The Herding Behavior in Chinese Stock Markets: Evidence from A-Share Markets during COVID-19

by

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ABSTRACT

This paper studies the presence of herding behavior in Chinese A-share markets using both individual firm and industry-level data before and after the pandemic. Using a sample of all firms listed over the period 10/08/2018 to 09/30/2021, I distinguish between the Shanghai and Shenzhen stock exchanges and find that herding behavior does not exist in overall Chinese A-share markets. However, comparing return dispersions for rising and declining market in different industries, I observe that investors exhibit different levels of herding behavior. I find evidence that COVID-19 increases herding behavior on the Shanghai and Shenzhen stock markets. The results report that herding behavior manifests during upward market movement. The results are important for investors and regulators to increase their understanding of stock markets. Moreover, studying herding behavior can be useful in controlling for financial risk.

LIST OF ABBREVIATIONS USED

LSV	Lakonishok, Shleifer, and Vishny (1992) Model
CH	Christie and Huang (1995) Model
CCK	Chan, Cheng, and Khorana (2000) Model
CSSD	Cross-Sectional Standard Deviation
CSAD	Cross Sectional Absolute Deviation
SHSE	Shanghai Stock Exchange
SZSE	Shenzhen Stock Exchange
SHA	Shanghai A-shares Market
SZA	Shenzhen A-shares Market

Chapter 1: Introduction

With the rise of behavioral finance in the 1980s, more and more researchers combined behavioral finance with other disciplines to study financial markets. One area that has been studied is herding behavior. In financial markets, herding indicates the process where market investors trade in the same way and their behavior converges to the consensus. It can be described as investors making investment decisions by imitating others' behaviors (Spyrou, 2013). The reasons for herding behavior are diverse. For example, Bikhchandani and Sharma (2000) indicate that herding can be separated by two parts: Investors who facing similar fundamental information set take similar decisions ("spurious" herding) and investors who imitate the behavior of others ("intentional" herding). Herding behavior is challenging the validity of the "efficient market hypothesis." Investor herding is defined as providing an explanation for investors' behavior that is contrary to the Efficient Market Hypothesis (EMH).

The first person to present the concept of "herding effect" in the stock market was the famous economist John Maynard Keynes (Keynes, 1936), who compared stock market investments to a " beauty contest": participants were asked to choose the six most beautiful pictures from 100 photos and the person who selects the photo with the most votes is the winner. It turns out that the winners often choose not the one they think is the most beautiful, but the one that most attracts other competitors. It allows competitors to guess the choice of other competitors, and to imitate this choice, regardless of whether they think the selected candidates are beautiful or not, which creates a herding effect.

Under the efficient-market hypothesis (Fama, 1970) and rational choice theory first describe by William Stanley Jevons, investors can receive all the new information and evaluate financial assets accurately. However, in reality, the cost of obtaining information is high, and some investment decisions can be made based on investors' irrational expectations. Some investors may adopt other investors' decisions without considering the information they hold. The research on herding behavior in the finance area can be traced back to 1972. Kraus and Stoll (1972) introduced a concept called parallel trading, pointing out that there is a phenomenon where institutional investors trade stocks in the same way at the same time in the stock market. That is herding behavior. However, they also state that this parallel trading might by chance, unintentional, or intentional. There was no unified definition of herding behavior in academia at that time. In early 1995, Christie and Huang first illustrated the cross-sectional standard deviation (CSSD) as a measure of return dispersion to study herding behavior in the stock market. They proposed that herding behavior exists in the stock market when return dispersion declines under periods of market stress (Christie & Huang, 1995). Later, Chang, Cheng, and Khorana (2000), based on the previous CSSD model, presented a cross-sectional absolute deviation of return (CSAD), which considered the entire distribution of market returns.

In the past few decades, with improved understanding of the financial market and the frequent financial crises, the herding effect has received more attention and research. The herding effect in financial market is caused by investors' cognitive bias, which ignores the actual value of information and imitates other investors' behavior, or over-relies on public opinion (Banerjee, 1992). The study of herding effects helps us understand the abnormal fluctuations in stock prices and avoid certain risks. It has a significant benefit for investors and the development of the stock market.

The Chinese stock market has experienced much development over the past 30 years. In 2008, the A-share stock market was successfully incorporated into the MSCI index and has become one of the most important stock markets in the world. However, the Chinese stock market has experienced two significant declines. On October 17, 2007, the Shanghai Stock Exchange (SHSE) Composite Index reached a peak of 6124 points from 1700 points in one year. One year after reaching the historical high, the SHSE Composite Index fell back to 1664 points with a decrease of 75%. In 2015, the Chinese stock market suffered another stock crisis. The SHSE Composite Index doubled within half a year, reaching 5100 points from 2600 points, but fell back to 2900 points within six months. Until now, the SHSE Composite Index has hovered between 2500 and 3500 points. During the pandemic, due to the policy of lockdown in most cities, the SHSE Composite Index dropped suddenly from 3092 points to 2745 points (Yahoo Finance, 2021).

In general, there are two exchanges in China. A-share includes Chinese companies' stocks traded on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). The SHSE was opened in 1990, and the SZSE began in 1991. The SHSE has over US-$7.62 trillion in total market capitalization and will become the fourth-ranked market in the world in 2021 (Yahoo Finance, 2021). Most companies listed on that exchange are large, state-owned companies which are commercial entities that are owned or controlled by governments. Those companies play an essential role in China's economic growth (Mei et al., 2004). The SZSE is the second exchange in China and eighth largest in the world. with market capitalization of $3.90 trillion in 2021. Most companies are listed on three different boards, the main board, the SME board, and the ChiNext market. These privately-owned companies focus heavily on being more innovative and more profitable. A large number of tech companies and start-ups are listed there (Mei et al., 2004). A-share can only be purchased and sold by domestic Chinese investors with the local currency (RMB). Most domestic traders in A-shares lack significant professional knowledge and experience in investments (Tan et al., 2008).

It is evident that there are significant fluctuations in the Chinese stock market. When it fluctuates violently, it is vital to understand whether herding plays a role and whether herding is obvious. Herding behavior is caused by investors' cognitive biases, which discard the value of information and adopt the behavior of other investors. With the development of the Chinese stock market, studying the herd effect helps us understand the fluctuations of stock prices, avoiding risks in essence. It brings significance to rational investment and stable development of the capital market.

At the end of 2019, case of a novel coronavirus first occurred in Wuhan, China. In January 2020, most provinces appeared to have confirmed cases, and the spread started across the country. Now declared a global pandemic, COVID-19 is still intensifying around the world, and the number of confirmed cases continues to increase. The pandemic in China has been brought under control by large-scale isolation measures adopted in the early stages. However, in the early period of COVID-19, the stock market fell sharply on February 3, 2020. With more than 3,000 affected on that day. The pandemic brings significant uncertainty to the stock market (Shehzad et al., 2020). Changes in investor sentiment are affected by the increasing risk in the stock market and those changes can cause the herding effect and exiting of the markets.

COVID-19 caused turbulence in global financial markets in early 2020. Stock market prices suffered a significant decline, which has put unprecedented pressure on global financial markets. In particular, the US stock market experienced two circuit breakers in one week in March 2020, which had never happened in its history. China's stock market suffered a severe shock as well. In the first three months of 2020, there were six days with a single-day crash of over 2% (total 59 trading days). In comparison, there were only 21 days in the same situation over the past three years (a total of 730 trading days) (Sun et al., 2021). Existing research has studied the impact of COVID-19 on volatility and stock market returns (Nadeem, 2020; Baker et al., 2020; Zhang et al., 2020a). Liu et al. (2021) find that the pandemic has impacted investor sentiment. Other researchers, Baig et al. (2021), find that investor sentiment has declined during the period of COVID-19. They present a time series plot of the coronavirus worldwide sentiment index, which computes the level of sentiment among all entities mentioned in the news related to coronavirus. It suggests that there was a decline in investor sentiment after the pandemic. Moreover, they observe that the related stocks had lower yields than usual during this event. In related research, Baker et al. (2020) studied the US stock market and concluded that the impact from COVID-19 is more powerful than any other infectious disease outbreak in the world.

This paper selects all the trade stock list in the Shanghai A-shares (SHA) and Shenzhen A-shares (SZA) as the research object to analyze the overall market of herding behavior. I further investigate whether herding exhibits asymmetric effects associated with market returns under different industries. The results indicate that herding displays strong asymmetry in the Chinese A-share market, especially during rising markets. In addition, to detect herding behavior under extreme market conditions caused by a pandemic, I compared the pre-COVID-19 and post-COVID-19 periods to learn about herding behavior in Chinese stock markets and understand investment behavior under these conditions. The present study focuses on herding behavior among investors during the pandemic. This study can enrich the literature about investment behavior in the Chinese stock market, particularly the impacts on investment behavior under COVID-19.

The remainder of the paper is organized as follows. Section 2 presents the comparative literature review. Section 3 reports the methodology used to test herding behavior. Section 4 describes the testing hypotheses. Section 5 describes the data. Section 6 explores the empirical results, and Section 7 provides a conclusion based on the findings.

Chapter 2: Literature Review

Due to a large number of institutional investors in the financial markets, several theoretical models of herding behaviour have been developed by Bikhchandani et al. (1992), Scharfstein and Stein (1990) and Wermers (1999). Existing herding literatures have mainly focused on finding the herding effects on specific market participants among mutual fund managers (Lakonishok et al., 1992) and financial analysts (Gleason & Lee, 2003; Clement & Tse, 2005).

According to Scharfeteki (1990), under certain circumstances, the reason for the herding effect is that managers mimic the investment decisions of others without considering substantive private information. Lakonishok et al. (1992) believe that the herd effect is reflected in different investors making the same decision simultaneously. Duarte et al. (2016) explore whether institutional investors and individual investors can be affected by external factors when making investment decisions, specifically by other investors' decisions, economic environment, and market information. During investment decisions, due to the incomplete effectiveness of the market, the cost of obtaining news differ among investors. Therefore, institutional investors and individual investors have the possibility of blindly following the trend of investment decision-making, which constitutes the herding effect.

In 1999, Choe and Kaminsky proposed that herding behavior caused the instability of the financial markets that led to the dramatic financial crisis during the last few months of 1997 in Korea. They use the herding effect concept to analyze the reasons for stock fluctuations. The herding effect underpins the theoretical foundation of behavioral finance. In general, the herding effect of two types: irrational herding and rational herding. According to Devenow and Welch (1996), investors' psychology focuses on other investors' behavior and disregard their own prior beliefs. On the other hand, for the rational view, Graham (1999) established a reputational herd behavior model. The basic idea of this model is that managers mimic others' investment decisions in order to maintain their reputation in the market. (Scharfstein & Stein, 1990; Graham, 1999).

Nowadays, stock trading behavior and return rates are two empirical models for testing herding behavior. The Lakonishok, Shleifer, and Vishny (LSV) model first uses the imbalance of transaction volume between buyers and sellers to measure herding behavior, as Lakonishok et al. (1992) describe. However, Christie and Huang (1995) and Chang et al. (2000) suggest using stock return data to test the herding effects in the stock market. By examining the US stock market, Christie and Huang measure the average proximity of individual asset returns by analyzing the cross-sectional standard deviation of returns (CSSD) to test herding behavior. They discuss the herding of CSSD from various market situations. They argue that if investors suppress their predictions about the stock market during large market movements, individual asset returns will not be significantly different from the overall market returns. Therefore, it caused a smaller CSSD than average in results.

Recently, Chang et al. (2000) proposed a new and powerful measure to detect herding based on equity return. Using non-linear regression, they test the relationship between the cross-sectional absolute deviation of returns (CSAD) and the overall market return. According to the rational asset pricing model, there is a positive relationship between CSAD and market return. However, they believe that the relationship should be negative when the herding behavior exist in the market due to the absolute market return value increase and the CSAD decrease or increase at a decline speed.

Chiang and Zheng (2010) studied the herding effect in international markets. They find evidence of herding in developed stock markets except for the US and Asian markets. The results show existing herding in both up and down markets, but herding is more pronounced in Asia when the market goes up. After exploring several financial crises for herding behavior, Chiang and Zheng (2010) find that the herding effect is more evident during financial crises. Ouarda, El Bouri, and Bernard (2013) also find that herding effects were significantly more significant during the financial crisis of 2007-2008.

For the Chinese stock market, Demirer and Kutan (2006) were the first to study the herding effect. They assume that investors tend to speculate because of the unique characteristics of the Chinese stock market, such as the imperfect legal framework and strong government involvement (such as regulation and central bank intervention). Demirer and Kutan (2006) apply the CH model to detect herding effects in the

Chinese stock market using daily stock return data from 1999 to 2002, covering 375 companies. The results illustrate that the herding effect does not exist in the overall Chinese stock market based on the study of both firm and sector-level data. However, if they only consider the upside or downside market movement, herding behavior can be found in a rising market but not in a falling market.

By detecting the herding phenomenon, the spill-over effects related to herding effects, and the investment styles. Ju (2019) discovered that the herding behaviour of Chinese A- and B-share markets was universal during the sample periods between 1992 and 2017. For investors in the A-share market, the herding effect exists on small and growth stock portfolios within up or down markets. However, investors herd when the market is down for large or value stock portfolios. In contrast, herding behaviour is related to various investment styles in the B-share market.

Ju (2019) also discussed that herding could be separated into two components: driven by fundamental information and non-fundamental information. Fundamental information means important macroeconomic information that is released by related organizations. Bikhchandani and Sharma (2000) first distinguish between investors who deal information by fundamentals (spurious herding) and investors who intentionally imitate the behavior of others (intentional herding). In the B-share market, sophisticated institutional investors prefer to herd more frequently by non-fundamentals but the situation I vague in the A-share market. Therefore, they conclude that herding on the A-share market is driven by fundamental information, whereas herding on the B-share market is motivated by non-fundamental information.

Christie and Huang (1995) calculated the herding coefficients and analysed the conditions of rising markets, high trading volume, and volatility. They concluded that herding behavior is more pronounced among A-share investors in the Shanghai and Shenzhen markets during upside market movement.

2.1 Two methods of Studies of Herding

In the empirical study of herding, researchers mainly focus on two methods.

2.1.1 From investors' perspective

The first method is based on the selected companies and trading volume of specific types of investors. By using institutional investors with mutual funds or pension funds as the research subjects, researchers analyze the trading price and trading volume of firms in order to conduct an empirical study on the herding effect.

A method of issuing questionnaires to study the existence and causes of the herding effect among institutional investors was first designed by Shiller (1990). The questionnaire covers securities investments from 1984 to 1985. The results indicate that investors' decision-making is significantly impacted by investors' social circles, news, and related reports.

Lakonishok et al. (1992) measured the herding effect by using the trading volume of buyers and sellers in the stock market. They proposed the Lakonishok, Shleifer, and Vishny (LSV) model to define the herding effect. By calculating the proportion of the buying and selling volumes of a single stock in the total trading volume in the same period, they studied whether the trading direction of market subjects is consistent. Lakonishok et al. (1992) test several transactions between buyers and sellers in the stock market to determine whether there is herding among different fund managers. However, the LSV method does not consider the transaction amount of each transaction.

Later on, Grinblatt et al. (1995) improved the LSV method by adding the transaction amount, which refers to the value of each transaction. The purpose is to distinguish the herding effect caused by the behaviors of those who buy and sell. The advantage is that it can measure the herding effect implied in the data with the same transaction volume but different values. In 1999, Wermers improved the LSV method again. He proposed the PCM (portfolio change measure) to test whether there is a herding effect in the market through the correlation between the changes in the proportion of stock holdings within two portfolios in two different periods. The results show that a herding effect does exist in the U.S. mutual fund market.

2.1.2 From the market perspective

The second method is based on the return on investment as the standard by taking the dispersion index, analyzing it from the perspective of the overall market, and studying it according to the trend of the market index.

Christie and Huang (1995) first put forward the cross-sectional absolute deviation of stock return. According to the rational asset pricing models, the dispersion of returns will increase when the absolute value of the market return increases because investors are trading based on their own information. However, during extreme market movements, investors tend to make investment decisions by following group actions. Investors' stock returns tend to move around the overall market return. For that reason, they argue that herding behavior will be more prevalent during periods of extreme market movement. To measure the return dispersion, a CSSD (CH) model was created by Christie and Huang (1995), using the standard deviation of individual stock returns and market portfolio returns to analyze herding effects. According to the results, herding behavior is not apparent in the US stock market. The disadvantage of the CSSD model is that it requires the definition of extreme returns. It identifies the upper and lower tails of the return distribution by considering the values of 1% and 5% as the cutoff points. Therefore, the return distribution could change in different periods due to investors having different opinions about the cause of extreme returns. In fact, herding behavior can occur all over the entire return distribution and become more pronounced under extreme market conditions. The CSSD model can only capture herding behavior during periods of extreme returns.

To address the defects of the above model, Chang et al. (2000) proposed a CCK model based on the CH model in 1995. The CCK model considers the asymmetric effects of market returns and captures the absolute deviation of cross-sectional stock returns. Chang et al. use Cross-Sectional Absolute Deviation (CSAD) to test herding in the stock market. They selected the daily trading data for more than ten years as the research sample from five stock markets - United States, Japan, South Korea, Hong Kong, and Taiwan. Two portfolios have been created, according to the market returns of the day. The rising market portfolio contains all the positive return trading days, and the declining market portfolio contains all the negative return trading days. Chang et al. (2000) uses those portfolios to test the correlation between stock return deviation and market return in different portfolios. The results show that no matter whether the market is rising or falling, the herding effect is not evident in the United States, Hong Kong, and Japan because they are mature capital markets. However, for South Korea and Taiwan, which are still emerging capital markets, the herding effect in their stock markets is very significant.

By summarizing various factors, the CH model requires a greater magnitude of non-linearity to find evidence of herding behavior. It captures herding behavior only during the periods of extreme returns. There are challenges when applying this method to Chinese stock market data since because the short sample periods of time make it difficult to identify the extreme returns. This paper author believes that the CCK model proposed by Chang, Cheng and Khorana in et al. (2000) is more extensive and accurate in capturing the herding behavior in the stock market. Particularly, the CCK model considers the relationship of non-linear between CSAD and market return during the extreme price movement and consider the squared market returns instead. Therefore, the CCK model is the more appropriate method to detect the herding effect in the Chinese stock market.

Chapter 3: Methodology

Christie and Huang (hereafter CH Model) (1995) and Chang et al. (hereafter CCK Model) (2000) are two popular studies that used models to prove the herding effects by using stock return data.

3.1 CH Model

Christie and Huang (1995) first proposed using cross-sectional standard deviation (CSSD) to measure the herding effect. CH models suggest that the overall market condition has a significant impact on the investment decision-making process used by investors. They state that if there is a herd effect in the stock market, investors will tend to use public market information to imitate decisions made by others. Under extreme market movements, investors tend to make their investment decisions based on the collective actions in the market. In contrast, rational asset pricing models predict an increase in dispersion because individual returns are excluded from the market return when stocks differ in their sensitivity to market movements. Therefore, they believe that herding behavior is more prevalent during periods of uncertain markets. CH models use the CSSD method to measure the return dispersion, which is expressed as:

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

Where $R_{i,t}$ is the observed stock return on firm i at time t, $R_{m,t}$ is the cross-sectional average of the N returns in the portfolio at time t, and N is the number of firms in the portfolio.

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \tag{2}$$

Where D_t^L=1 if the daily average market return lies in the extreme lower tail of the return distribution. Otherwise, when D_t^L=0

D_t^U=1 if the daily average market return lies in the extreme upper tail of the return distribution. Otherwise, when D_t^U=0

The CH model indicates that when herding behavior occurs, the return dispersions decrease because investors will make similar decisions. Therefore, significantly negative estimates of β^L and β^U in equation 2 would indicate the presence of herding behavior.

3.2 CCK Model

The CCK model is a method of measuring herding effects based on the CH model. Christie and Huang (1995) proposed the CH model, which is also called CSSD. It tests the degree of similarity in the behavior of market investors by quantifying return dispersion. However, it only works when there are significant movements in the markets. The existence of herding behavior can be detected when most investors have decision consistency. To overcome the shortcomings of the CH model, a CCK model, also called cross-sectional absolute deviation (CSAD), was proposed by Chang et al. (2000). They detected the herding by using this method and found no evidence of herding in the developed markets of Hong Kong and the US. However, there is evidence of herding in emerging markets such as Taiwan and South Korea. The CCK model can test herding over an entire distribution of the market by following this specification:

$$CSAD_{\mathrm{t}} = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{3}$$

where $R_{m,t}$ is the weighted average stock return in the portfolio. To avoid conflicting results in the presence of herding behavior, Chang et al. consider a general quadratic relationship between $CSAD_t$ and $R_{m,t}$ for all positive $R_{m,t}$ value.

$$CSAD_t = \alpha + \beta_1\left|R_{m,t}\right| + \beta_2\left|R_{m,t}\right|^2 + \varepsilon_t \tag{4}$$

According to the rational asset pricing model of Black et al. (1972), Chang et al. (2000) assume that the equity return dispersions are an increasing function of the market return, and the relationship is linear as well. The dispersion in individual investor returns will increase with the absolute value of the market return increases. However, individual investors may make the same investment decision, exhibiting herding behavior, during periods of large market price movements. This behavior will increase the correlation within individual asset returns, and the return dispersion will decrease. For this reason, a non-linear market return $|R_{m,t}^2|$ is included in equation 4, and a significantly negative coefficient β_2 indicates the occurrence of herding behavior. The analysis of this model is shown below:

CAPM can be expressed as follows:

$$E_t(R_i) = r_f + \beta_i[E_t(R_m) - r_f] \tag{5.1}$$

Where R_i is the return on asset i, $E_t(R_m)$ is the expectation in the market portfolio, r_f is market risk free rate, and β_i is the systematic risk measure of the security.

Based on equation 5.1, I can get:

$$E_t(R_i) - E_t(R_m) = (\beta_i - 1)[E_t(R_m) - r_f] \tag{5.2}$$

Due to the absolute value of the deviation, $E_t(R_m) > r_f$, I can get:

$$|E_t(R_i) - E_t(R_m)| = |(\beta_i - 1)|[E_t(R_m) - r_f] \tag{5.3}$$

Based on equations 5.1 and 5.3, I can define the expected cross-sectional absolute deviation of stock returns (ECSAD) in periods t :

$$E(CSAD_t) = \frac{1}{N}\sum_{i=1}^{N} |(\beta_i - 1)|[E_t(R_m) - r_f] \tag{5.4}$$

The linear and increasing relationship between dispersion and the market's expected returns can be expressed as:

$$\frac{\partial CSAD_t}{\partial R_{m,t}} = \frac{1}{N}\sum_{i=1}^{N} |(\beta_i - 1)| > 0 \text{ and } \frac{\partial^2 E(CSAD_t)}{\partial E_t(R_m)^\wedge 2} = 0 \tag{5.5}$$

From equation 5.5, the first-order partial derivatives of CSAD are > 0 and the second-order partial derivatives of CSAD are =0. It means there is a linear relation between CSAD and $R_{m,t}$ based on the rational asset pricing model. Therefore, this relation would not exist when herding exists in the market. The dispersion will increase when the market return decreases in the CSAD measure. Another important thing is that CSAD is not a measure of herding, instead the relationship between $CASD_t$ *and* $R_{m,t}$ is used to detect herding behavior. If market participants are more likely to the herd during periods of large price movements, there would be a less than proportional increase (or even decrease) in the CSAD measure. CSAD is not a measure of herding, instead the relationship between $CSAD_{\mathrm{t}}$ and $R_{m,t}$ is used to detect herd behavior.

$$CSAD_t^{UP} = \alpha + \beta_1^{UP}\left|R_{m,t}^{UP}\right| + \beta_2^{UP}\left|R_{m,t}^{UP}\right|^2 + \varepsilon_t \tag{6.1}$$

$$CSAD_t^{DOWN} = \alpha + \beta_1^{DOWN}|R_{m,t}^{DOWN}| + \beta_2^{DOWN}\left|R_{m,t}^{DOWN}\right|^2 + \varepsilon_t \tag{6.2}$$

where $CSAD_t^{UP}$ and $CSAD_t^{DOWN}$ indicate the degree of deviation in both up and down markets.

In this paper, I use a non-linear model (CCK Model) to capture the absolute deviation of cross-sectional stock returns (CSAD).

$$CSAD_{\mathrm{t}} = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \tag{7}$$

$$CSAD_t = \gamma_0 + \gamma_1|R_{m,t}| + \gamma_2\left|R_{m,t}\right|^2 + \varepsilon_t \tag{8}$$

where $|R_{m,t}|$ is the absolute value of the market return at time t. $|R_{m,t}|^2$ is the squared market return at time t. The CCK model indicates that a rational asset pricing model suggests a linear relationship between the dispersion in asset return and market portfolio return. The increase in absolute value of the market return can lead to an increase in the dispersion of individual asset returns. Therefore, the coefficient for the relationship between CSAD and market returns should be positive. However, if individual investors make investment decisions by imitating other investors, the CASD will decrease or continue to increase with a declining speed. Thus, we expect that the coefficient γ_2 should be negative and statistically significant when there is herding behavior.

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2 + \varepsilon_t \tag{9}$$

In the above equation, D is a dummy variable, if $R_{m,t} < 0$ then D=1, otherwise D=0. I can study the non-linear relationship of market returns during up and down markets by setting D. In this equation, there is a herd effect in the bull market when γ_3 is negative and statistically significant and there is a herd effect in the bear market when γ_4 is negative and statistically significant.

Chapter 4: Hypotheses

There is pronounced information asymmetry in the Chinese stock market, and the results can easily lead to a herding effect in the capital market. At the same time, regulators in the Chinese stock market stipulate that the stock market can only be long- but not short-selling for investment. Therefore, investors can only earn profits when the stock price rises. In terms of investors' experience in the A-share market, market volatility will become more intense if the market is a two-way trading market. Under this situation, most investors follow others since they do not understand the principle of the rising and falling market. Under this condition, the herding phenomenon is prevalent in the Chinese A-share market (Ju, 2019). With this regulation, trading volume will continue to increase when the stock price rises, but if the stock price falls, trading volume will not continue to grow. It illustrates that, under different market stages, the herding effect is manifested to different degrees. Yao, Ma, and He (2014) used an approach based on Christie and Huang (1995) and CCK (2000) to detect the herding effect among investors. The cross-sectional standard deviation of returns is calculated for both rising and declining periods in the Chinese stock market. They discover that herding behavior is more vital in the A-share market when it is declining.

4.1 Hypothesis 1: Herding behavior does not exist in Shanghai and Shenzhen A-share markets.

Using the CAPM model, several researchers state that systemic risks have existed in the Chinese stock market. Various industries' systemic risks are different due to factors such as the environment and policies. Dai and Li (2019) analyzed the systemic risk of different industries in China's stock market. The results showed that the structure of systemic risk among various industries is different due to the influence of the market. Therefore, the second hypothesis assumes that:

4.2 Hypothesis 2: Herding behavior would be the same for each industry.

Liu et al. (2021) studied the relationship between the COVID-19 pandemic and the risk of a stock crash in China. The results show that COVID-19 increased the Chinese stock market's crash risk. Moreover, they find out that investors' fears about the coronavirus increase the possibility of stock market crash risk even when the number of confirmed cases is not significant. Therefore, in this paper, because investors do not have high expectations of the stock market, there will be lower market trading volume and lower market volatility during COVID-19 (Guosong et al. 2020). I can assume that:

4.3 Hypothesis 3: Herding behavior in the pre COVID-19 is the same as post COVID-19 in A-share markets.

Current methods for testing the herding effect include three models: LSV, CH, and CCK. Among them, based on incomplete information and the asymmetric effect of herding behavior in the Chinese stock market, I believe that the CCK model has advantages over the other two methods. First, the CCK model considers the relationship of non-linear between CSAD and market return during extreme price movements and considers the squared market returns instead. Second, the CCK model analyzes the asymmetric effect of herd behavior, which is compatible with the asymmetry of China's stock market.

Chapter 5: Data

In this paper, the dataset is collected from the Thomson DataStream database. I collect data on stock returns for all firms listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). Moreover, I collect the Shanghai A share (SHA) composite index as well as the Shenzhen A share (SZA) index. In order to investigate herding behavior during the periods of pre-COVID and post-COVID, the available data periods are from October 8, 2018, to September 29, 2021, equalling 729 days after removing weekends and holidays. There are 1594 Shanghai A-share firms (SHA) and 1970 Shenzhen A-share firms (SZA), and the firms are grouped into six different industries. All the companies have been divided into six different industries: Industrial, Utility, Transportation, Bank/Savings & Loan, Insurance and Other Financial.

The daily stock returns for each firm are calculated as:

$$R_t = (\frac{P_t}{P_{t-1}} - 1)$$

*P_t is the stock's close price on t time.

On January 9, 2020, the World Trade Organization (WTO) reported that Chinese authorities had determined that the outbreak was caused by a novel coronavirus. Considering the impact COVID-19 has had on investors' investment decisions, this paper used the pre–COVID-19 and post–COVID-19 periods as two samples to analyze whether there is herding behavior in China's A-share stock market. January 9, 2020 is set as the cutoff point for these two sample periods because the WTO announced on that date that COVID-19 could be transmitted from person to person.

Chapter 6: Empirical Results

Figure 1

Figure 1 shows the composite index for the Shanghai A-share and Shenzhen A-share stock markets. Although there are two different exchanges for stock trading, obviously, there is the same fluctuation between the two stock exchanges.

Plot of CSAD against Rm for the SHA

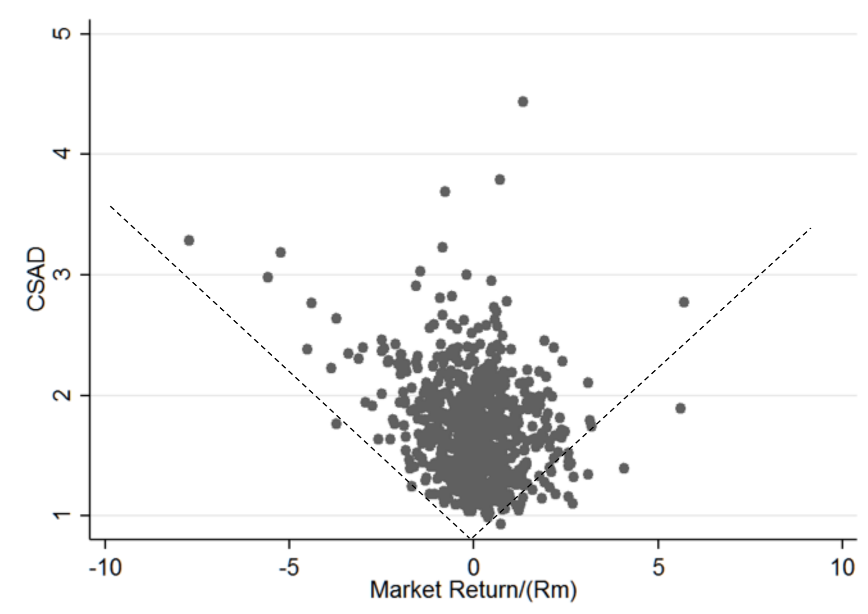

Figure 2. Relationship between daily cross-sectional absolute deviation ($CSAD_t$) and the corresponding equally weighted market return ($R_{m,t}$) for the Shanghai A-Share market. The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021.

Plot of CSAD against Rm for the SZA

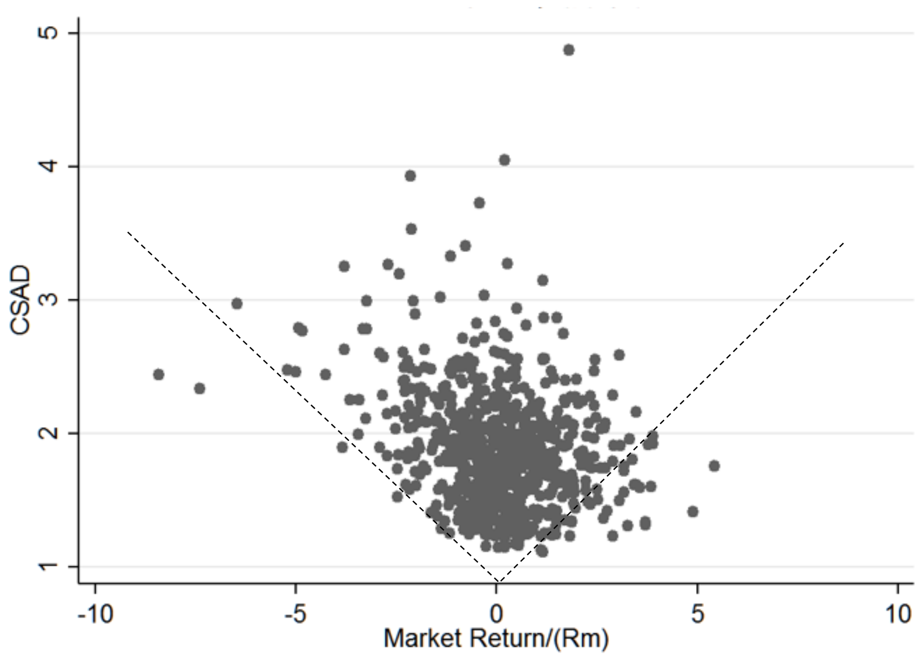

Figure 3. Relationship between daily cross-sectional absolute deviation ($\mathbf{CSAD_t}$) and the corresponding equally weighted market return ($\mathbf{R_{m,t}}$) for Shenzhen A-Share market. The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021.

Using the plot chart between the daily CSAD measure and the corresponding equally weighted market return to observe the magnitude of the non-linearity in the CSAD and market return relationship. The plot for the linear CSAD-market relation should show a line trend in the graph whether the market return is positive or negative. Figure 2 presents a linear CSAD-market relation for the SHA market. However, figure 3 illustrates that there is a non-linear relationship between the CSAD and the return on the market portfolio, whether in an up or down market. It is obvious that the average market returns become larger in absolute terms, as the return dispersions increase. In other words, when the market rises and falls sharply, CSAD is obviously smaller than the linear relationship prediction, so there may be a nonlinear relationship between them, which means herding behavior. The results are consistent with the finding from Chang et al. (2000). They report that Hong Kong has a linear CSAD-market relation. The plot for South Korea indicates a non-linear CSAD-market relation. One reason for the differences in herding behavior may be the high degree of government intervention. The SHA market is similar to the Hong Kong market and the SZA market is consistent with the South Korean market.

Although the corporate structure of listed companies in the SHA market looks similar to listed companies in the West, the ownership structure of these companies is different from those in Western countries. In 1992, the 14th Party Congress announced the establishment of a modern corporate system. Later, in 1994, the State Council proposed a pilot scheme in a few large state-owned enterprises. However, most of the companies listed in the SHA market have shares owned directly or indirectly by the government. As a result, the government dominates the ownership and control of many firms in the SHA market (Sun & Tong, 2003). According to Christie and Huang (1995), the difference in herding behavior in different markets may be the result of a high degree of government intervention, such as relatively frequent monetary policy changes or large buy or sell orders in the stock market.

6.1 Descriptive statistics

Table 1-1

Descriptive statistics of cross-sectional absolute deviations (SHA)

Statistic	Observations	Minimum (%)	Maximum (%)	Mean (%)	Standard deviation (%)
			All Industries		
SH A-share	729	0.939	4.125	1.653	0.371
			By Industry		
Bank/Savings & Loan	729	0.281	5.137	1.164	0.671
Industrial	729	0.954	4.112	1.681	0.377
Insurance	729	0.164	6.494	1.543	0.983
Other Financial	729	0.389	6.745	1.525	0.828
Transportation	729	0.483	4.266	1.461	0.461
Utility	729	0.804	5.541	1.581	0.469

Note: This table shows descriptive statistics of daily equally weighted cross-sectional absolute deviations ($CSAD_t$) for Shanghai A-share (SHA) stock markets. The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021.

Tables 1-1 and 1-2 report univariate statistics for the CSAD measure for Shanghai (SHA) and Shenzhen (SZA) A-share markets and different industries. The data period is October 8, 2018, to September 30, 2021. According to the definition, CSADs move to zero when all returns move in unison with the market.

The level of CSAD increases when individual returns start to deviate from the market return. From Tables 1-1 and 1-2, I observe that the mean of daily CSAD in the SHA (0.983) is lower than that in the SZA (1.820) which means the return dispersion in SZA is higher than in SHA. The comparison of the maximum and minimum values of the daily CSAD shows that Insurance has the highest value for both SHA (9.006) and SZA (8.011). In addition, a higher standard deviation means more informed investors will respond to market information and diversify their investments. Insurance (1.543) and Other Financial (0.828) in SHA and Insurance (1.195), Bank/Savings & Loan (0.886), and Other Financial (0.719) in SZA indicate that those industries may be more resistant to the herding effect than the overall market.

Table 1-2

Descriptive statistics of cross-sectional absolute deviations (SZA)

Statistic	Observations	Minimum (%)	Maximum (%)	Mean (%)	Standard deviation (%)
		All Industries			
SZ A-share	729	1.110	4.303	1.820	0.378
		By Industry			
Bank/Savings & Loan	729	0.128	6.233	1.445	0.886
Industrial	729	1.121	4.360	1.830	0.385
Insurance	729	0.002	8.011	1.238	1.195
Other Financial	729	0.414	5.823	1.468	0.719
Transportation	729	0.516	4.681	1.615	0.513
Utility	729	0.945	3.781	1.825	0.459

Note: This table shows descriptive statistics of daily equally weighted cross-sectional absolute deviations ($CSAD_t$) for Shenzhen A-share (SZA) stock markets. The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021.

Comparing the results with the literature studied by Chang et al. (2000) shows the first order autocorrelation of CSAD is 0.3918 for the US, 0.3227 for Japan, 0.5298 for South Korea, and 0.4656 for Taiwan. Obviously, the SHA and SZA markets are similar to the market in the US and Japan during the sample periods. In general, the results should be consistent with Asian markets instead of Western markets. There are two possible explanations. First, China’s stock market was immunized earlier by the pandemic compared with other countries. Second, China's stock market has become more and more mature and has strong pressure resistance when facing an uncertain shock.

6.2 An Empirical Analysis of Herding Behavior during COVID-19

To test the first hypothesis, I confirm the evidence of herding behavior in SHA and SZA. Using the CCK model, mentioned in equation (8), a weighted average SHA and SZA market portfolio is conducted on listed stocks. The results are shown in Tables 2-1 and 2-2:

Table 2-1

Analysis of herding behavior in SHA stock market

	γ_0	γ_1	γ_2	Adj.R^2
Regression results for daily data				
SHA Market (729)	1.565***	0.078***	0.005	0.066
	(66.736)	(2.966)	(1.296)	
Pre-COVID (309)	1.302***	0.106***	0.007	0.191
	(48.362)	(3.120)	(1.155)	
Post-COVID (419)	1.731***	0.088***	0.002	0.071
	(63.009)	(2.833)	(0.451)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre-COVID and post-COVID periods. Numbers in parentheses are t-statistics based on **Newey–West (1987)** consistent standard errors.* p < 0.1, ** p < 0.05, *** p < 0.01, respectively.

Table 2-2

Analysis of herding behavior in SZA stock market

	γ_0	γ_1	γ_2	Adj.R^2
Regression results for daily data				
SZA Market (729)	1.718***	0.090***	0.001	0.063
	(73.812)	(3.591)	(0.157)	
Pre-COVID (309)	1.476***	0.094***	0.003	0.139
	(53.000)	(3.045)	(0.548)	
Post-COVID (419)	1.876***	0.104***	-0.001	0.084
	(68.285)	(3.072)	(-0.180)	

Note: The data is from Thomson DataStream database. The sample period is from 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre-COVID and post-COVID periods. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors.* p < 0.1, ** p < 0.05, *** p < 0.01, respectively.

Reviewing the regression results on CSAD for SHA and SZA. Both coefficients are positive in SHA and SZA. As mentioned before, there is evidence of a herding effect in the market. I expect that there is a negative non-linear relationship between the CSAD of the weighted market stock portfolio and $R_{m,t}^2$, as shown by the negative statistically significant γ_2 coefficient. Tables 2-1 and 2-2 show that there is no herding behavior in SHA and SZA. In other words, there is currently no conclusive evidence that the SHA and SZA have herding behavior.

The results are consistent with the study by Demirer and Kutan (2006). There is no evidence of herding behavior in the SHA and SZA from observing both markets' firm- and sector-level data. However, my results using daily data differ from those of Tan et al. (2008), who find evidence of herding using only 87 firms with dual-list shares in Chinese stock markets. It is likely that the difference in the sample of firms explains the results.

I also investigated herding behavior under the extreme market conditions induced by COVID-19. To address the significance of herding behavior in the two Chinese stock markets pre– and post–COVID-19, I ran the regression of periods on pre-COVID (October 8, 2018–January 9, 2020) and post-COVID (January 9, 2020–September 30, 2021). The results failed to reject my first and third hypotheses. In other words, it shows that herding behavior does not exist in the overall SHA and SZA markets during either sample period.

6.3 An Empirical Analysis of Herding Behavior during COVID-19 (Up and Down)

Due to stock market volatility, I also consider the asymmetric effects of investing during the up and down markets. To this end, I added a dummy variable to the original model of the CCK model. To explain the influence of the upper and lower markets, set the dummy variable $R_{m,t}$< 0 then D=1, otherwise D=0. Tables 3-1 and 3-2 show the results of this equation.

Table 3-1

Analysis of herding behavior in SHA during rising and declining market conditions

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results for daily data						
SHA Market (729)	1.556***	-0.186***	0.038	-0.008**	-0.003	0.118
	(63.063)	(-6.062)	(0.920)	(-1.995)	(-0.208)	
Pre-COVID (309)	1.290***	-0.219***	0.080	-0.006	-0.006	0.279
	(46.239)	(-5.657)	(1.637)	(-1.190)	(-0.507)	
Post-COVID (419)	1.733***	-0.177***	0.009	-0.009**	0.012	0.118
	(57.635)	(-4.906)	(0.180)	(-2.139)	(0.734)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refers to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Table 3-2

Analysis of herding behavior in SZA during rising and declining market conditions

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results for daily data						
SZA Market (729)	1.705***	-0.224***	0.045	-0.016***	-0.008	0.152
	(69.764)	(-7.450)	(1.188)	(-3.631)	(-0.809)	
Pre-COVID (309)	1.466***	-0.227***	0.041	-0.012**	-0.002	0.277
	(51.179)	(-6.261)	(0.926)	(-2.429)	(-0.209)	
Post-COVID (419)	1.870***	-0.231***	0.036	-0.017***	-0.001	0.180
	(63.861)	(-6.177)	(0.743)	(-2.842)	(-0.048)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refers to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Using this market condition adjustment model, there are coefficients to show there is a herding effect in up and down markets. In this model, a negative and statistically significant γ_3 means there is evidence of herding behavior in the up market. The same is true for γ_4; there is herding behavior in the down-market if γ_4 is negative and statistically significant. Tables 3-1 and 3-2 illustrate that herding behavior occurs only during upward movements in SHA (-0.008**) and SZA (-0.016***) due to the negative coefficients that are statistically significant. Although, for the down movements, I found that the coefficients are negative, but none of them is statistically significant for SHA and SZA markets. The results suggest that herding behavior is stronger for both markets during rising markets, but no asymmetry exists during the decreasing markets. The results are consistent with the findings from Tan et al. (2008). Under the high-volume state, the coefficient for all of the SHA and SZA markets is significantly negative in their results. If the regression was running by only considering the upside or downside markets, the results would report that hypothesis one can be rejected when only considering the upside markets. This suggests that herding occurs in these markets during periods of rising prices.

Analysis of the pre- and post-COVID periods shows the coefficient is -0.006 but not statistically significant for pre-COVID during both up and down markets in SHA. However, the coefficient for rising markets is significantly negative (-0.009**), which means herding exists after the pandemic.

For the other sample periods, SZA has the same results for the entire market. There are negative coefficients and statistical significance for both the pre- and post-COVID periods during the upward movements. Hypothesis three can be rejected since there are different coefficients between pre- and post-COVID for the SHA market during the upward movements. However, no evidence can prove the existence of herding behavior during the downward movements in the SZA market.

6.4 An Empirical Analysis of Herding Behavior in the Industry during COVID-19

In this section, my next step is to segment the Chinese A-share market by industry. I have decomposed the Chinese A-share market into Bank/Savings & Loan, Industrial, Insurance, Other Financial, Transportation, and Utility. For each industry, a market portfolio of equal weight has been created. Using the daily return of each company in the stock portfolio, I calculate the daily CSAD of each company during the sample period from October 8, 2018, to September 29, 2021. A test can be run to check the evidence of herding behavior by using these daily CSADs. To this end, I used the same CCK model to test the herding effect in both SHA and SZA. The investment preferences of investors can change due to different industry sectors during rising and declining markets. Therefore, it might cause a herding effect in different industries.

Table 4-1

Analysis of herding behavior in SHA by industries

	γ_0	γ_1	γ_2	Adj.R^2
Regression results by industries				
Bank/Savings & Loan	0.874^{***}	0.383^{***}	0.010	0.239
	(19.293)	(5.964)	(-0.604)	
Pre-COVID (309)	0.762^{***}	0.274^{***}	0.019	0.296
	(11.398)	(2.819)	(0.784)	
Post-COVID (419)	0.957^{***}	0.367^{***}	-0.027^{**}	0.169
	(18.037)	(5.444)	(-2.380)	
Industrial	1.612^{***}	0.057^{**}	0.007^{*}	0.051
	(67.566)	(2.126)	(1.864)	
Pre-COVID (309)	1.336^{***}	0.090^{***}	0.007	0.160
	(50.216)	(2.643)	(1.221)	
Post-COVID (419)	1.791^{***}	0.066^{**}	0.005	0.057
	(64.581)	(2.096)	(1.174)	
Insurance	1.276^{***}	0.320^{**}	-0.022	0.048
	(21.940)	(2.468)	(-1.230)	
Pre-COVID (309)	1.336^{***}	0.400^{**}	-0.004	0.049
	(50.216)	(2.017)	(-0.250)	
Post-COVID (419)	1.428^{***}	0.322^{***}	-0.036^{**}	0.026
	(18.665)	(3.096)	(-2.409)	
Other Financial	1.279^{***}	0.289^{***}	-0.013	0.072
	(25.517)	(3.884)	(-0.853)	
Pre-COVID (309)	1.185^{***}	0.313^{**}	-0.002	0.109
	(13.702)	(2.429)	(-0.070)	
Post-COVID (419)	1.325^{***}	0.294^{***}	-0.021^{*}	0.047
	(24.104)	(3.937)	(-1.779)	
Transportation	1.345^{***}	0.117^{***}	-0.007	0.037
	(46.378)	(3.537)	(-1.198)	
Pre-COVID (309)	1.203^{***}	0.103^{*}	0.001	0.047
	(26.478)	(1.943)	(0.081)	
Post-COVID (419)	1.434^{***}	0.148^{***}	-0.011^{**}	0.038
	(40.455)	(3.768)	(-2.276)	
Utility	1.512^{***}	0.112^{***}	0.001	0.057
	(47.469)	(3.383)	(0.158)	
Pre-COVID (309)	1.258^{***}	0.160^{***}	-0.002	0.170
	(38.823)	(3.931)	(-0.249)	
Post-COVID (419)	1.674^{***}	0.104^{**}	-0.001	0.035
	(37.308)	(2.293)	(-0.218)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre- and post-COVID periods. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors.* p < 0.1, ** p < 0.05, *** p < 0.01, respectively.

Tables 4-1 and 4-2 report the following regression results of the SHA and SZA markets: $CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2 + \mu_t$, where $R_{m,t}$ is the equal-weight market portfolio return rate at t time, and $CSAD_t$ is the cross-sectional absolute deviation of return. The sample period is from October 8, 2018, to September 29, 2021. The numbers in parentheses are based on the t-statistics of Newey-West (1987) heteroskedasticity autocorrelation consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4-1 shows the herding behavior in different industries in SHA. Among the six independent industries, the γ_2 coefficients of three industries (Bank/Savings & Loan, Industrial, and Utility) are both positive, which means no herding behavior can be found in those industries. I do find the negative γ_2 coefficients for the rest of the three industries (Insurance, Other Financial, and Transportation). However, the individual p-value is too significant and does not pass the 90th percentile t-test for statistical significance. Therefore, no evidence that can prove herding behavior exists broken down by industries in the SHA market.

During the COVID-19 periods, herding behavior was seen in various industries. I observed the CSAD during the spread of COVID-19 from six industries in the SHA market. I run the same regression in equation (3) and report the results in Table 4-1. Analysis of the γ_2 shows that herding behavior did not exist during the periods of pre-COVID because I noticed that Bank/Savings & Loan, Insurance, Other Financial, and Utility have negative γ_2 coefficients, but the γ_2 is statistically insignificant. However, I found that the coefficient of $R_{m,t}^2$ is significantly negative for Bank/Savings & Loan, Insurance, Other Financial, and Transportation during the post-COVID period, which implies that herding behavior exists in those industries during that period. Overall, the finding of herding behavior for different industries is consistent with the finding in Table 2-1, which shows that no herding behavior existed during the whole sample period. However, the results show that herding behavior can be found in specific industries post–COVID-19.

Table 4-2 shows the herding behavior in different industries in the SZA market. The coefficient of $R_{m,t}^2$ for all industries except Industrial, which has a negative sign. Only Utility is negative (-0.012**) and statistically significant. In summary, I cannot find evidence of herd behavior broken down by industries in the SZA market except Utility, where the results are consistent with Table 2-2.

For the COVID periods, there is no evidence of herding behavior shown in the pre-COVID period in the SZA market. During the post-COVID periods, the results indicate that the coefficient γ_2 is significantly negative in five industries, including Bank/Savings & Loan, Insurance, Other Financial, Transportation and Utility, which implies that herding behavior exists for five industries in the SZA market. In other words, investors whom at most industries in the SZA market tend to make investment decisions by following others after the pandemic.

Although the results indicate no herding behavior exists in the overall SHA and SZA markets pre– and post–COVID-19. However, Tables 4-1 and 4-2 clearly report evidence of herding behavior in certain parts of the industries in SHA and SZA markets during COVID-19. As a result, the herding behavior that occurs at the industry level can be explained as specific industry risks. These risks are unique to the Chinese market, such as market effects from government policies or investment news from the media. Moreover, individual investors opinions diverge about COVID-19 due to a lack of knowledge about the unprecedented pandemic, which implies that they will prefer to follow others' investment decisions when the market is under uncertain conditions.

Table 4-2

Analysis of herding behavior in SZA by industries

	γ_0	γ_1	γ_2	Adj.R^2
Regression results by industries				
Bank/Savings & Loan	1.106***	0.306***	-0.002	0.123
	(18.635)	(3.285)	(-0.091)	
Pre-COVID (309)	1.154***	0.112	0.039	0.151
	(12.310)	(0.801)	(1.069)	
Post-COVID (419)	1.061***	0.471***	-0.038**	0.125
	(16.444)	(6.010)	(-2.475)	
Industrial	1.733***	0.084***	0.001	0.058
	(73.270)	(3.293)	(0.281)	
Pre-COVID (309)	1.478***	0.090***	0.003	0.137
	(53.636)	(2.906)	(0.657)	
Post-COVID (419)	1.901***	0.097***	0.001	0.080
	(68.572)	(2.823)	(0.125)	
Insurance	0.970***	0.278***	-0.016	0.032
	(12.344)	(2.903)	(-0.883)	
Pre-COVID (309)	1.042***	0.162	-0.001	0.014
	(7.366)	(0.961)	(-0.015)	
Post-COVID (419)	0.906***	0.380***	-0.029*	0.049
	(10.334)	(3.507)	(-1.650)	
Other Financial	1.244***	0.224***	-0.011	0.066
	(29.482)	(4.172)	(-1.011)	
Pre-COVID (309)	1.281***	0.200**	0.001	0.087
	(18.751)	(2.440)	(0.079)	
Post-COVID (419)	1.220***	0.247***	-0.024***	0.048
	(24.598)	(4.402)	(-3.093)	
Transportation	1.490***	0.130***	-0.010	0.032
	(45.669)	(3.688)	(-1.395)	
Pre-COVID (309)	1.348***	0.082*	0.001	0.037
	(29.674)	(1.660)	(0.054)	
Post-COVID (419)	1.580***	0.181***	-0.017**	0.045
	(36.864)	(4.023)	(-2.059)	
Utility	1.690***	0.148***	-0.012**	0.049
	(57.018)	(4.446)	(-1.975)	
Pre-COVID (309)	1.578***	0.153***	-0.010	0.072
	(40.314)	(3.548)	(-1.519)	
Post-COVID (419)	1.758***	0.158***	-0.015*	0.042
	(43.429)	(3.452)	(-1.686)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre- and post-COVID periods. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

To detect herding behavior in individual industry stock portfolios from the data samples, I used the market adjustment model I mentioned in equation (9) to test herding behavior in SHA and SZA markets by industries under up and down market conditions. For the results, if the γ_3 and γ_4 coefficients are significantly negative it means it is a non-linear regression and there is herding behavior in the market. During periods of market volatility and the periods of COVID-19, I distinguish between the relative returns of a rising market and a declining market to prove the herding behavior of a particular industry. Therefore, hypothesis two, which is that herding behavior would be the same for each industry, can be rejected.

6.5 An Empirical Analysis of Herding Behavior in the Industry during COVID-19 for SHA (Up and Down)

Table 5-1

Analysis of herding behavior in SHA by industries during rising and declining market conditions

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results by industries						
Bank/Savings & Loan	0.894***	-0.305***	0.259**	-0.007	0.025	0.165
	(19.578)	(-3.930)	(2.545)	(-0.391)	(0.602)	
Industrial	1.604***	-0.176***	0.019	-0.007*	-0.004	0.112
	(63.818)	(-5.677)	(0.461)	(-1.724)	(-0.304)	
Insurance	1.514***	-0.242	0.051	-0.015	0.102	0.027
	(15.640)	(-1.604)	(0.274)	(-0.663)	(1.633)	
Other Financial	1.341***	-0.168***	0.094	-0.005	0.087**	0.088
	(26.487)	(-2.742)	(0.774)	(-0.411)	(2.421)	
Transportation	1.338***	-0.219***	0.075	-0.018***	-0.011	0.063
	(43.287)	(-5.669)	(1.351)	(-3.623)	(-0.701)	
Utility	1.497***	-0.211***	0.111**	-0.010*	-0.019	0.072
	(44.199)	(-5.201)	(2.063)	(-1.901)	(-1.279)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refer to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

For Table 5-1, under the decreasing market in the SHA, I find that the coefficients of γ_4 are not significant for all industries. However, under rising movement markets, I find that γ_3 is significantly negative for Industrial (-0.007*), Transportation (-0.018***), and Utility (-0.010*). The results from Table 3-1, analysis of herding behavior in SHA during rising and declining market conditions, confirm the findings. There is no herding behavior under downward movements in the entire market or broken down by industries in the SHA market.

Table 5-2

Analysis of herding behavior in SHA by industries during rising and declining markets – Pre-COVID

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results by industries						
Bank/Savings & Loan	0.764***	-0.292***	0.254**	0.016	0.016	0.292
	(11.088)	(-2.596)	(2.031)	(0.616)	(0.616)	
Industrial	1.321***	-0.217***	0.064	-0.007	-0.008	0.275
	(48.580)	(-5.744)	(1.354)	(-1.386)	(-0.703)	
Insurance	1.194***	-0.262	0.249	-0.002	0.072	0.053
	(7.754)	(-1.190)	(0.955)	(-0.054)	(1.035)	
Other Financial	1.256***	-0.172*	0.112	0.004	0.099***	0.141
	(14.427)	(-1.727)	(0.624)	(0.210)	(2.668)	
Transportation	1.190***	-0.216***	0.079	-0.012	-0.013	0.082
	(24.903)	(-3.784)	(0.933)	(-1.540)	(-0.635)	
Utility	1.218***	-0.257***	0.161***	-0.012*	-0.020	0.247
	(37.834)	(-5.568)	(2.738)	(-1.828)	(-1.227)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refer to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Tables 5-2 and 5-3 show the herding behavior under different market volatilities by six different industries during COVID-19. Obviously, for Table 5-2, I observe that all coefficients are not significant except for the Utility of the SHA by industries during the rising and declining market before COVID-19. In other words, there is no evidence of herding behavior during the pre-COVID period. The results are consistent with the finding for Table 3-1, which shows that the coefficients are statistically insignificant for the pre-COVID period during both up and down markets in the SHA market.

Table 5-3

Analysis of herding behavior in SHA by industries during rising and declining markets – Post-COVID

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results by industries						
Bank/Savings & Loan	1.001***	-0.280***	0.213	-0.020*	0.054	0.114
	(15.964)	(-3.351)	(1.064)	(-1.914)	(0.562)	
Industrial	1.791***	-0.168***	-0.014	-0.008*	0.014	0.118
	(59.190)	(-4.584)	(-0.274)	(-1.771)	(0.862)	
Insurance	1.495***	-0.241**	0.048	-0.032**	0.092	0.032
	(17.487)	(-1.998)	(0.188)	(-2.349)	(0.823)	
Other Financial	1.356***	-0.225***	0.197	-0.018*	0.030	0.048
	(21.370)	(-3.069)	(0.934)	(-1.762)	(0.348)	
Transportation	1.439***	-0.230***	0.059	-0.022***	0.006	0.064
	(36.587)	(-4.536)	(0.817)	(-3.607)	(0.274)	
Utility	1.661***	-0.207***	0.087	-0.014**	-0.016	0.048
	(33.987)	(-3.716)	(1.077)	(-1.649)	(-0.696)	

Note: The data is from Thomson DataStream database. The sample period is from 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for the pre-COVID and post-COVID periods. The regression indicated that γ_3 refer to the days when market returns are positive, γ_4 refer to the days when market returns are Negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Table 5-3 illustrates the herding behavior post COVID-19 in the SHA market by industry during up and down movements. All the coefficients are negative and statistically significant in rising markets, which are -0.020* for Bank/Savings & Loan, -0.008* for Industrial, -0.032** for Insurance, -0.018* for Other Financial, -0.022*** for Transportation, and -0.014** for Utility. However, almost all the industries have positive γ_4 during post-COVID, indicating that no evidence of herding behavior can be found in the declining markets. Therefore, herding behavior is more significant in the upside market movement than in the downside market movement in the SHA market after the COVID-19 periods.

6.6 An Empirical Analysis of Herding Behavior in the Industry during COVID-19 for SZA (Up and Down)

Table 6-1 reports empirical results of the regression **(9)** for many industries during the up and down markets. The regression results are reported in Tables 6-2 and 6-3; however, they are separated by different COVID-19 samples. As shown in Table 6-1, more industries can find herding behavior on up days than on down days. In the rising markets, γ_3 is -0.015***, -0.026***, and -0.030*** for Industrial, Transportation, and Utility, respectively; the coefficients are statistically significant. It indicates that herding in these industries is in a rising market state. However, under conditions of a declining market, the coefficient of utility is negative (-0.026*) and significant. It means that the utility industry in the SZA market can find herding behavior compared to the SHA market. Overall, the results are consistent with the findings in the SHA market.

Table 6-1

Analysis of herding behavior in SZA by industries during rising and declining markets

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results by industries						
Bank/Savings & Loan	1.122***	-0.311***	0.236**	-0.005	0.022	0.122
	(19.628)	(-3.084)	(2.360)	(-0.187)	(0.661)	
Industrial	1.720***	-0.220***	0.040	-0.015***	-0.008	0.148
	(69.098)	(-7.201)	(1.033)	(-3.435)	(-0.791)	
Insurance	1.027***	-0.109	0.163	-0.002	0.055	0.048
	(12.224)	(-1.131)	(0.978)	(-0.095)	(1.024)	
Other Financial	1.280***	-0.175***	0.111	-0.009	0.037	0.072
	(28.711)	(-3.357)	(1.105)	(-1.006)	(1.121)	
Transportation	1.486***	-0.264***	0.049	-0.026***	-0.006	0.080
	(43.639)	(-6.490)	(0.899)	(-3.814)	(-0.347)	
Utility	1.669***	-0.304***	0.110**	-0.030***	-0.026*	0.129
	(53.996)	(-8.083)	(2.183)	(-4.871)	(-1.891)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refer to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Table 6-2

Analysis of herding behavior in SZA by industries during rising and declining markets – Pre-COVID

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results by industries						
Bank/Savings & Loan	1.165^{***}	-0.116	0.069	0.037	0.052	0.146
	(12.954)	(-0.765)	(0.516)	(0.935)	(1.509)	
Industrial	1.467^{***}	-0.224^{***}	0.040	-0.012^{**}	-0.003	0.280
	(51.870)	(-6.210)	(0.912)	(-2.305)	(-0.277)	
Insurance	1.131^{***}	0.008	-0.062	0.008	0.102	0.037
	(7.479)	(0.052)	(-0.234)	(0.292)	(1.475)	
Other Financial	1.332^{***}	-0.141^{*}	0.042	0.001	0.063^{*}	0.099
	(18.207)	(-1.798)	(0.296)	(0.128)	(1.768)	
Transportation	1.352^{***}	-0.235^{***}	-0.041	-0.019^{*}	0.015	0.120
	(28.968)	(-4.061)	(-0.592)	(-1.745)	(0.795)	
Utility	1.563^{***}	-0.336^{***}	0.084	-0.031^{***}	-0.018	0.207
	(38.143)	(-6.916)	(1.217)	(-4.617)	(-1.045)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refer to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Table 6-3

Analysis of herding behavior in SZA by industries during rising and declining markets – Post-COVID

	γ_0	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Regression results by industries						
Bank/Savings & Loan	1.087^{***}	-0.467^{***}	0.355^{*}	-0.040^{***}	0.006	0.123
	(14.594)	(-4.748)	(1.875)	(-2.744)	(0.079)	
Industrial	1.894^{***}	-0.227^{***}	0.026	-0.016^{***}	0.001	0.179
	(64.102)	(-6.003)	(0.529)	(-2.682)	(0.071)	
Insurance	0.944^{***}	-0.208^{*}	0.352	-0.008	0.012	0.056
	(9.724)	(-1.732)	(1.434)	(-0.474)	(0.116)	
Other Financial	1.223^{***}	-0.218^{***}	0.257	-0.021^{**}	-0.022	0.044
	(21.856)	(-3.655)	(1.601)	(-2.567)	(-0.342)	
Transportation	1.578^{***}	-0.292^{***}	0.102	-0.032^{***}	-0.010	0.074
	(34.432)	(-5.687)	(1.306)	(-4.258)	(-0.413)	
Utility	1.745^{***}	-0.281^{***}	0.123	-0.030^{***}	-0.026	0.085
	(39.794)	(-5.327)	(1.624)	(-3.462)	(-1.173)	

Note: The data are from Thomson DataStream database. The sample period is 10/08/2018 to 09/30/2021. 01/09/2020 is the cutoff point for pre- and post-COVID periods. The regression indicated that γ_3 refers to days when market returns are positive, γ_4 refer to days when market returns are negative. Numbers in parentheses are t-statistics based on Newey–West (1987) consistent standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Tables 6-2 and 6-3 show that more industries can find herding behavior in rising markets for post-COVID than pre-COVID. In particular, the coefficients of Bank/Savings & Loan and Other Financial industries in rising markets turned negative and significant during the COVID-19 periods. The γ_3 for both industries are -0.040*** and – 0.021**, which means that investors become herds in Bank/Savings & Loan and Other Financial industries after COVID-19 in rising markets.

Compared to the SHA market, more evidence of herding behavior can be found in SZA's rising markets during periods of pre-COVID. The reason could be that the SZA market is composed mainly of smaller firms, which are less likely to be state-owned. The stock price for those companies is more volatile and causes more returns in a short time. Therefore, investors tend to herd more whatever the market is up or down, as they believe that the government will intervene and boost the smaller firms to develop based on the political perspective.

As a result, in the SHA and SZA market, Industrial, Transportation, and Utility can find herding behavior during rising markets. At the same time, herding behavior is more significant in the upward movement than in the downward movement for both sample periods in the SHA market. For SZA market, the results are consistent with the finding in Table 3-2 that herding behavior exists both pre- and post-COVID in the entire SZA market. The coefficient for downward markets is insignificant for both pre- and post-COVID. In other words, there is no evidence of herding behavior in either of the sample periods. Therefore, there are no significant differences in the SZA market during the periods of pre- and post-COVID-19.

6.7 Summary of Herding Behavior in the Industry

Table 7

Summary of Herding Behavior

SHA	Up	Down	SZA	Up	Down
Overall Market	Yes	No		Yes	No
Bank/Savings & Loan	No	No	Bank/Savings & Loan	No	No
Industrial	Yes	No	Industrial	Yes	No
Insurance	No	No	Insurance	No	No
Other Financial	No	No	Other Financial	No	No
Transportation	Yes	No	Transportation	Yes	No
Utility	Yes	No	Utility	Yes	Yes

Note: This table summarizes the herding situation under different industries during upside and downside markets. Up denotes the upward market movement and Down denotes the downward market movement.

Chapter 7: Conclusions

This paper investigates herding behavior in Shanghai A-share (SHA) and Shenzhen A-share (SZA) markets from different perspectives. The sample period is from October 8, 2018 to September 30, 2021. I am using the CCK model to detect herding behavior by industry differences and COVID-19 periods. Through empirical analysis, the conclusions are as follows:

First of all, the herding phenomenon is not prevalent for the entire sample periods on SHA and SZA markets, which is consistent with the study by Demirer and Kutan (2006). They found no evidence of herding behaviour in the overall market by using firm-level data from the Chinese A-share market.

Second, there was herding when I divided the market based on market returns. Investors on the A-share market herd on up markets. Moreover, from the comparison of SHA and SZA markets, herding behavior is a more widespread phenomenon on the SZA market than on the SHA market. Compared to the SZA market, the SHA market is composed mainly of larger companies, which are state-owned. The SZA market is composed mainly of smaller companies, which the more innovative and profitable companies (Mei et al., 2004). My results differ from those of Tan et al. (2008) who believe that Chinese investors in the SHA market tend to be more optimistic and confident of government intervention because the SHA market is composed mainly of larger state-owned companies. However, my results suggest that individual investors tend to invest in more innovative and more profitable firms instead of stabilizing firms. The SZA market is more volatile than the SHA market in both upward and downward market movement. Since the A-share markets are dominated by domestic individual investors, when the market falls, investors tend to herd less because they believe the government will intervene and prevent the market from declining (Tan et al., 2008).

Third, there are differences in the herding of various industries. Table 7 shows herding under different industries during upside and downside markets. Among these industry groups, Industrial, Transportation, and Utility have the strongest degree of herding and have been significantly impacted by COVID-19. An important extension of this paper would be to study how COVID-19 impacts different industries in Chinese stock markets.

Fourth, the results proved that herding behavior was significantly higher than usual in Chinese A-share stock markets during the pandemic. Moreover, in the pandemic, herding behavior is more significant in upward market movement in almost every industry for both SHA and SZA markets. The beginning of the pandemic brought a decline in stock market returns and increased the possibility of extreme downturns in stock prices (Liu et al., 2021). Later on, the Chinese stock market started to adapt to the continued impact of a pandemic and the stock markets began to recover. This finding suggests that investors are not comparatively rational in SHA and SZA markets. Herding behavior is significantly higher than usual during the COVID-19, which means the Chinese stock market, especially in rising markets, is not stable and efficient under pandemic situations.

7.1 Contribution

As part of its contribution, this paper provides an important implication. Herding does not exist in the overall Chinese A-share markets, suggesting that most market participants can make investment decisions rationally. However, evidence of herding behavior in rising markets indicates that Chinese policymakers need to be concerned about potential destabilizing effects. It is also interesting to note that the results for SHA and SZA markets are not consistent. First, investors in the SHA market are not as informed as investors in the SZA market. Second, differences in herding behavior may be due to the high degree of government intervention in the SHA market. Third, herding behavior exists in the SZA market due to the presence of more speculators within short investment periods.

This paper investigates how the pandemic affects Chinese A-share markets. It provides evidence of herding behavior during COVID-19. It enriches the literature on how COVID-19 can impact financial markets by studying different investment behavior in Chinese stock markets. Based on the findings, the two Chinese stock markets, especially SZA, are less efficient during the pandemic in terms of market information. Therefore, policymakers have to consider inefficiencies in the SHA and SZA markets during the pandemic.

The pandemic has had an economic impact. Pandemic-related news can cause anxiety among investors, which can affect their investment decisions. This could cause informed agents to use investor sentiment to referee the market. This possible scenario requires deeper analysis in future. Also, individual investors need to understand that they should not pursue high returns caused by the pandemic to avoid any loss in the market due to significant herding behavior. All in all, the results from this paper are of interest to the stock markets and related regulators to maintain financial stability for the post–COVID-19 period.

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