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Herding behaviour of Chinese A- and B-share markets

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Abstract

Purpose – The purpose of this paper is to examine the evidence of herding phenomenon, spill-over effects related to herding and whether herding is driven by fundamentals or non-fundamentals for various sub-periods and sub-samples.

Design/methodology/approach – The cross-sectional absolute deviation model is applied to China's A- and B-share markets in combination with fundamental information.

Findings – Herding is prevalent on both A- and B-share markets. In detail, investors on A-share market herd for small and growth stock portfolios irrespective of market states while they only herd for large or value stocks in down market, therefore leading the whole herding behaviour to be pronounced in down market. Comparatively, on B-share market, herding is robust for various investment styles (small or large, value or growth) or market situations. Additionally, spill-over effects related to herding do not exist no matter from A-shares to B-shares or from B-shares to A-shares. Moreover, investors on B-share markets tend to herd as the response to non-fundamental information more frequently during financial crisis.

Originality/value – Investors on A- and B-share markets tend to herd as the response to non-fundamental information more frequently during financial crisis. Analysing the herding behaviours could be helpful in controlling the financial risk.

Keywords Herding, Chinese share market

Paper type Case study

1. Introduction

Herding, originally documented by Keynes (1936) in the discussion of "Beauty Contest", can be interpreted as a situation when traders make decisions by imitating others' behaviour (Spyrou, 2013). Financial research works on herding have been very popular for many decades because herding detection not only helps to explain price deviations but also provides potential trading opportunities. In practice, by applying macro-data-based models (Christie and Huang, 1995; Chang *et al.*, 2000), results are mixed for diverse markets and sensitive to various samples and empirical tools.

Comprehension of herding on financial market arouses the following issues: the detection and possible explanations of herding. Besides detection of herding, interpretation of this behaviour is diverse as well. From two comparative perspectives, behavioural finance and neoclassical finance, interpretation on herding can be roughly divided into two parts: irrational and rational herding. Rational herding is mainly supported by three theories: pay-off externality (Admati and Pfleiderer, 1988; Chowdhry and Nanda, 1991; Dow and Gorton, 1994; Hirshleifer *et al.*, 1994; Chen, 1999), information cascades (Bikhchandani *et al.*, 1992; Welch, 1992; Avery and Zemsky, 1998; Banerjee and Fudenberg, 2004) and principal–agent theory (Scharfstein and Stein, 1990; Graham, 1999; Stickel, 1990, 1992; Boyson, 2010). Comparatively, behavioural finance studies explain herding through various irrational psychological factors, including conservative bias (Barberis *et al.*, 1998), over confidence

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(Hirshleifer *et al.*, 2004; Bernardo and Welch, 2001), conformity (Hirshleifer, 2001), congruity (Prast, 2000), etc.

The above theories focus only on one angle of views and ignore the counterpart. However, the combination of irrational and rational motivations could possibly contribute to a more comprehensive decision making. Bikhchandani and Sharma (2000) distinguish "spurious" herding, simply efficient asset reallocation driven by the similar information set, from "intentional" herding. However, Bikhchandani and Sharma (2000) only focus on the explanations of "intentional" herding through rational perspective, neglecting irrational motivations. Baddeley (2010) criticises that it is stark and narrow to simply categorise herding as either rational or irrational behaviour. A better approach to improve the cognition of herding is to blend social and psychological elements together. Spyrou (2013) supports Baddeley's (2010) viewpoints by raising an issue of time-varying herding. Spyrou (2013) doubts if people herd for the same purpose all the time. From this perspective, the models adopted in this paper allow for both "spurious" herding and "intentional" herding in order to capture variations of different herding motivations from time to time.

Afterwards, Galariotis *et al.* (2015) adopt Bikhchandani and Sharma's (2000) hypotheses and test whether investors herd on fundamentals or non-fundamentals by using leading stocks' data in the USA and the UK.

Chinese stock market provides another interesting empirical background for comparison: A- and B-share markets. Generally speaking, both A- and B-shares are Chinese companies' stocks and are traded concurrently on the Shanghai Stock Exchange (SHSE or SH Exchange) and the Shenzhen Stock Exchange (SZSE or SZ Exchange). However, compared with B-shares, dominated by most sophisticated institutional investors, A-shares are designed for domestic traders, who lack professional investment knowledge (Tan *et al.*, 2008). According to this difference, it is reasonable to compare the two stock markets related to herding phenomenon. Therefore, this paper attempts to apply Galariotis's (2015) theory to Chinese A- and B-share markets for a comparative discussion. First, does herding exist in Chinese stock market? Further, if so, whether investors herd on fundamentals or non-fundamentals? When does it happen? Do stock characteristics (i.e. size or book-to-market ratio) matter in this case? Are there any spill-over effects relevant to herding? By comparing of previous studies focussing on Chinese market herding behaviour (Tan *et al.*, 2008; Yao *et al.*, 2014), I bring Galariotis *et al.*'s (2015) theory, which focusses on the US and UK stock markets, into Chinese market as another empirical test and additionally examine herding during unique Chinese financial situations, such as A-share Crash.

2. Data and methodology

2.1 Data

I collect the information of all the listed stocks of A- and B-shares from the database of SHSE and SZSE. The available periods are from 25 November 1997 to 30 June 2017; from 22 July 1992 to 30 June 2017; from 23 August 1991 to 30 June 2017; and from 5 July 1993 to 30 June 2017, respectively. As being discussed in Tan *et al.*'s (2008) paper, herding is proved to last for very short duration, daily data are chosen. In addition, China time deposit rate in three months is regarded as risk-free rate.

For A- and B-share markets with the above two exchanges, three factor returns and daily factor portfolio returns are downloaded from RESSET database (www.resset.com). Available periods of A- and B-share markets are from 1 July 1992 to 30 June 2017 and from 4 July 1994 to 30 June 2017, respectively.

2.2 Methodology

A non-linear model (Chang *et al.*, 2000) that allows for asymmetric effects of market returns is used. First, I adopt Chang's measure to capture the absolute deviation of cross-sectional stock returns (cross-sectional absolute deviation (CSAD)). However, when applying this model, the estimated dispersion of returns is based on the estimated β rather than true values; therefore the possibility of estimation error increases (Tan *et al.*, 2008). Hence, instead of estimating individual stocks' sensitivities (βs, coming from the market model), I follow Tan *et al.* (2008) who use stock returns to calculate dispersion of returns, as expressed in the following equation:

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

Note that CSAD_t does not represent the level of herding. Herding is further measured by the following regression (Chang *et al.*, 2000; Hwang and Salmon, 2001):

$$\mathrm{CSAD}_t = \alpha + \beta\left|R_{m,t}\right| + \gamma R_{m,t}^2 + \varepsilon_t, \tag{2}$$

where $|R_{m,t}|$ denotes the absolute value of market return at time t; and $R_{m,t}^2$ the squared market return. This model is derived from Christie and Huang's (1995) theory. When the market experiences fluctuations, rational pricing models indicate that the dispersion of individual returns will enlarge because of diverse individual returns' sensitivities to the changes of market portfolio returns, leading to the increase of CSAD (or at least the decrease of this variable with an increasing speed). If so, the coefficient that captures the relationship between CSAD and the market returns will be positive. However, if investors imitate with each other, CSAD will decline or at least climb at a decreasing speed, causing the coefficient to be negative. Based on this theory, Chang *et al.* (2000) consider the relationship to be non-linear especially with extreme price movement on the market and use the squared market returns instead. That is to say, opposite to rational pricing models' predictions, the coefficient γ tends to be significantly negative when herding behaviour becomes pervasive. Note that according to Chang *et al.*'s (2000) model, the coefficient β is only used for comparisons of the linear term.

Speaking to the market situation, not only Chang *et al.* (2000) but also many other researchers such as Christie and Huang (1995) believe herding is probably more prominent when the market is faced with huge fluctuation, especially during the bear market period. Therefore, by applying Galariotis *et al.*'s (2015) idea, I further divide the whole sample into several sub-samples according to market returns (positive or negative) or economic situations (whether financial crisis happened). Similar to Galariotis *et al.*'s (2015) definition, I consider the Peso Crisis ranging from December 1994 to July 1995; the Russian Crisis ranging from August 1998 to March 1999; the Dotcom Bubbles ranging from January 2000 to June 2000; and the Subprime Crisis ranging from January 2008 to April 2011. However, when considering the specific financial market pressure that Chinese market confronted, I treat the period from July 1997 to July 1998 as the period before Soros, the private fund manager, hit Hong Kong stock market during the Asian Crisis (denoted as "early Asian Crisis"). And the period from August 1998 to September 1998 is reflected as the time span of Hong Kong event (denoted as "later Asian Crisis"). Additionally, during the period from June 2015 to February 2016, there was an A-share Crash in Chinese stock market, which should also be taken into consideration.

Moreover, the effects of stock characteristics on herding have been considered (Chang *et al.*, 2000; Caparrelli *et al.*, 2004; Lam and Qiao, 2015; Galariotis *et al.*, 2015). Therefore, all stocks are sorted into 2×2 groups by size and BM independently. Larger (smaller) size group is denoted as "Large" ("Small") sub-sample and higher (lower) BM group is denoted as "Value" ("Growth") sub-sample.

In addition, since A- and B-share markets are components of Chinese stock market, Tan *et al.* (2008) use the information of dual-listed stocks on the two markets to examine the spill-over effects of herding. However, Tan *et al.* (2008) only focus on dual-listed stocks. It particularly arouses concern to further test the whole sample. By using Galariotis *et al.*'s (2015) measure, the spill-over effect is tested by the following regression equations:

$$\mathrm{CSAD}_{A,t} = \alpha + \beta\left|R_{A,t}\right| + \gamma_1 R_{A,t}^2 + \gamma_2 R_{B,t}^2 + \varepsilon_t\ , \tag{3}$$

$$\mathrm{CSAD}_{B,t} = \alpha + \beta\left|R_{B,t}\right| + \gamma_1 R_{B,t}^2 + \gamma_2 R_{A,t}^2 + \varepsilon_t, \tag{4}$$

where a significant negative γ_2 indicates the spill-over effect from one market to another.

Besides, the detection of herding is not enough to explain where herding derives from. To investigate the motivation of herding further, Bikhchandani and Sharma (2000) distinguish "spurious" herding from "intentional" herding. Further, Galariotis *et al.* (2015) take Bikhchandani and Sharma's (2000) theory into practice by adding four risk factors into the model. Similarly, Hwang and Salmon (2004) use risk factors to capture fundamental information but only adopt three risk factors (Fama and French, 1993). Note that in Galariotis's (2015) paper, not only the Fama–French three risk factors but also the momentum factor (Carhart, 1997) is taken into consideration. However, Bikhchandani and Sharma (2000) interpret momentum strategies as one type of herding. Comparatively, Lam and Qiao (2015) regard risk-free rates and dividend-to-price ratio as the fundamental factors and four risk factors along with the liquidity factor as systematic factors. Hence, proxy variables that capture fundamental information are various. Due to data availability, I further decompose CSAD by utilising Fama and French's (1993) three risk factors as follows:

$$\mathrm{CSAD}_t = \alpha + \beta_1\left(R_{m,t} - r_f\right) + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \varepsilon_t. \tag{5}$$

Since risk factors capture the fundamental information on the whole stock market, CSAD is decomposed into two parts by Equation (5): the CSAD driven by fundamentals ($\mathrm{CSAD}_t - \varepsilon_t$) and by non-fundamentals (ε_t).

Similar to Equation (2), whether fundamentals motivate herding is further detected as follows:

$$\mathrm{CSAD}_{\mathrm{fundamental},t} = \alpha + \beta\left|R_{m,t}\right| + \gamma R_{m,t}^2 + \varepsilon_t, \tag{6}$$

$$\mathrm{CSAD}_{\mathrm{non-fundamental},t} = \alpha + \beta\left|R_{m,t}\right| + \gamma R_{m,t}^2 + \varepsilon_t. \tag{7}$$

3. Empirical analysis

3.1 Herding detection

In Figure 1, I report CSAD_t of A-share market during the period from 24 August 1991 to 30 June 2017. Comparatively, CSAD_t of B-share market between 23 July 1992 and 30 June 2017 is reported in Figure 2. By comparing Figure 1 with Figure 2, the whole patterns are relatively similar with one exception where return absolute deviations for A-share market fluctuate a lot from 1991 to 1995 but those for B-share market are comparatively stable from 1992 to 1995. Since a series of policies were promulgated to stimulate the development of the Chinese stock market in 1992 and the B-share market was set up in that year, probably distinct policy stimulus and life periods for the two markets lead to this difference. Besides, the return absolute deviations for both markets drop during three periods: the Dotcom

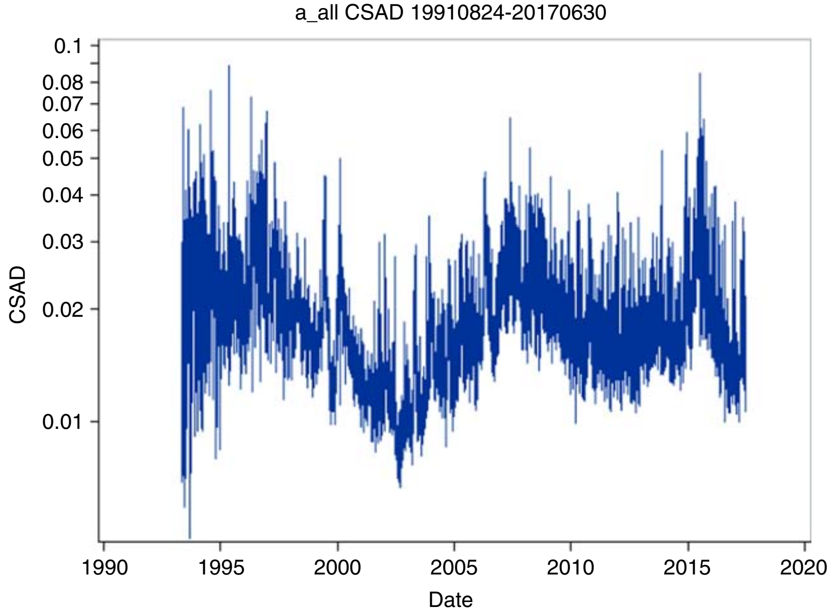

Figure 1. Cross-sectional absolute deviation (CSAD) on Chinese A-share market

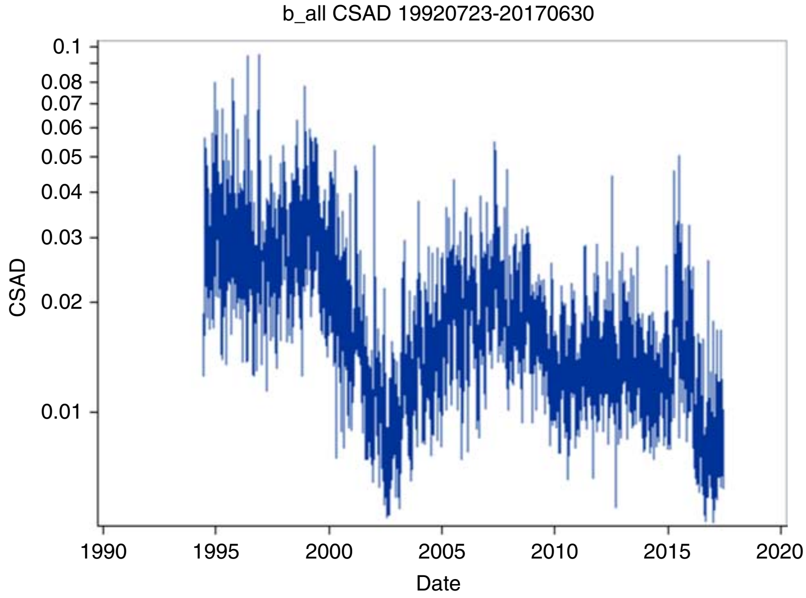

Figure 2. Cross-sectional absolute deviation (CSAD) on Chinese B-share market

Bubbles around 2000, the Subprime Crisis around 2007 to 2011 and the A-share Crash around 2015 to 2016. Under Christie and Huang's (1995) theory (also see Chang *et al.*, 2000), it is highly possible that herding phenomenon would exist during those time spans with extreme market stress.

Table I reports the estimated results of the regression (2) for A- and B-share markets. In Panel A, the coefficient γ for A-share market is significantly negative no matter for any Chinese stock exchange or for the whole sample, indicating a significant herding phenomenon. This result is consistent with Chang *et al.*'s (2000) viewpoint that the existence of herding is discovered in emerging stock markets as well as Tan *et al.*'s (2008) conclusion that a robust herding phenomenon is found on dual-listed A- and B-share markets in China. However, Yao *et al.* (2014) conclude that no evidence of herding exists in the A-share markets. Probably the difference comes from distinct sample periods and empirical testing models.

Similarly, from Panel B, significant herding evidence on B-share market is presented. Comparing with Tan *et al.*'s (2008) and Yao *et al.*'s (2014) similar finding, this result is not surprising. Although there is no herding evidence in the USA and Hong Kong (Chang *et al.*, 2000), Tan *et al.* (2008) point out that the dominant participants in B-share market, the USA or Hong Kong investors, have different behaviour tendencies on B-share market comparing with what they perform in their domestic stock markets.

To further interpret herding behaviour, Table II reports empirical results of the regression (2) for different sub-samples. In Panel A, γ is significantly negative on the "down" days and this is robust across all the four investment styles. For example, for large stocks, γ is −2.280 with a *t*-statistic of −6.641 on those "down" days, indicating the significant evidence of herding. In contrast, on those "up" days, γ is insignificant or even shows an opposite pattern with two exceptions where the sample only concludes small stocks and where the sample constituents are growth stocks. Although the asymmetric effect of market returns exists for all samples, large stocks and value stocks, the significant negative γ is robust for small stocks and growth stocks. From above findings, on the A-share market, the asymmetric effects of market returns could come from large stocks and value stocks. Tan *et al.* (2008) point out that the participants on A-share market are inclined to herd more on the "up" days than on the "down" days, which seems opposite to my results. However, Tan *et al.* (2008) pay more attention to the dual-listed market in Chinese stock market, while I focus on the whole Chinese stock market, reasonably leading to different results. More support comes from Demirer *et al.* (2010), who put forward that herding is more pronounced if the market experiences losses.

In Panel B, things are a little different. It shows that on Chinese B-share market, γ is significantly negative no matter for "up" days, "down" days or for any investment styles, indicating the no asymmetric effects of investment styles related to herding on the B-share market. This result is consistent with Tan *et al.* (2008).

Sample	α	*t*-statistic	β	*t*-statistic	γ	*t*-statistic
Panel A: herding on A-share market						
All sample	0.016	112.325	0.193	23.576	*−0.165*	*−3.195*
SH Exchange	0.013	81.184	0.348	18.998	*−2.491*	*−7.763*
SZ Exchange	0.014	110.158	0.192	23.988	*−0.492*	*−7.324*
Panel B: herding on B-share market						
All sample	0.013	60.651	0.513	29.422	*−3.565*	*−15.617*
SH Exchange	0.011	55.384	0.670	34.776	*−5.262*	*−20.277*
SZ Exchange	0.013	64.310	0.291	16.110	*−1.735*	*−7.489*

Notes: Sample contains all the individual stocks on each market. The sample periods for all sample, SH Exchange and SZ Exchange on A(B)-share market are from 1 July 1992 to 30 June 2017 (from 4 July 1994 to 30 June 2017), from 26 November 1997 to 30 June 2017 (from 23 July 1992 to 30 June 2017) and from 24 August 1991 to 30 June 2017 (from 6 July 1993 to 30 June 2017), respectively. A significantly negative γ indicates herding behaviour, which is showed in italic

Table I.
Detection of herding in Chinese A-share and B-share market

Sample	α	*t*-statistic	β	*t*-statistic	γ	*t*-statistic
Panel A: herding on A-share market						
All sample						
All period	0.016	112.325	0.193	23.576	*−0.165*	*−3.195*
Up	0.016	96.052	0.169	19.103	−0.067	−1.352
Down	0.017	55.588	0.410	15.306	*−2.418*	*−6.781*
Large						
All period	0.016	113.877	0.194	24.694	−0.058	−1.172
Up	0.015	96.588	0.177	20.648	0.019	0.390
Down	0.016	55.079	0.386	14.951	*−2.280*	*−6.641*
Small						
All period	0.017	106.606	0.193	21.679	*−0.273*	*−4.879*
Up	0.016	91.552	0.161	16.884	*−0.154*	*−2.882*
Down	0.018	54.049	0.435	15.093	*−2.558*	*−6.664*
Growth						
All period	0.018	110.735	0.187	20.471	*−0.243*	*−4.234*
Up	0.017	93.492	0.168	16.822	*−0.153*	*−2.743*
Down	0.019	54.405	0.417	14.021	*−2.915*	*−7.366*
Value						
All period	0.015	97.582	0.193	22.718	−0.071	−1.327
Up	0.014	81.204	0.167	17.797	0.035	0.660
Down	0.015	49.778	0.424	15.931	*−2.560*	*−7.233*
Panel B: herding on B-share market						
All sample						
All period	0.013	60.651	0.513	29.422	*−3.565*	*−15.617*
Up	0.012	45.893	0.551	26.802	*−3.874*	*−14.938*
Down	0.015	39.837	0.480	14.218	*−3.520*	*−7.208*
Large						
All period	0.012	64.424	0.408	25.660	*−3.050*	*−14.628*
Up	0.012	49.260	0.442	23.380	*−3.427*	*−14.386*
Down	0.014	41.898	0.361	11.784	*−2.410*	*−5.451*
Small						
All period	0.013	50.350	0.611	28.081	*−4.012*	*−14.070*
Up	0.012	38.098	0.651	25.663	*−4.195*	*−13.119*
Down	0.015	32.535	0.608	13.996	*−4.773*	*−7.599*
Growth						
All period	0.014	71.958	0.450	28.416	*−3.233*	*−15.588*
Up	0.013	56.312	0.467	25.473	*−3.367*	*−14.545*
Down	0.015	44.977	0.467	14.753	*−3.647*	*−7.972*
Value						
All period	0.012	43.823	0.574	25.767	*−3.836*	*−13.150*
Up	0.011	31.964	0.630	23.582	*−4.278*	*−12.688*
Down	0.014	30.579	0.503	12.118	*−3.515*	*−5.858*

Notes: The sample period for A-share market is from 1 July 1992 to 30 June 2017, while that for B-share market is from 4 July 1994 to 30 June 2017. Sample contains all the individual stocks on each market. "Up" refers to the days when market returns are positive while "Down" refers to the days when market returns are negative

Table II. Detection of herding by sub-sample analysis

From the comparison of Panels A and B, herding is a more widespread phenomenon on B-share market than on A-share market. It is of interest to observe more evident herding behaviour on B-share market where most participants are foreign and institutional investors who are inclined to be more rational than that on A-share market where traders are domestic investors. Tan *et al.* (2008) try to provide a possible explanation that investors on the B-share market behave differently comparing with their behaviour on their domestic markets. However, further study is still needed to explain this difference.

3.2 Spill-over effects related to herding

Since the results from Table II show that herding is very noticeable on those "down" days for both A- and B-share markets, I pick up those periods that experience financial crisis to estimate spill-over effects (Table III).

Both in Panels A and B, spill-over effects do not exist and this finding is robust during different financial crises. For example, in Panel A, during A-share Crash, although a significant negative γ_1 (−8.113 with a *t*-statistic of −4.250) indicates strong evidence of herding, a positive γ_2 represents for no spill-over effects. It can be interpreted that during A-share Crash the investors' herding behaviour on the A-share market is not affected by the information of B-shares. By using dual-listed stocks to investigate spill-over effects, Tan *et al.* (2008) support my results.

Although it is natural to hypothesise that there would be some cross-market effects on these two markets because they are sections of Chinese stock market and feedback relationship exists on the two markets (Chen *et al.*, 2001), actually herding behaviour is hard to be driven by the other market's situations or information. Even during the period of A-share Crash, the market returns of A-share market did influence the cross-sectional dispersion of B-shares' returns.

3.3 Herding and fundamentals

Table IV provides the estimated parameters from regressions (2), (6) and (7) along with corresponding *t*-statistics in parentheses. As discussed above, the CSAD is decomposed to two parts, the CSAD caused by fundamentals ($CSAD_{fundamental,t}$) and non-fundamentals ($CSAD_{non-fundamental,t}$), in order to further distinguish herding derived from fundamentals and herding derived from non-fundamentals.

In Panel A, on A-share market, during the whole sample period the existence of herding (γ is −0.165 with a *t*-statistic of −3.195) derives from fundamental information (γ is −0.108 with a *t*-statistic of −10.663). Conversely, during Peso Crisis, Dotcom Bubbles and A-share Crash, herding phenomenon is driven from non-fundamentals. During A-share Crash, γ of

Period	α	*t*-statistic	β	*t*-statistic	γ_1	*t*-statistic	γ_2	*t*-statistic
Panel A: spill-over from B- to A-shares								
4 July 1994 to 30 June 2017	0.016	111.191	0.195	21.721	−0.179	−3.494	−0.003	−0.040
Peso Crisis	0.017	15.912	0.230	6.377	−0.315	−2.256	2.102	1.506
Asian Crisis (early)	0.019	35.398	−0.006	−0.120	1.233	1.239	0.058	0.323
Asian Crisis (later)	0.020	18.262	−0.150	−1.635	3.089	2.317	−0.591	−1.585
Russian Crisis	0.017	38.239	−0.063	−1.361	2.099	2.526	−0.077	−0.382
Dotcom Bubbles	0.019	17.016	0.236	2.616	−2.991	−2.371	−0.383	−1.011
Subprime Crisis	0.019	47.087	0.124	4.010	−1.163	−2.073	0.589	1.514
A-share Crash	0.023	12.353	0.401	2.985	−8.113	−4.250	3.600	5.098
Panel B: spill-over from A- to B-shares								
4 July 1994 to 30 June 2017	0.013	60.772	0.506	28.921	−3.553	−15.577	0.152	3.481
Peso Crisis	0.030	15.212	0.057	0.369	6.703	2.515	−0.072	−0.820
Asian Crisis (early)	0.022	36.638	0.623	13.389	−5.092	−8.726	−0.713	−1.269
Asian Crisis (later)	0.022	7.534	0.896	4.693	−7.227	−2.856	0.429	0.385
Russian Crisis	0.025	21.508	0.641	6.387	−3.281	−2.253	−0.399	−0.393
Dotcom Bubbles	0.018	18.908	0.679	8.924	−6.641	−7.497	0.795	1.323
Subprime Crisis	0.013	46.696	0.204	8.688	−1.255	−3.205	0.154	0.604
A-share Crash	0.013	15.940	0.284	4.988	−2.226	−3.496	−0.327	−0.771

Notes: Spill-over effects are related to herding by estimating the regressions (3) and (4). A significant negative γ_2 indicates spill-over effects from one market to the other market

Table III.
Spill-over effects related to herding

Table IV. Herding and fundamentals

Period	Total CSAD α	Total CSAD β	Total CSAD γ	Fundamental CSAD α	Fundamental CSAD β	Fundamental CSAD γ	Non-fundamental CSAD α	Non-fundamental CSAD β	Non-fundamental CSAD γ
Panel A: A-share market in China									
All period	0.016***	0.193***	*−0.165****	0.019***	−0.002	*−0.108****	−0.003***	0.195***	−0.056
	(112.325)	(23.576)	(*−3.195*)	(675.357)	(−1.093)	(*−10.663*)	(−21.661)	(24.641)	(−1.131)
Peso Crisis	0.017***	0.218***	*−0.222**	0.022***	0.023	0.230***	−0.004***	0.194***	*−0.452****
	(20.588)	(6.323)	(*−1.728*)	(42.592)	(1.133)	(2.994)	(−5.080)	(5.887)	(*−3.668*)
Asian Crisis (early)	0.019***	−0.006	1.245	0.020***	−0.081***	1.126***	−0.001**	0.075	0.120
	(35.825)	(−0.110)	(1.255)	(134.142)	(−5.449)	(4.013)	(−2.229)	(1.519)	(0.128)
Asian Crisis (later)	0.020***	−0.168*	3.178**	0.020***	−0.183***	2.418***	−0.001	0.014	0.760
	(17.954)	(−1.818)	(2.342)	(30.680)	(−3.271)	(2.952)	(−0.719)	(0.199)	(0.716)
Russian Crisis	0.017***	−0.065	2.095**	0.017***	−0.101***	1.506***	−0.001	0.036	0.589
	(38.714)	(−1.404)	(2.528)	(165.430)	(−9.031)	(7.510)	(−1.376)	(0.819)	(0.745)
Dotcom Bubbles	0.019***	0.228**	*−3.123***	0.022***	−0.022	−0.469	−0.003**	0.250***	*−2.654***
	(16.999)	(2.544)	(*−2.489*)	(67.075)	(−0.850)	(−1.290)	(−2.588)	(2.959)	(*−2.244*)
Subprime Crisis	0.019***	0.120***	−0.644	0.020***	0.057***	*−0.845****	−0.001***	0.063***	0.201
	(47.430)	(3.900)	(−1.448)	(73.433)	(2.695)	(*−2.762*)	(−4.296)	(2.812)	(0.623)
A-share Crash	0.024***	0.354**	*−4.136***	0.028***	−0.002	0.789	−0.004**	0.356***	*−4.926****
	(12.029)	(2.473)	(*−2.224*)	(23.245)	(−0.022)	(0.712)	(−2.298)	(3.132)	(*−3.335*)
Panel B: B-share market in China									
All period	0.013***	0.513***	−3.565***	0.019***	0.002***	0.011	−0.006***	0.511***	−3.576***
	(60.651)	(29.422)	(−15.617)	(2,207.27)	(2.965)	(1.157)	(−29.228)	(29.257)	(−15.641)
Peso Crisis	0.029***	0.067	6.228**	0.028***	0.338***	−0.471	0.002	−0.271*	6.699**
	(15.208)	(0.435)	(2.397)	(78.913)	(12.173)	(−1.003)	(0.936)	(−1.725)	(2.522)
Asian Crisis (early)	0.022***	0.616***	*−5.062****	0.029***	0.006	0.011	−0.007***	0.610***	*−5.073****
	(37.038)	(13.317)	(*−8.671*)	(220.751)	(0.621)	(0.085)	(−12.366)	(13.268)	(*−8.750*)
Asian Crisis (later)	0.022***	0.883***	*−7.005****	0.034***	0.183	−0.947	−0.012***	0.700***	*−6.058****
	(8.077)	(4.751)	(*−2.874*)	(14.038)	(1.115)	(−0.441)	(−5.031)	(4.420)	(*−2.916*)
Russian Crisis	0.025***	0.641***	*−3.320***	0.034***	−0.017	1.770***	−0.009***	0.658***	*−5.090****
	(21.798)	(6.405)	(*−2.291*)	(83.772)	(−0.488)	(3.510)	(−6.827)	(6.102)	(*−3.260*)
Dotcom Bubbles	0.018***	0.701***	*−6.725****	0.026***	0.017	0.123	−0.008***	0.684***	*−6.848****
	(18.840)	(9.403)	(*−7.586*)	(150.620)	(1.269)	(0.783)	(−7.684)	(8.982)	(*−7.560*)

(*continued*)

Table IV.

Period	Total CSAD α	Total CSAD β	Total CSAD γ	Fundamental CSAD α	Fundamental CSAD β	Fundamental CSAD γ	Non-fundamental CSAD α	Non-fundamental CSAD β	Non-fundamental CSAD γ
Subprime Crisis	0.013***	0.205***	*−1.138****	0.015***	0.017*	−0.233	−0.003***	0.188***	*−0.904****
	(46.716)	(8.839)	(*−3.351*)	(124.840)	(1.674)	(−1.527)	(−10.474)	(8.969)	(*−2.955*)
A-share Crash	0.013***	0.270***	*−2.287****	0.016***	0.018	0.067	−0.003***	0.252***	*−2.353****
	(16.061)	(5.004)	(*−3.623*)	(38.819)	(0.624)	(0.201)	(−4.984)	(5.331)	(*−4.252*)

Notes: *t*-statistics are showed in parentheses. "Total CSAD" refers to results from regression (2):

$$\mathrm{CSAD}_t = \alpha + \beta |R_{m,t}| + \gamma R_{m,t}^2 + \varepsilon_t.$$

"CSAD caused by fundamentals" refers to results from regression (6):

$$\mathrm{CSAD}_{\mathrm{fundamental},t} = \alpha + \beta |R_{m,t}| + \gamma R_{m,t}^2 + \varepsilon_t.$$

"CSAD caused by non-fundamentals" refers to the results from regression (7):

$$\mathrm{CSAD}_{\mathrm{non-fundamental},t} = \alpha + \beta |R_{m,t}| + \gamma R_{m,t}^2 + \varepsilon_t.$$

The "All period" for A-share market is from 1 July 1992 to 30 June 2017, while that for B-share market is from 4 July 1994 to 30 June 2017. Sample contains all the individual stocks on each market. Note that if the estimated parameter γ is significantly negative, herding phenomenon exists. *,**,***Statistically significant at the 10, 5 and 1 per cent levels, respectively total CSAD is −4.136 with a t-statistic of −2.224, indicating a herding behaviour. Further, γ of fundamental CSAD is positive (0.789) and insignificant (t-statistic is 0.712), while γ of non-fundamental CSAD is significantly negative (−4.926 with a t-statistic of −3.335), manifesting that herding is driven by non-fundamental information.

What is more, results from Panel A show the importance of differentiating multiple motivations of herding or it is possible to misinterpret this phenomenon because of cancelling-out effects. During Subprime Crisis, fundamental-driven herding is significant. However, when total CSAD rather than the fundamental-driven CSAD is used to detect herding behaviour, the parameter γ is insignificant, indicating little evidence of herding. Therefore, if total CSAD is the only dependent variable taken into consideration, herding will be neglected and misunderstood during Subprime Crisis. Also, this interesting finding is in line with Galariotis *et al.* (2015).

In Panel B, on B-share market, no matter for any period of financial crisis or for the whole period, the total herding behaviour attributes to the non-fundamental information with one exception when the period experienced the Peso Crisis. During the period of Dotcom Bubbles, total herding is significant. Further, herding motivated by fundamentals is non-existent (γ is 0.123), while herding driven by non-fundamentals is significant (γ is −6.848 and t-statistic is −3.260). Therefore, it can be interpreted that during the period of Dotcom Bubbles, herding is motivated by non-fundamental information on B-share market. In contrast, during the Peso Crisis on B-share market, there is no herding evidence no matter driven by fundamentals or non-fundamentals.

By comparing Panels A and B, three main findings are the following: first, for all sample period, herding on A-share market is driven by fundamental information, while that on B-share market is driven by non-fundamental information. However, it is a little surprising to observe that A-share market investors seem to be more rational than B-share investors. Tan *et al.* (2008) consider that behaviour of US and Hong Kong investors on B-share market is different from that on their domestic markets. If so, the explanation is more applicable to my sample analysis. Note that the data stream records 3,304 listed stocks on the A-share market but only 99 listed stocks on the B-share market during my sample period. In contrast, there are over 7,500 stocks listed on NYSE, AMEX or NASDAQ of the USA. Probably the number of stocks that can be invested limits participants' behaviour, resulting in different behaviours of those foreign traders or institutional investors. Moreover, on A-share market, of all the four financial crises that are faced with herding, three of them experience herding as the response to non-fundamentals, while the whole sample period experiences fundamental-driven herding. One possible reason is that investors on A-share market would like to herd on fundamentals when the market is relatively stable.

Second, during Peso Crisis, investors herd on non-fundamental information on A-share market, while there is no presence of herding on B-share market.

Third, during Asian Crisis (early), Asian Crisis (later) and Russian Crisis, herding phenomenon does not exist on A-share market, while market participants tend to herd on non-fundamentals on B-share market.

From all above financial crises, two crises that would mostly possible incur extreme price fluctuations are the Asian Crisis (later) and A-share Crash, which directly affect Chinese stock market. From Chang *et al.*'s (2000) theory, herding inclines to be more pronounced when the market fluctuates extremely. Therefore, it is not surprising to detect the presence of herding phenomenon, especially caused by non-fundamentals, on both A- and B-share markets during A-share Crash. However, the result for the period of Asian Crisis (later) is partly contrary to my prediction. Note that "Asian Crisis (later)" refers to the period when Foreign Private Fund Manager George Soros intended to hit Hong Kong stock market. During this time span, it is reasonable to discover herding behaviour on B-share market because Hong Kong investors are the important component of B-share market participants and Hong Kong stock market confronted extreme financial turmoil. In contrast, it is interesting to find that little evidence of herding exists on A-share market. One possible reason is that before 2000, A-share market participants were only domestic traders and the B-share market functioned as the firewall to absorb most shocks from international financial crises (Su, 2009).

3.4 Herding and fundamentals by sub-sample analysis

Tables V and VI report whether investors herd on fundamental information or not for different investment styles during various periods of financial crises on A- and B-share markets.

In Table V, Panel A illustrates that of all the seven financial crisis periods, only during the Subprime Crisis is the herding behaviour driven by fundamental information on A-share market and this is robust no matter for any investment styles (larger or small stocks, growth or value stocks). For instance, for large portfolio stocks, investors tend to herd on each other (γ is negative, −0.728) significantly (t-statistic is −2.785).

In Panel B, during the periods of Peso Crisis, Dotcom Crisis and A-share Crash, herding is driven by non-fundamentals for all the four sub-samples, including larger, small, growth and value stock portfolios on A-share market.

The finding from Table V is consistent with the results in Panel A of Table IV. For the seven financial crisis periods on A-share market, herding induced by fundamental information emerges during the Subprime Crisis, while non-fundamental-driven herding exists during the periods of Peso Crisis, Dotcom Bubbles and the A-share Crash. Moreover, the results in Table V additionally attest that if the period experiences extreme price fluctuation, the herding driven by fundamental information or the herding driven by non-fundamental information is pervasive across various investment styles (large vs small; high BM vs low BM).

Similarly, Panel A in Table VI reports if there is any evidence of herding caused by fundamentals on B-share market when the market experiences extreme stress. Apparently fundamental-driven herding is rare during different financial crises on B-share market, only emerging during the periods of Asian Crisis (early) and Dotcom Bubbles for the large stock portfolio and during the Peso Crisis for the value stock portfolio. Although the evidence of herding phenomenon motivated by fundamental information exists during those three periods, that evidence is relatively weak.

Considerably strong evidence of non-fundamental-driven herding is discovered in Panel B. During the periods of Asian Crisis (early), Dotcom Bubbles, Subprime Crisis and the A-share Crash, the phenomenon that traders on B-share market imitate each other based on non-fundamentals is robust across all sub-samples, which is in consistent with the results in Table IV. Additionally, investors on B-share market tend to herd as the response to non-fundamentals during periods of Asian Crisis (later) and Russian Crisis with one exception for the growth stock portfolio where herding behaviour (indicated by the negative γ of −2.645 and −2.355, respectively) is not statistically significant (t-statistics: −1.173 and −1.197, respectively). It can be interpreted that during the two periods, investors on B-share market tend to herd on value stocks (low BM) instead of growth stocks (high BM).

By the comparison of Panels A and B, I acquire another interesting finding: some market participants may herd as the result of reaction to fundamental information and other investors may herd due to non-fundamental information at the same period. This applies to the period of Asian Crisis (early) and Dotcom Bubbles for the large stock portfolio. However, only a few traders imitate others because of the reaction to fundamental information and a large number of investors actively follow others' investment decisions as the response to non-fundamentals. Therefore, without sub-sample analysis, the overall herding evidence only indicates non-fundamental-motivated herding phenomenon during above two periods.

Table V. A-share market: herding and fundamentals by sub-sample analysis

Sample	Peso Crisis β	Peso Crisis γ	Early Asian Crisis β	Early Asian Crisis γ	Later Asian Crisis β	Later Asian Crisis γ	Russian Crisis β	Russian Crisis γ	Dotcom Bubbles β	Dotcom Bubbles γ	Subprime Crisis β	Subprime Crisis γ	A-share Crash β	A-share Crash γ
Panel A: CSAD caused by fundamentals														
Large	0.039	0.270***	−0.064***	0.850***	−0.111**	1.355**	−0.031***	0.482***	−0.025	−0.417	0.045**	*−0.728****	−0.003	0.748
	(1.591)	(2.931)	(−5.408)	(3.823)	(−2.532)	(2.105)	(−6.436)	(5.605)	(−0.888)	(−1.064)	(2.499)	*(−2.785)*	(−0.037)	(0.739)
Small	0.007	0.189***	−0.099***	1.402***	−0.254***	3.481***	−0.171***	2.532***	−0.019	−0.521	0.070***	*−0.968****	−0.003	0.853
	(0.414)	(3.007)	(−4.905)	(3.706)	(−3.615)	(3.375)	(−8.607)	(7.097)	(−0.761)	(−1.471)	(2.841)	*(−2.738)*	(−0.027)	(0.710)
Growth	0.016	0.275***	−0.097***	1.317***	−0.245***	3.200***	−0.148***	2.134***	−0.032	−0.488	0.055***	*−0.804****	0.025	0.371
	(0.657)	(3.111)	(−5.430)	(3.916)	(−3.094)	(2.759)	(−8.844)	(7.115)	(−1.151)	(−1.266)	(2.624)	*(−2.637)*	(0.277)	(0.320)
Value	0.073**	0.291**	−0.088***	1.281***	−0.157***	2.094***	−0.095***	1.538***	−0.013	−0.452	0.059***	*−0.885****	−0.025	1.162
	(2.397)	(2.561)	(−4.845)	(3.759)	(−3.338)	(3.035)	(−7.069)	(6.366)	(−0.431)	(−1.111)	(2.729)	*(−2.844)*	(−0.302)	(1.086)
Panel B: CSAD caused by non-fundamentals														
Large	0.186***	*−0.409****	0.086*	0.123	0.028	0.998	0.025	1.071	0.302***	*−3.311****	0.092***	−0.216	0.359***	*−4.868****
	(5.615)	*(−3.305)*	(1.769)	(0.136)	(0.373)	(0.892)	(0.589)	(1.393)	(3.383)	*(−2.653)*	(4.204)	(−0.681)	(3.371)	*(−3.514)*
Small	0.201***	*−0.490****	0.065	0.117	0.0003	0.522	0.047	0.107	0.198**	*−1.990**	0.032	0.636*	0.352***	*−4.981****
	(5.642)	*(−3.679)*	(1.210)	(0.115)	(0.004)	(0.483)	(0.974)	(0.125)	(2.432)	*(−1.746)*	(1.337)	(1.819)	(2.887)	*(−3.142)*
Growth	0.250***	*−0.708****	0.188***	−1.888	0.035	0.502	0.050	0.328	0.299***	*−3.259***	0.049**	0.353	0.333***	*−5.062****
	(6.229)	*(−4.726)*	(2.682)	(−1.435)	(0.418)	(0.410)	(0.936)	(0.338)	(3.305)	*(−2.573)*	(1.995)	(0.987)	(2.838)	*(−3.320)*
Value	0.215***	*−0.441****	0.082	0.712	−0.022	1.633	0.017	1.192	0.200**	*−2.016**	0.076***	0.064	0.380***	*−4.836****
	(5.880)	*(−3.234)*	(1.292)	(0.593)	(−0.275)	(1.364)	(0.325)	(1.232)	(2.471)	*(−1.786)*	(3.531)	(0.205)	(3.335)	*(−3.261)*

Notes: Panel A refers to the results from regression (6):

$$\mathrm{CSAD}_{\mathrm{fundamental},t} = \alpha + \beta |R_{m,t}| + \gamma R_{m,t}^2 + \varepsilon_t,$$

while Panel B refers to the results from regression (7):

$$\mathrm{CSAD}_{\mathrm{non-fundamental},t} = \alpha + \beta |R_{m,t}| + \gamma R_{m,t}^2 + \varepsilon_t.$$

t-statistics are showed in parentheses. Note that if the estimated parameter γ is significantly negative, herding phenomenon exists. *,**,***Statistically significant at the 10, 5 and 1 per cent levels, respectively

Table VI.
B-share market: herding and fundamentals by sub-sample analysis

Sample	Peso Crisis β	Peso Crisis γ	Early Asian Crisis β	Early Asian Crisis γ	Later Asian Crisis β	Later Asian Crisis γ	Russian Crisis β	Russian Crisis γ	Dotcom Bubbles β	Dotcom Bubbles γ	Subprime Crisis β	Subprime Crisis γ	A-share Crash β	A-share Crash γ
Fundamental CSAD of Panel A														
Large	0.183***	−0.090	0.016	−0.217*	0.220	−2.285	0.023	0.180	0.014	−0.557**	0.015*	−0.204	0.012	0.075
	(7.069)	(−0.205)	(1.620)	(−1.775)	(1.453)	(−1.150)	(0.800)	(0.425)	(0.721)	(−2.478)	(1.656)	(−1.512)	(0.532)	(0.293)
Small	0.452***	−0.829	−0.003	0.180	0.147	0.316	−0.046	2.863***	0.021	0.763***	0.020*	−0.264	0.023	0.059
	(15.220)	(−1.653)	(−0.276)	(1.255)	(0.811)	(0.133)	(−1.081)	(4.678)	(0.927)	(2.812)	(1.684)	(−1.532)	(0.670)	(0.144)
Growth	0.234***	−0.586	0.012	−0.184	0.230	−2.142	0.022	0.446	0.025	−0.166	0.019*	−0.246	0.021	0.069
	(8.163)	(1.210)	(1.369)	(−1.625)	(1.374)	(−0.977)	(0.630)	(0.863)	(1.374)	(−0.761)	(1.725)	(−1.549)	(0.645)	(0.176)
Value	0.481***	−1.315*	−0.005	0.293*	0.186	−0.310	−0.046	2.816***	0.009	0.375***	0.016	−0.218	0.014	0.066
	(12.188)	(−1.972)	(−0.361)	(1.806)	(0.948)	(−0.120)	(−1.033)	(4.413)	(0.839)	(2.809)	(1.588)	(−1.488)	(0.587)	(0.238)
Non-fundamental CSAD of Panel B														
Large	−0.279	6.332**	0.384***	−3.678***	0.348**	−3.292*	0.359***	−2.977**	0.434***	−4.582***	0.162***	−0.760**	0.283***	−2.493***
	(−1.549)	(2.081)	(7.756)	(−5.884)	(2.474)	(−1.786)	(4.526)	(−2.595)	(6.302)	(−5.591)	(7.712)	(−2.472)	(5.515)	(−4.156)
Small	−0.214	5.898	0.834***	−6.333***	1.082***	−9.086***	0.894***	−6.421**	0.915***	−8.854***	0.214***	−1.056***	0.225***	−2.227***
	(−0.922)	(1.501)	(12.534)	(−7.544)	(4.263)	(−2.730)	(5.239)	(−2.600)	(8.162)	(−6.639)	(8.324)	(−2.813)	(4.535)	(−3.850)
Growth	−0.291*	6.583**	0.445***	−4.424***	0.337*	−2.645	0.390***	−2.355	0.532***	−5.351***	0.207***	−0.929**	0.316***	−3.203***
	(−1.665)	(2.228)	(9.294)	(−7.320)	(1.960)	(−1.173)	(3.584)	(−1.497)	(6.913)	(−5.848)	(8.172)	(−2.510)	(5.648)	(−4.891)
Value	−0.305	8.144*	0.830***	−6.261***	0.944***	−8.225**	0.953***	−8.240***	0.823***	−8.185***	0.171***	−0.935***	0.196***	−1.602***
	(−1.054)	(1.665)	(11.651)	(−6.961)	(3.707)	(−2.463)	(6.672)	(−3.986)	(8.163)	(−6.830)	(8.605)	(−3.222)	(4.370)	(−3.050)

Notes: *t*-statistics are showed in parentheses. Note that if the estimated parameter γ is significantly negative, herding phenomenon exists. *,**,***Statistically significant at the 10, 5 and 1 per cent levels, respectively

And this is the possible reason why the overall herding detection only indicates that investors herd on non-fundamental information during early Asian Crisis and Dotcom Bubbles on B-share market, which is reported in Table IV. Different results show that herding can be motivated by fundamentals or non-fundamentals or both, and this behaviour varies across different portfolios and periods. Besides, cancelling-out effects interfere with herding detection. Therefore, decomposition is important for herding detection. Similar to Yao *et al.*'s (2014) implications, differences of behaviour on A- and B-share markets imply that the universal pricing model is not applicable in Chinese stock market. When herding on non-fundamentals is detected, diversification investment strategies could not be as valid as that on non-herding market.

4. Conclusions

By comparing Chinese A- and B-share markets, this paper investigates the existence of herding phenomenon, the spill-over effects related to herding, whether herding is incurred by investors' reaction to fundamental or non-fundamental information for the whole sample period as well as for diverse financial crises, and whether investment styles affect herding phenomenon. The main conclusions are as follows.

First of all, herding phenomenon is prevalent for the whole sample period on Chinese A- and B-share markets.

Second, investors on A-share market herd on small and growth stock portfolios, regardless of up or down markets. In contrast, for value or large stock portfolio, investors on A-share market herd only when the market is down. Comparatively, on B-share market, herding is irrespective of various investment styles.

Third, for the whole sample period or various financial crises, herding behaviour on the A(B)-share market does not depend on the B(A)-share market's information. That is to say, the spill-over effects from A-share market to B-share market do not exist, and vice versa.

Fourth, herding can be disintegrated into two components: driven by fundamental information and by non-fundamental information. During financial crisis, market participants tend to herd as the reaction to non-fundamentals more frequently on B-share market but vague on A-share market. Specifically, non-fundamental herding exists during the period of Peso Crisis, Dotcom Crisis and A-share Crash on A-share market, while fundamental-driven herding presents in the Subprime Crisis. Note that there is no evidence of herding on A-share market during the period of Asian Crisis or Russian Crisis. On the other hand, on B-share market, herding caused by non-fundamentals is robust no matter for the whole period or diverse financial crises with one exception for Peso Crisis where no herding behaviour exists. Also, herding on A-share market is motivated by fundamentals.

Fifth, decomposition is important for herding detection because of cancelling-out effects. On the one hand, the overall herding phenomenon is not significant but fundamental-driven herding exists. On the other hand, most traders on B-share market imitate each other as the response to non-fundamentals and a few of them herd on fundamentals. But the herding detection that focusses on all the B-shares only indicates the evidence of non-fundamental-driven herding during this period.

Finally, if investors herd on A-share market during financial crisis, herding caused by non-fundamentals is dominant with one exception of Subprime Crisis, irrespective of various investment styles. Similarly, on B-share market, for various time phases of financial crisis and for different investment styles, most investors herd as the reaction to non-fundamental information.

One noticeable limitation of this paper is the choice of proxy variables that represent for fundamental information. How to understand herding and momentum, whether the momentum factor should be represented as one fundamental information proxy when discussing herding behaviour, and what variables indicate fundamentals need to be carefully considered. It is highly possible that three risk factors are not enough to stand for fundamentals or extra robustness is needed. The last but not least, the results of herding detection are mixed and vary with diverse empirical models. Further studies are needed to polish those empirical tools.

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