** (5.699)	0.707%	0.303%*** (4.267)	0.449%*** (7.339)
Shenzhen Stock Exchange	1.122	0.268 (1.285)	1.312*** (6.290)	1.062	0.511*** (6.551)	0.996*** (10.410)

(*), significance at 10%; (**), significance at 5%.
*** Significance at 1%.

sub-period is from May 3, 1993 to July 1, 1997 and the second is from January 1, 1998 to November 16, 2001. In the case of Shenzhen data, the first sub-period is from July 20, 1994 to July 1, 1997 and the second sub-period is from January 1, 1998 to November 16, 2001.

The second model we estimated is based on Wang and Firth (2004). In this model, we used a dummy variable, D_{Oct}, which takes the value of unity between October 23, 1997, when the Hang Seng Index collapsed, and October 28, 1997 (Hong Kong time), when the US stock market collapsed, and zero otherwise. This model has the following form:

$$\text{S.D.}_t = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \beta_{\text{Oct}} D_{\text{Oct}} + \varepsilon_t. \tag{3}$$

Finally, to further check the sensitivity of the results, we constructed an additional model in which we introduce a dummy variable, D_{July}, which takes the value of unity between July 1, 1997 and November 1, 1997, and zero otherwise. Our rationale for the third model is to account for any lagged effects of the crisis period. This model can be expressed as:

$$\text{S.D.}_t = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \beta_{\text{July}} D_{\text{July}} + \varepsilon_t. \tag{4}$$

Panels A and B results in Table 6 provide our results for the sub-periods. We find that the regressions yield statistically significant and positive β_{i} (i = D, U) coefficients, indicating that herd formation does not exist in these markets. The results are consistent with the full sample findings. One interpretation of the results is that the crisis did not affect stock markets in China. Hatemi-J and Roca (2004) also reported that the Asian crisis hardly affected China.

The results for regressions with the October and July dummy variables are reported in panels A and B in Table 7. In both models, the estimated coefficients for the dummy variables are generally insignificant indicating that the crisis period had no significant impact on cross-sectional standard deviations. The only exception is the October dummy for Shenzhen where we observe significantly positive coefficients, but at 10% level. This result may be explained by the observation that this market includes many export companies. Nevertheless, as far as herd formation is concerned, the additional tests do not change our conclusions about herd formation.

5.4.2. The impact of regulation changes

An interesting feature of the Chinese stock markets is that these markets operate under governmental intervention. For example, Su and Fleisher (1998) argue that stock market volatility may be associated with exogenous changes in government stock market regulation. Therefore, we tested several models to examine whether regulation changes had any effect on our results. Su and Fleisher (1998) observe several volatility spikes common to Shanghai and Shenzhen markets after the removal of daily price-change limits: during December 1992 and January 1993, in January 1994, during July and August 1994 and in June 1995. The background on these dates is as follows (as provided by Su and Fleisher): in January 1994, the State Planning Committee announced an annual quota of US$ 700 million for new issued in that year, which was much lower than the market had anticipated. In addition, the China Securities Regulatory Committee (CSRC) temporarily prohibited new issue and trading of legal entity shares, which were held by many state-owned enterprises and accounted for more than 15% of total market capitalization. On July 1994, the CSRC announced a

Table 6
Sub-period analysis: regression coefficients for $\text{S.D.}_{\cdot t} = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \varepsilon_t$ using sector index returns (t-ratios in parentheses)

Return dispersions	Market return in the extreme upper/lower 1% of the return distribution			Market return in the extreme upper/lower 5% of the return distribution		
Industry	α	β_{D}	β_{U}	α	β_{D}	β_{U}
Panel A: sub-period 1						
Shanghai Stock Exchange	0.847%	0.298% (1.626)	0.869%*** (5.015)	0.824%	0.195%** (2.232)	0.359%*** (4.213)
Shenzhen Stock Exchange	1.165	0.190 (0.730)	1.513*** (5.808)	1.066	0.437*** (3.376)	1.199*** (9.483)
Panel B: sub-period 2						
Shanghai Stock Exchange	0.599%	0.041% (0.156)	−0.232% (−0.521)	0.590%	0.188%* (1.732)	0.306%** (2.467)
Shenzhen Stock Exchange	1.085	0.544 (1.124)	−0.363 (−0.751)	1.058	0.692*** (4.763)	0.355** (2.276)

Following Hatemi-J and Roca (2004), we broke the sample into two sub-periods and ran separate regressions for each sub-period. Panels A and B present regression coefficients for $\text{S.D.}_{\cdot t} = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \varepsilon_t$ for each sub-period. Regarding Shanghai data, the first sub-period is from May 3, 1993 to July 1, 1997 and the second is from January 1, 1998 to November 16, 2001. In the case of Shenzhen data, the first sub-period is from July 20, 1994 to July 1, 1997 and the second sub-period is from January 1, 1998 to November 16, 2001.

* Significance at 10%.

** Significance at 5%.

*** Significance at 1%.

Table 7
Full sample period results for the models with alternative Asian crisis variables

Return dispersions	Market return in the extreme upper/lower 1% of the return distribution				Market return in the extreme upper/lower 5% of the return distribution			
	α	β_{D}	β_{U}	β_{Oct}	α	β_{D}	β_{U}	β_{Oct}
Panel A: the model with the October dummy as suggested by Wang and Firth (2004) $\mathrm{S.D.}_t = \alpha + \beta_{\mathrm{D}} D_t^{\mathrm{L}} + \beta_{\mathrm{U}} D_t^{\mathrm{U}} + \beta_{\mathrm{Oct}} D_{\mathrm{Oct}} + \varepsilon_t$								
Shanghai Stock Exchange	0.735%	0.303%** (2.270)	0.909%*** (6.245)	0.079% (0.251)	0.713%	0.262%*** (3.900)	0.430%*** (6.416)	0.035% (0.113)
Shenzhen Stock Exchange	1.119	0.270 (1.295)	1.314*** (6.304)	0.741* (1.785)	1.060	0.504*** (5.376)	0.998*** (10.647)	0.674* (1.670)
Panel B: the model with the July dummy $\mathrm{S.D.}_t = \alpha + \beta_{\mathrm{D}} D_t^{\mathrm{L}} + \beta_{\mathrm{U}} D_t^{\mathrm{U}} + \beta_{\mathrm{July}} D_{\mathrm{July}} + \varepsilon_t$								
Shanghai Stock Exchange	0.735%	0.330%** (2.269)	0.909%*** (6.239)	−0.008% (−0.122)	0.713%	0.262%*** (3.911)	0.430%*** (6.409)	−0.011% (−0.162)
Shenzhen Stock Exchange	1.115	0.267 (1.281)	1.319*** (6.324)	0.126 (1.367)	1.054	0.506*** (5.405)	1.002*** (10.683)	0.136 (1.517)

t-Ratios in parentheses. Panel A presents regression coefficients for the model $\mathrm{S.D.}_t = \alpha + \beta_{\mathrm{D}} D_t^{\mathrm{L}} + \beta_{\mathrm{U}} D_t^{\mathrm{U}} + \beta_{\mathrm{Oct}} D_{\mathrm{Oct}} + \varepsilon_t$. Following Wang and Firth (2004), we included a dummy variable, D_{Oct}, which takes the value of unity between October 23, 1997, when the Hang Seng Index collapsed, and October 28, 1997 (Hong Kong time), when the US stock market collapsed, and zero otherwise. Panel B presents regression coefficients for the model $\mathrm{S.D.}_t = \alpha + \beta_{\mathrm{D}} D_t^{\mathrm{L}} + \beta_{\mathrm{U}} D_t^{\mathrm{U}} + \beta_{\mathrm{July}} D_{\mathrm{July}} + \varepsilon_t$ where D_{July} is a dummy variable, which takes the value of unity between July 1, 1997 and November 1, 1997, and zero otherwise. Our rationale for the third model is to account for any lagged effects of the crisis period.

* Significance at 10%.

** Significance at 5%.

*** Significance at 1%.

Table 8
Full sample period results with regulation variables (t-ratios in parentheses)

	Shanghai Stock Exchange		Shenzhen Stock Exchange	
	Market return in the extreme upper/lower 1% of the return distribution	Market return in the extreme upper/lower 5% of the return distribution	Market return in the extreme upper/lower 1% of the return distribution	Market return in the extreme upper/lower 5% of the return distribution
α	0.721%	0.701	1.118%	1.064
β_D	0.264%* (1.809)	0.226*** (3.385)	0.182% (0.868)	0.480*** (5.043)
β_U	0.780%*** (5.396)	0.382*** (5.766)	1.267%*** (6.012)	0.977*** (10.347)
β_{Oct}	0.094% (0.301)	0.056 (0.181)	0.742%* (1.794)	0.676* (1.679)
β_1	0.214% (1.570)	0.184 (1.503)		
β_2	0.683%*** (7.063)	0.693*** (7.206)	0.191% (1.240)	0.096 (0.646)
β_3	−0.391%*** (−2.932)	−0.382*** (−2.872)	−0.471%*** (−2.656)	−0.439** (−2.542)
β_4	0.212% (1.563)	0.155 (1.156)	0.410%** (2.286)	0.203 (1.162)

This table presents regression coefficients for $\text{S.D.}_t = \alpha + \beta_D D_t^L + \beta_U D_t^U + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \varepsilon_t$. In order to examine the effects of regulation changes, we introduced the following dummy variables: D_1 takes the value of unity during January 1994, and zero otherwise; D_2 takes the value of unity during July and August 1994, and zero otherwise; D_3 takes the value of unity during June 1995, and zero otherwise and finally D_4 takes the value of unity during December 1996, and zero otherwise. In estimations, we also maintain the October crisis dummy (the results did not change when the July dummy variable is employed). Note that the Shenzhen data starts in July 1994; therefore, the regression for Shenzhen does not include the dummy variable D_1.

* Significance at 10%.

** Significance at 5%.

*** Significance at 1%.

series of market support market liberalization policies which included: (1) a ban on new listing of A shares for the rest of 1994; (2) the provision of a US$ 1.15 billion credit line for qualified security firms to encourage trading; (3) supporting the establishment of new mutual funds and possible foreign participation in the domestic A-share market and (4) a promised merger of the A- and B-share categories within 5 years. In June 1995, the CSRC suspended market trading of futures on government bonds and, at the same time, the central bank set an interest-rate ceiling for corporate and municipal bonds. As a consequence, a large amount of funds were transferred from the bonds markets into the stock markets. In addition to the dates listed by Su and Fleisher, we also examined the impact of a new regulation introduces in December 1996 that reintroduced price limits, which were removed in 1992.

In order to examine the effects of regulation changes, we introduced the following (0,1) dummy variables: D_1 takes the value of unity during January 1994, and zero otherwise; D_2 takes the value of unity during July and August 1994, and zero otherwise; D_3 takes the value of unity during June 1995, and zero otherwise and finally D_4 takes the value of unity during December 1996, and zero otherwise.

Table 8 provides regression estimates for the model

$$\text{S.D.}_t = \alpha + \beta_{\text{D}} D_t^{\text{L}} + \beta_{\text{U}} D_t^{\text{U}} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \varepsilon_t. \tag{5}$$

In estimations, we also maintain the October crisis dummy. Using alternative dates of the crisis did not change our conclusions. Note that the Shenzhen data starts in July 1994; therefore, the regression for Shenzhen does not include the dummy variable D_1. Consistent with our previous findings, regression results reported in Table 8 lead to statistically significant and positive estimates for β_{i} (i = D, U), adding support to the conclusion that herd formation does not exist in Chinese markets. However, our analysis leads to an interesting finding that the actions of the Central Bank might be an important factor. Out of all the regulation dummies, the only one that is statistically significant is D_3, which corresponds to June 1995, during which the Central Bank set an interest-rate ceiling for corporate and municipal bonds, causing a large amount transfer of funds from the bond market into the stock market. The estimate for this dummy, β_3, is statistically significant and negative for both Shanghai and Shenzhen markets, indicating that cross-sectional standard deviations were significantly smaller during June 1995. Because D_3 is the only dummy variable that corresponds to a regulatory change by the Central Bank, our results indicate that CSRC-based related regulatory changes may be better discounted by market participants, while the actions of the Bank is harder to predict. Another interpretation of the result is that traders tend to speculate on what the government will do in the market. However, one needs to have more information about the goals of the central bank policies and their intervention before making these claims as they are somewhat subjective and subject to interpretations. We believe this issue deserves further research.

6. Conclusions and suggestions for further research

In this paper, we test formation of herds along the lines of Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2003, 2004). The testing methodology is based on the assumption that investors would be more likely to ignore their private information and go with the market consensus during periods of market stress. Consistent with prior studies, perhaps surprisingly, we find no evidence of herd formation, using both firm- and sector-level data from the Shanghai and Shenzhen Stock Exchanges.

The findings have important policy implications. Evidence suggests that market participants in Chinese stock markets make investment choices rationally. This is useful for modeling stock behavior in Chinese markets and the findings support rational asset pricing models. In addition, the lack of evidence of herd behavior should provide confidence for Chinese policymakers that they do not have to be concerned about potential destabilizing effects. It is also interesting to note that the results for both the Shanghai and Shenzhen exchanges are consistent, indicating that traders in the Shanghai market are as informed as those in the Shenzhen market. This indicates a smooth transition of information between markets, as reported in earlier studies. An important implication of our findings is that stock market segmentation is not necessarily a barrier for efficient flow of information.

An important extension of this paper would be to study the impact of the dual structure of Chinese firms on potential herd formation. As reported earlier, a number of studies have reported that A- and B-shares have significantly different statistical properties and sensitivities to global forces. Furthermore, due to the fact that market B is characterized by greater institutional investor participation, one may expect that these investors have access to a broader range of information on the market than domestic investors. Given the existing debate on this issue (e.g. Chakravarty et al., 1998 and Yang, 2003), it would be interesting to analyze returns on A- and B-type shares separately and examine whether herd formation could be identified when we differentiate between domestic and foreign investors in Chinese markets. In addition, the impact of central bank actions and government regulations on herd behavior requires further scrutiny. Finally, the results may be sensitive to different approaches for testing for herd formation.

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