3. INVESTOR HERDING IN THE CHINA STOCK MARKET: AN EXAMINATION OF CHINEXT

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Abstract

This research investigates the presence and the asymmetric effects of investor herding in the ChiNext market over the period from October 30, 2009, to April 30, 2020, providing an interesting setting for herding analysis that has not yet been covered by the literature. We build our methodology based on Christie and Huang (1995) and Chang et al. *(2000) and present empirical results showing that herding strongly exists in the market, even after controlling for the effect of COVID-19. The herding behavior also displays asymmetric effects associated with market conditions, industry, and firm size and is more pronounced in an up market and a bearish context, more prevalent in manufacturing and IT sectors, and stronger for large- and small-size portfolios. The results have investment implications for investors who seek out profitable trading opportunities in the China stock markets and policy implications for the China government that is endeavoring to better regulate its domestic financial markets.*

Keywords: herding, return dispersion, China stock market, asymmetric effect, ChiNext, A- and B-shares

JEL Classification: G14, G15

1. Introduction

Herding denotes 'individuals who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions' and has emerged as an important theme in the finance literature (Christie and Huang, 1995). Academic researchers are interested in whether herding exists, because the behavioral effect may affect asset returns and risk characteristics, thus offering implications

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for asset pricing. Herding also attracts attention from practitioners, because a stronger reliance on collective information is likely to cause price deviations from fundamentals and thus generate profitable trading opportunities. This paper thus expands this theme to discuss issues related to herding in the ChiNext market.

As China's Nasdaq-style stock market, ChiNext provides an interesting setting for herding analysis. It was launched in October 2009 as a second-tier market of the Shenzhen Stock Exchange (SZSE) in order to offer convenience for the financing of innovative and fast-growing companies in China, particularly those in the high-tech industry. It thus has unique attributes that challenge traditional asset pricing models and the theory of rationality given the facts that the market is populated by such companies and is dominated by domestic individual investors (Fang *et al*., 2014).[4] Evidence, for instance, shows that the recent market boom, which started from the beginning of 2013, witnessed a sharp rise of 500% in the ChiNext Composite Index (CCI), whereas the increase in the Shanghai Composite Index (SCI) was only 100% during the same period.

Though investigating market herding in ChiNext has important investment and policy implications, to the best of our knowledge, scant studies have ever done such an analysis. The existing finance literature has mainly focused on exploring herding behavior in China's A- and B-share markets (*e.g.* Tan *et al.,* 2008; Chiang *et al*., 2010; Yao *et al*., 2014; Luo and Schinckus, 2015; Xie *et al*., 2015; Chen *et al*., 2018; Mahmud and Tinic, 2018). Our research examines whether herding exists in the ChiNext market and whether it exhibits asymmetric effects associated with market conditions, industry, and firm size. The results herein highlight significant herding behavior that also holds after we control for the effect of COVID-19. Furthermore, herding by investors displays strong asymmetric effects: it is more pronounced in an up market and in a bearish context, is more prevalent in the IT and manufacturing industries, and stronger for large- as well as small-size portfolios.

The paper thus contributes to the existing literature in several important ways. First, it sheds new light on the asset pricing features of the China stock markets and profitable investment opportunities that may subsequently arise. Second, it adds to the literature by considering the effect of COVID-19, which is the most recent global shock, on investor herding. Third, the finding of strong herding in the manufacturing sector runs in contrast to previous studies which state that herding is more prevalent in high-tech sectors.

The rest of the paper runs as follows. Section 2 briefly reviews the literature. Section 3 presents methodology used to detect herding behavior. Section 4 describes the data. Section 5 reports evidence of herding behavior based on a least-square estimator. Section 6 tests asymmetries in herding in response to market conditions, industry, and firm size. Section 7 concludes the paper.

2. Literature Review

There are basically two conceptual streams of empirical investigation of herding in the China finance literature. The first stream focuses on exploring herding formation among a certain type of investors. For example, Li *et al.* (2018) show that there are differences between individual and institutional investors in herding. Less-informed individual investors tend to allocate their investment evenly across stocks and herd in both up and down markets. In contrast, better-informed institutional investors trade more selectively and are more likely to

[4] *According to Fang* et al. *(2014), the market is dominated by individuals who account for approximately 60% of the total number of investors and 80% of market trading by share volume.*

herd in an up market. Zheng *et al.* (2015) further find a greater likelihood of herding among institutional investors when they trade smaller, growth or illiquid stocks.

The second stream examines market-wide herding behavior (mainly in China' A- and B-share markets), measured by the dispersion of individual stock returns from market returns. Theoretically, due to the distinct characteristics of the market, such as weak legal framework and rule of law, heavy government involvement, few alternatives for investors, and lack of transparency, investors in China are more likely to base their actions on the decisions of those who are better informed by following the market consensus (Demirer and Kutnan, 2006). However, empirical findings in the literature are mixed. On the one hand, Demirer and Kutan (2006) and Fu (2010) show no evidence of significant herding in the China stock markets. On the other hand, Tan *et al*. (2008) find that herding strongly exists in its markets. Other studies argue that the presence of herding heavily relies on the type of markets investigated. For example, Chiang *et al*. (2010) show that herding is only present in the A-share markets, which are dominated by domestic individual investors, while Yao *et al*. (2014) and Mahmud and Tinic (2018) detect strong evidence of herding in B-share markets, which predominantly consist of foreign investors. One possible reason for such a contradiction, as Li *et al*. (2018) note, is that herding is dynamic and changes over time.

Apart from testing for the presence of herding, there are also studies that examine whether herding exhibits asymmetric effects in the China stock markets. For example, Lao *et al*. (2011) document that herding behavior is greater when the market is declining. Luo and Schinckus (2015) find different levels of herding in both bullish and bearish contexts. Lee *et al.* (2013) demonstrate strong evidence of industry herding within the high-tech sector, which significantly explains other sectors' herding activity. Chen and Lu (2019) report presence of herding for both large and small capitalization stocks, especially during the 2015 crash in China. Further exploring the asymmetric effects of herding, Yao *et al*. (2014) find that herding behavior is more pronounced under conditions of declining markets, is more prevalent at the industry level, and is stronger for the largest and the smallest stocks as well as growth stocks.

Though the aforementioned studies provide evidence about herd formation, not one research deals with the ChiNext market, which is now playing an important role in the China economy. We fill this gap in the literature by examining both the presence and the asymmetric effects of herding associated with market conditions, industry, and firm size in this market. To the best of our knowledge, it is the first of its kind on this issue in the China stock markets.

3. Detecting Investor Herding Behavior

We build upon the methodology used in Christie and Huang (1995) (hereafter, CH) and Chang *et al.* (2000) (hereafter, CCK). Specifically, the herding test of CCK features the detection of herding with the following equation:

$$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \varepsilon_t \ , \tag{1}$$

where: $R_{m,t}$ = the equal-weighted average stock return in the portfolio at time t; and $CSAD_t$ = the cross-sectional absolute deviation of returns at time t, given by:

$$CASD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \ , \tag{2}$$

where: N = the number of companies in the portfolio; and $R_{i,t}$ = the observed stock return of company i at time t.

Both the $\left|R_{m,t}\right|$ and $R_{m,t}^2$ terms appear in the right-hand side of Equation (1). CCK note that the Capital Asset Pricing Model (CAPM) implies a linear relationship between the dispersion in individual stock returns and the return on the market portfolio. However, under extreme market conditions investors tend to follow the market consensus, leading to a decrease or at least an increase in the corresponding dispersion among returns at a less-than-proportional rate with the market return. CCK thus include a non-linear market return, $R_{m,t}^2$, in the test equation, and a significantly negative quadratic term γ_2 suggests evidence of herding behavior.

While the herding test proposed by CCK has a sound theoretical foundation, there are several potential issues. First, the $CASD$ measure is derived from CAPM and thus suffers from specification errors of the model. Second, parameter estimates could be imprecise and difficult to interpret due to the high level of multicollinearity between the explanatory variables $R_{m,t}$ and $R_{m,t}^2$.Third, severe serial correlation is likely to correlate with the high frequency data of $CSSD$ as is usually the case in the existing literature, which will lead to biased estimates of the parameters. Finally, the model does not consider asymmetric investor behavior in different market conditions. We thus modify the CCK model as:

$$CSSD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3\left(R_{m,t} - \overline{R}_m\right)^2 + \gamma_4 CSSD_{t-1} + \gamma_5 CSSD_{t-2} + \cdots + \varepsilon_t, \qquad (3)$$

where: $\bar{R}_m$ = the arithmetic mean of $R_{m,t}$; and $CSSD_t$ = the cross-sectional standard deviation ($CSSD$) of returns at time t proposed by Christie and Huang (1995), which is given by:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}\left(R_{i,t} - R_{m,t}\right)^2}{N-1}}, \qquad (4)$$

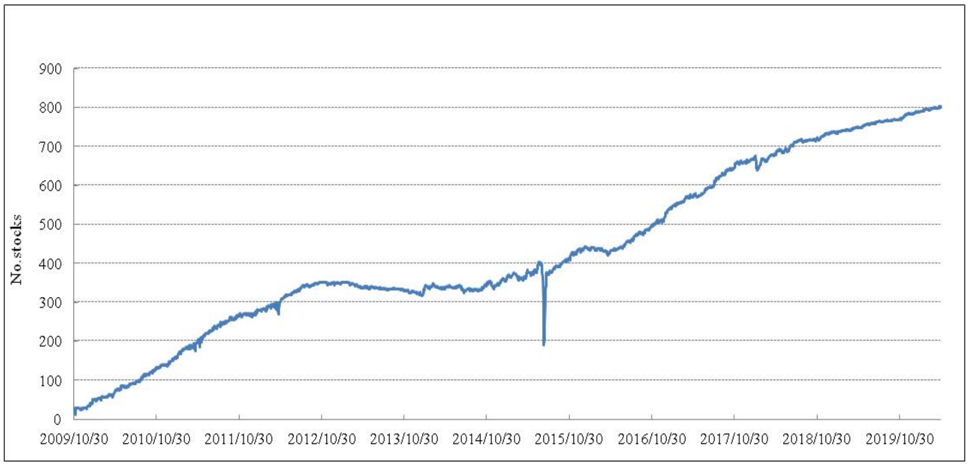
We determine the number of lags for $CSSD$ by both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Under the model, $\gamma_1 + \gamma_2(\gamma_2 - \gamma_1)$ captures the relationship between the return dispersion and the return on the market portfolio when $R_{m,t} > 0$ $(R_{m,t} \leq 0)$.The ratio of $\frac{\gamma_1+\gamma_2}{\gamma_1-\gamma_2}$ further measures the relative amount of asymmetry between the two variables (Duffee, 2001). The introduction of $CSSD$ avoids a potential specification error associated with $CASD$. Adding $\bar{R}_m$ to $R_{m,t}$ further removes a large proportion of multicollinearity between explanatory variables. Since a high level of serial correlation is expected with high frequency market data, lags of the dependent variable $CSSD$ are included as regressors. If no herding exists in the market, then the regression should demonstrate linearity (*i.e.*, $\gamma_3 = 0$). A significantly negative coefficient γ_3 is consistent with the presence of herding behavior.

4. Data

We collect daily data used for empirical testing over the period of October 30, 2009 (the first trading day of the ChiNext market) to April 30, 2020, from CSMAR, a leading company that provides financial information and software services in China. Data on stock prices for all companies listed on ChiNext adjusted for dividends and stock splits are used to calculate individual stock returns. The returns involved are simple close-to-close returns. Market portfolio returns are equally weighted.

Figure 1

Market Portfolio Size



It is important to notice that we exclue the first-day return of newly-listed stocks from the sample to avoid biased market portfolio returns. Furthermore, any stock suspended from trading is temporally moved out of the portfolio and moved back in when it resumes trading. Just like newly-listed stocks, we also exclude the first-day return of those stocks that resume trading. The actual number of stocks used to calculate market portfolio returns changes over time as shown in Figure 1. On average, the market portfolio size increases, from less than 100 in the beginning to around 800 stocks by April 2020. The sharp decline of portfolio size in July 2015 was triggered by the market crash.

5. Empirical Results

5.1 Descriptive Statistics

Table 1 reports summary statistics for daily cross-sectional standard deviations ($CSSD_t$) and market returns ($R_{m,t}$) over the period under investigation. It highlights that both series are non-normally distributed as indicated by the values of skewness and kurtosis as well as by the Jarque-Bera statistics. However, since the sample used in this paper has a sufficiently large size (2554 observations), we still employ the Ordinary Least Square (OLS) method to conduct the regression analysis.[5] There is also a very high level of autocorrelation in the time series of $CSSD_t$, which is even significant after 20 lags. This supports the use of lagged $CSSD$ in the regression. The augmented Dickey-Fuller test statistics are significant for both $CSSD_t$ and $R_{m,t}$, suggesting that the null hypothesis of a unit root can be rejected and both series are stationary. Therefore, it is safe to include the variables in the regression.

[5] *According to the central limit theorem, a large sample size allows test statistics to asymptotically follow the appropriate distribution in the absence of error normality.*

5.2 Evidence on Herding

Before the formal herding test, we first investigate the dispersion-market return relationship. Figure 2 shows that the relationship is far from linear: the return dispersion clusters (disperses) as the market return approaches (deviates from) zero. Moreover, consistent with the intution that herding occurs during periods of market stress (Christie and Huang,1995), as $|R_{m,t}|$ exceeds a certain threshold, $CSSD_t$ actually tends to become narrower.

Table 2 further tests for herding behavior based on Equation (3). We use the Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors to estimate the regression coefficients and apply this practice thoughout the rest of the paper. There is indeed a non-linear relationship between $CSSD_t$ and $R_{m,t}$, as shown by the significantly negative coefficient γ_3 (-2.13) at the 1% level. This evidence, along with a large coefficient on $CSSD_{t-1}$, which is highly statistically significant, justfies to a certain extent the inclusion of the lagged variable in the regression and suggests that strong non-linearity is largely due to actual investor herding rather than the auto-correlated nature of the return dispersions. Since the ChiNext market is populated by small and fast-growing companies and is dominated by domestic individual investors, the findings of herding behavior may not be surprising, as they are consistent with previous studies on the A- and B-share markets as well as other emerging markets (*e.g.* Demirer *et al*., 2010; Yao *et al*., 2014; Mahmud and Tinic, 2018; Indars *et al*., 2019).

Figure 2

The Dispersion-Market Return Relationship

As a robustness investigation, we test the potential effect of the novel coronavirus (shortened as COVID-19) on our results. Equation (3) is upgraded by adding a dummy variable to highlight the pandemic disease:

$$CSSD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t} - \bar{R}_m)^2 + \gamma_4 D(R_{m,t} - \bar{R}_m)^2 + \gamma_5 CSSD_{t-1} + \varepsilon_t, \quad (5)$$

where: D = a dummy variable that equals one during the period from January 1, 2020 to April 30, 2020, and zero otherwise.[6]

[6] *The first cases of COVID-19 were reported to the World Health Organization (WHO) on Decemeber 31, 2019.*

Results in Table 3 indicate that the estimated coefficent γ_4 has a small magnitude but is highly statistically significant, suggesting that COVID-19 has a large influence on the herding behavior. These results differ from those of Tan *et al*. (2008), who find a much weaker connection between herding and macroeconomic shocks in both A- and B-share markets. The potential reason might be that companies listed on the ChiNext market are growth companies, which are more sensitive to changes in economic conditions. Investors thus tend to follow the actions of others particularly under extreme conditions. However, the inclusion of the dummy variable does not change both the sign and the importance of γ_3. Therefore, we conclude that herding strongly exists in the ChiNext market even after accounting for the effect of COVID-19.

Table 1

Descriptive Statistics of Cross-Sectional Standard Deviations and Market Returns

	Mean	*STD*	*Min*	*Max*	*Skewness*	*Kurtosis*	*Jarque-Bera*	*AC (1)*	*AC (2)*	*AC (5)*	*AC (20)*	*ADF*	*N*
$CSSD_t$	*0.03*	*0.01*	*0.00*	*0.06*	*1.36*	*7.32*	*2274.00****	*0.68*	*0.58*	*0.56*	*0.49*	*-17.27****	*2554*
$R_{m,t}$	*0.00*	*0.02*	*-0.10*	*0.10*	*-0.53*	*5.53*	*799.30****	*0.10*	*-0.01*	*0.01*	*0.02*	*-34.85****	*2554*

*Notes: This table reports the daily mean, standard deviation (STD), minimum, maximum, skewness and kurtosis of cross-sectional standard deviations ($CSSD_t$) and market returns ($R_{m,t}$) for the ChiNext market over the period from October 30, 2009 to April 30, 2020. In addition, serial correlation of $CSSD_t$ and $R_{m,t}$ is also presented for lags of 1, 2, 5 and 20, along with the test statistics of the Jarque-Bera test for nomality and the augmented Dickey-Fuller test for stationarity. *** indicates significance at the 1% level.*

Table 2

Analysis of Herding Behavior in the ChiNext Market

α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (10.63***)	-0.09 (-11.45***)	0.14 (6.20***)	**-2.13 (-5.05*****	0.69 (25.12***)	0.55

*Notes: This table reports the estimated coefficients and adjusted R^2 of Equation (3) using daily data over the period from October 30, 2009 to April 30, 2020. The number of lags included is determined by AIC and BIC. The entries in the parenthesis are t-statistics based on Newey and West (1987)'s heteroscedasticy and autocorrelation-consistent standard errors. *** indicates significance at the 1% level.*

Table 3

An Examination of the Effects of COVID-19 Using Dummy Variables

α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	$\boldsymbol{\gamma_4}$	γ_5	Adjusted R^2
0.01 (10.63***)	-0.09 (-11.45***)	0.14 (6.17***)	**-2.11 (-5.01***)**	**0.00 (3.40***)**	0.68 (24.56***)	0.56

*Notes: This table reports the estimated coefficients and adjusted R^2 of Equation (5) using daily data over the period from October 30, 2009 to April 30, 2020. The number of lags included is determined by AIC and BIC. The entries in the parenthesis are t-statistics based on Newey and West (1987)'s heteroscedasticy and autocorrelation-consistent standard errors. *** indicates significance at the 1% level.*

6. Does Herding Have a Pattern?

In this section, we examine whether the herding documented above exhibits asymmetric effects. Specifically, we investigate potential asymmetries in herding behavior in response to market conditions, industry, and firm size.

6.1 Herding under Different Market Conditions

6.1.1 Herding under Up and Down Markets

Various studies have documented the asymmetric effect of herding on the days when the market is *up* vis-à-vis when the market is *down* (*e.g.* Chang *et al*., 2000; Demirer and Kutan, 2006; Chiang and Zheng, 2010). To further test this, we introduce a dummy variable and estimate the following equation:

$$CSSD_t = \alpha + \gamma_1(1\text{-}D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3\,(1\text{-}D)(R_{m,t}\text{-}\bar{R}_m)^2 + \gamma_4 D\left(R_{m,t}\text{-}\bar{R}_m\right)^2 +$$
$$+\gamma_5(1\text{-}D)CSSD_{t\text{-}1} + \gamma_6 D\left(R_{m,t}\text{-}\bar{R}_m\right)^2 + \varepsilon_t, \qquad (6)$$

where: D = a dummy variable that equals one when $R_{m,t} \leq 0$ and zero otherwise. Significantly negative coefficients γ_3 and γ_4 imply herding on *up*- and *down*-market days, respectively. Table 4 reports the regression results.

Persistent herding in the ChiNext market is quite obvious across *up* and *down* market conditions. Furthermore, the absolute value of γ_3 (-2.50) is larger than that of γ_4 (-1.78), suggesting that investors herd more when the market rises, which may be attributed to the 'disposition effect'. In other words, investors actively engage in stock buying on *up*-market days, expecting a further rise in the near future, while they tend to tolerate small losses and hold their positions in stocks on *down*-market days with the belief that losses can be reverted unless the market suffers a severe decline. According to Li & Yeh (2011), such an effect is widespread among individual investors in China. Our results differ from those of previous studies on the China stock markets such as Lao *et al*. (2011) and Yao *et al*. (2014) but are consistent with those of Tan *et al*. (2008), who state that herding is stronger when A-share markets rise.

Table 4

Estimates of Herding Behavior in Up and Down ChiNext Markets

α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	$\boldsymbol{\gamma_4}$	γ_5	γ_6	Adjusted R^2
0.01 (10.61***	0.09 (2.35**)	-0.20 (-7.49***)	**-2.50** **(-3.04***)**	**-1.78** **(-4.55***)**	0.66 (21.47***)	0.72 (28.38***)	0.56

*Notes: This table reports the estimated coefficients and adjusted R^2 of Equation (6) using daily data over the period from October 30, 2009 to April 30, 2020. The number of lags included is determined by AIC and BIC. The entries in the parenthesis are t-statistics based on Newey and West (1987)'s heteroscedasticy and autocorrelation-consistent standard errors. *** and ** indicate significance at the 1% and 5% levels, respectively.*

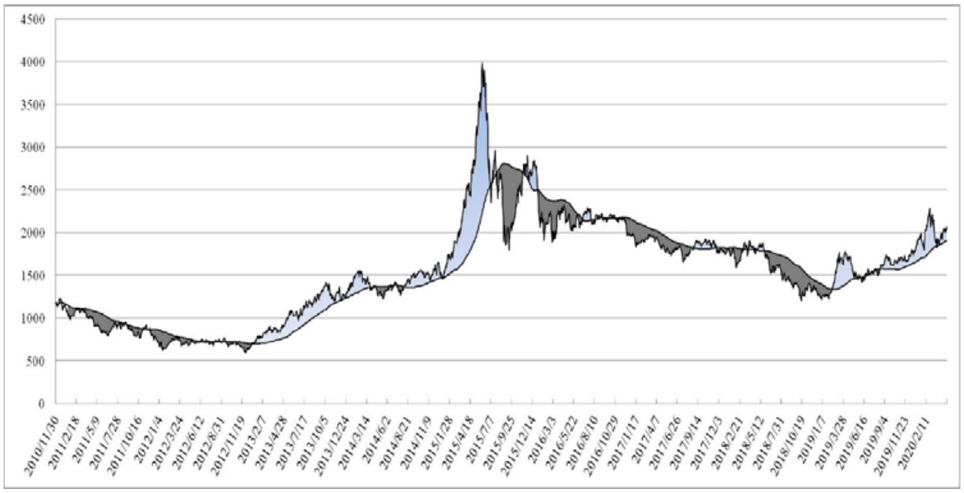
6.1.2 Herding under Bull and Bear Markets

Previous studies document that herding is pronounced in asymmetric market conditions, such as the *bullish* versus *bearish* context (*e.g*. Luo and Schinckus, 2015; Munkh-Ulzii *et al*., 2018). We further examine how herding evolves between peaks and troughs of the market using the CCI whose data go back to June 1, 2010. As bullish and bearish periods are determined by a 120-day moving average line as shown by Chen (2009) and Asem and Tian

(2010), our data actually start from November 30, 2010 to April 30, 2020. [7] Figure 3 illustrates that if the index continuously remains below the bull-bear line for at least 6 months, then the market is bearish and vice versa.

Figure 3

Bull versus Bear Markets



Specifically, the shadowed area in the figure presents the difference between the index and its 120-day moving average line: the dark gray (light gray) shadow area shows the time when the index runs below (above) the bull-bear line. Overall, we argue that the market is bearish (bullish) during the periods from November 2010 to June 30 2012 and July 4, 2016 to February 12, 2019 (from July 1 2012 to July 3, 2015 and February 13, 2019 to April 30, 2020), spanning 1263 (1029) trading days.

We separately estimate the herding regression for bullish and bearish conditions using the models given by:

$$CSSD_t^{Bull} = \alpha + \gamma_1^{Bull} R_{m,t}^{Bull} + \gamma_2^{Bull} \left|R_{m,t}^{Bull}\right| + \gamma_3^{Bull} \left(R_{m,t}^{Bull} - \bar{R}_{m,t}^{Bull}\right)^2 + \gamma_4 CSSD_{t-1}^{Bull} + \varepsilon_t, \quad (7)$$

$$CSSD_t^{Bear} = \alpha + \gamma_1^{Bear} R_{m,t}^{Bear} + \gamma_2^{Bear} \left|R_{m,t}^{Bear}\right| + \gamma_3^{Bear} \left(R_{m,t}^{Bear} - \bar{R}_{m,t}^{Bear}\right)^2 + \gamma_4 CSSD_{t-1}^{Bear} + \varepsilon_t, \quad (8)$$

where: $R_{m,t}^{Bull}$ = the average stock return in the portfolio at time t in bull markets; $\bar{R}_{m,t}^{Bull}$ = the arithmetic mean of $R_{m,t}^{Bull}$; and $CSSD_t^{Bull}$ = $CSSD$ at time t corresponding to $R_{m,t}^{Bull}$. Similarly, the variables with superscript 'bear' refer to the scenario of bear markets.

Table 5 reports the regression results of Equations (7) and (8). Herding strongly exists in both *bull* and *bear* markets with significantly negative coefficents γ_3. A comparison of the estimated coefficients γ_3 yields interesting results: the statistic from a 2-sample *t*-test in Panel C rejects the null hypothesis of γ_3^{Bull} = γ_3^{Bear}. Along with the fact that the absolute value of γ_3^{Bull} (-1.90) is smaller than γ_3^{Bear} (-2.54), the results suggest that investors herd

[7] *We use the 'native approach' rather than parametric and non-parametric approaches such as Markov regime switching models, because it is easy to understand and implement in practice.*

more in *bearish* markets. This runs in sharp constrast with the findings above where investors are less likely to follow the actions of others in a *down* market. One possible reason might be that investor confidence significantly drops when the market continuously moves down below the threshold and their preference for risk aversion rises compared to that during a down market. Furthermore, this finding appears to be consistent with Luo and Schinckus (2015) who show that a bearish context generates herding behavior for A-shares.

Table 5

Estimates of Herding Behavior in Bullish and Bearish ChiNext Markets

Panel A: Estimates of Herding Behavior in Bullish Markets					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (6.86***)	-0.09 (-10.37***)	0.12 (4.27***)	**-1.90 (-3.31***)**	0.77 (25.88***)	0.65
Panel B: Estimates of Herding Behavior in Bearish Markets					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01(7.96***)	-0.10 (-8.74***)	0.18 (5.79***)	**-2.54 (-4.91***)**	0.62 (13.96***)	0.52
Panel C: 2-sample *t*-test H_0: γ_3^{Bull} = γ_3^{Bear}					
0.64 (7.66***)					

*Notes: This table reports the estimated coefficients and adjusted R^2 of Equations (7) and (8) using daily data over the bearish periods from November 2010 to June 30 2012 and July 4, 2016 to February 12 and the bullish periods from July 1 2012 to July 3, 2015 and February 13, 2019 to April 30, 2020, respectively. The number of lags included is determined by AIC and BIC. The entries in the parenthesis are t-statistics based on Newey and West (1987)'s heteroscedasticy and autocorrelation-consistent standard errors. *** indicate significance at the 1% level.*

The results in Section 6.1 overall suggest that herding in the ChiNext market varies with market conditions. It is persistently strong across asymmetric market conditions but is more pronounced in an *up* market and *a bearish* context.

6.2 Industry Herding

Even since the seminal research of Christie and Huang (1995), an increasing number of studies have studied the patterns of industry herding. The evidence to date tends to support more prevalent herding within high-tech sectors such as the information technology (IT) industry, due to their high correlation with the international IT industry (*e.g.* Lee *et al*., 2013; Yao *et al*., 2014; Demirer *et al*., 2015; Zheng *et al*., 2015). This section examines whether the same applies to the ChiNext market.

Table 6 shows the industrial composition of the listed stocks on the market. It is apparent that manufacturing companies dominate the market (552 out of 1729 stocks) with IT companies ranking the second (143 out of 1729). The other industries are the minority (113 altogether out of 1729) and are thus named as 'other' industries. We further compute $CSSD$ and construct three equally-weighted industry portfolios for the manufacturing, IT, and 'other' industries as described in Section 3. Table 7 reports the regression results for each industry based on Equation (3).

As with the evidence of strong herding behavior detected at the aggregate market level in Section 5, we also find herding at the industry level, with two industry portfolios yielding significantly negative coefficients γ_3 in both Panels A and B. This does not agree with Yao *et al*. (2014), who do not detect herding for the all-industries portfolio, but note strong herding at the industry level in the A- and B-share markets.

Table 6

Industrial Composition of Listed Stocks on the ChiNext Market

Industry	No. Of Stocks
Manufacturing	552
IT	143
Research & Development	25
Transportation	2
Public Health	4
Wholesale & Retail	8
Media	16
Construction	7
Business Support	13
Environmental Protection	17
Mining	5
Agriculture	8
Utility	3

Notes:This table shows the industrial composition of the listed stocks on the ChiNext market over the period from October 30, 2009 to April 30, 2020.
Source: SZSE

Among those industry groups, both the *manufacturing* and the *IT* sectors have a strong degree of herding, with their estimated coefficients γ_3 of -2.01 and -3.88 significant at the 1% level, respectively. 'Other' industries yield non-significantly negative γ_3 , indicating that investors do no herd towards the industry consensus in the group. The findings are consistent with those reported by Yao *et al.* (2014) and Zheng *et al.* (2015) that investors tend to follow sentiments in industries such as *Manufacturing* and *IT* in the A- and B-share markets.

Table 7

Estimates of Industry Herding in the ChiNext Market

Panel A: Estimates of Herding in the Manufacturing Industry					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (8.90***)	-0.08 (-10.56***)	0.14 (6.93***)	**-2.01 (-5.45***)**	0.69 (22.97***)	0.58
Panel B: Estimates of Herding in the IT Industry					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (5.23***)	-0.11 (-5.64***)	0.23 (2.83***)	**-3.88 (-2.49**)**	0.68 (11.85***)	0.51
Panel C: Estimates of Herding in 'Other' Industries					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (6.48***)	-0.09 (-7.21***)	0.07 (1.41)	**-1.01 (-1.30)**	0.68 (13.08***)	0.51

*Notes:This table reports the estimated coefficients and adjusted R^2 of Equation (3) using daily data over the period from October 30, 2009 to April 30, 2020 for the manufacturing, IT and 'other' industries, respectively. The number of lags included is determined by AIC and BIC. The entries in the parenthesis are t-statistics based on Newey and West (1987)'s heteroscedasticy and autocorrelation-consistent standard errors. *** and ** indicate significance at the 1% and 5% levels, respectively.*

6.3 Firm Size Herding

McQueen *et al.* (1996) report that larger stocks usually respond faster to market news, because they are covered by more analysts and have a higher level of liquidity. This further indicates that smaller stocks receive less attention from the media and thus are more susceptible to herding. We test this hypothesis in the ChiNext market.

We construct three size-ranked portfolios: large, medium, and small. Each portfolio includes one-third of the stocks in the market ranked by their market capitalizations at the beginning of each yearly sub-period.[8] The portfolios are reweighted each sub-period to reflect any changes in the market capitalization of individual stocks. It is important to note that newly listed stocks during each sub-period are not included in any of the portfolios in that period but are included in subsequent periods. Table 8 lists the regression results for each size-based portfolio.

We observe that the estimated herding coefficients γ_3 are negative for all three size-ranked portfolios (-1.90, -0.03 and -2.90 for the large-, median-, and small-size portfolios, respectively), but only statistically significant for the largest and the smallest portfolios. The findings suggest that herding behavior is much stronger among the large- and small-size portfolios than the medium-size portfolio.

An intuitive explanation for such observations is that larger stocks gain more media coverage and are traded more frequently by domestic individual investors. According to Yao *et al.* (2014), retail investors in the China stock markets usually lack expertise and experience and tend to follow analyst recommendations. We argue that it is likely that those traders make investment decisions based on the market trend. Conversely, smaller stocks receive less analyst coverage and also have less public information available, which therefore can drive investors to put more weight on the market consensus when making their own decisions. The findings are consistent with those documented in Yao *et al.* (2014), who offer evidence of herding only for large- and small-size stocks.

Table 8

Estimates of Firm Size Herding in the ChiNext Market

Panel A: Regression Results for Large-size Portfolio					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (5.65***)	-0.08 (-5.71***)	0.16 (4.21***)	**-1.90 (-2.63***)**	0.65 (12.14***)	0.49
Panel B: Regression Results for Medium-size Portfolio					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (7.44***)	-0.08(-10.71***)	0.11 (4.87***)	**-0.03 (-1.25)**	0.74 (24.22***)	0.52
Panel C: Regression for Small-size Portfolio					
α	γ_1	γ_2	$\boldsymbol{\gamma_3}$	γ_4	Adjusted R^2
0.01 (7.04***)	-0.11 (-7.33***)	0.14 (2.97***)	**-2.09 (-2.33**)**	0.68 (14.26***)	0.57

*Notes: This table reports the estimated coefficients and adjusted R^2 of Equation (3) using daily data over the period from October 30, 2009 to April 30, 2020 for the large-, medium- and small-size portfolios, respectively. The number of lags included is determined by AIC and BIC. The entries in the parenthesis are t-statistics based on Newey and West (1987)'s heteroscedasticy and autocorrelation-consistent standard errors. *** and ** indicate significance at the 0.01 and 0.05 levels, respectively.*

[8] *We divide the entire sample period into six sub-sample periods: October 2009 to May 2010, June 2010 to May 2011, June 2011 to May 2012, June 2012 to May 2013, June 2013 to May 2014, and June 2014 to May 2015.*

7. Conclusion

This research examines the market-wide herding behavior in the ChiNext market over the period from October 30, 2009 to April 30, 2020. The methodology used is bulit upon Christie and Huang (1995) and Chang *et al*. (2000). Specifically, we adopt $CSSD$ in Christie and Huang (1995) as a measure for the return dispersion and a modified testing model of Chang *et al*. (2000) that corrects for issues such as multicollinearity and serial correlation in the dataset.

Our results yield several interesting findings. Herding tests show evidence of an investor's behavioral tendency to follow the actions of others even when controlling for the effect of COVID-19. After breaking up the data based on market conditions, we further see that herding behavior is more pronounced in an up market and a bearish context. In addition, we find that herding behavior is stronger in manufacturing and IT sectors and among large- and small-size portfolios.

The findings have important investment and policy implications. First, the evidence of strong herding suggests that traditional asset pricing models cannot be applied to the ChiNext market. Second, profitable investment opportunities may show up when herding drives asset prices far from their fundemantals. Third, the asymmetric pattern of herding suggests that the China government might be able to better regulate the market by focusing on certain types of shocks (for instance, industries that are more susceptible to herding) and under certain market conditions.

Though this paper sheds new light on the asset pricing features of the China stock markets and profitable investment opportunities, it could be improved in several aspects. First, the study aims to look for market-wide herding and thus does not preclude the possibility of the presence of other types of herding in the ChiNext market. Second, there is still space to improve herding detection techniques to distinguish true herding from spurious herding. Third, STAR, also as a Nasdaq-style stock market, was launched in 2019. Further studies that compare herding formation in both the ChiNext and STAR markets (when more data become available) might present interesting results.

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