Herding behavior in the Chinese stock market and the impact of COVID-19*

Conducta manada en el mercado bursátil de China y el impacto del COVID-19

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Abstract

We analyze herding behavior in the Chinese stock markets in the context of the COVID-19 pandemic using the cross-sectional absolute deviation (CSAD) model proposed by Chang et al. (2000) to detect herding behavior in the time period between January 30, 2001, and June 12, 2020. We consider stock prices for all firms listed (A-shares) on the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) in China. We report the presence of herding behavior during the period under study and that herding behavior becomes stronger after December 31, 2019 (the COVID-19 event date). We also study herding activity in the context of potential asymmetries in market return and volatility states. The results show that when the market return is high and the volatility is low, there is a more predominant herding behavior trend. Our results do not depend on using different time windows. Results do not change when time-varying coefficients are considered using rolling regressions. Other control variables which may be relevant in explaining CSAD do not change the results when included in the estimations.

Key words: *Herding behavior, investor behavior, COVID-19, chinese stock market and cross-sectional absolute deviation (CSAD) model.*

JEL Classification: *G12, G14, G40.*

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Resumen

En este estudio analizamos la conducta manada en los mercados accionarios de China en el contexto de la pandemia COVID-19, usando el modelo de desviación absoluta de corte transversal (CSAD) propuesto por Chang et al. (2000) para detectar conducta manada entre el 30 de enero de 2001 y 12 de junio de 2020. Consideramos los precios accionarios de todas las firmas listadas (acciones clase A) en el mercado bursátil de Shanghai (SHSE) y el mercado accionario de Shenzhem (SZSE) en China. Reportamos la presencia de conducta manada durante el período bajo estudio y esta conducta se hace más fuerte después del 31 de diciembre de 2019 (la fecha del evento COVID-19). Adicionalmente estudiamos la actividad de manada en el contexto de potenciales asimetrías en estados asociados al retorno de mercado y la volatilidad. Los resultados muestran que cuando el retorno del mercado es alto y la volatilidad es baja es más predominante la tendencia hacia conducta manada. Nuestros resultados no dependen de usar ventanas de tiempo diferentes. Los resultados tampoco cambian cuando se incorporan coeficientes que varían en el tiempo por medio de regresiones con ventanas móviles. Al incorporar otras variables de control que pudieran ser relevantes al momento de explicar CSAD, los resultados no se alteran.

Palabras clave: *Conducta manada, conducta del inversionista, COVID-19, mercado accionario chino y modelo de desviación absoluta de corte transversal (CSAD).*

Clasificación JEL: *G12, G14, G40.*

1. Introduction

The COVID-19 virus was first identified in the city of Wuhan in the Hubei region of China and led to a global sanitary crisis. On March 11, 2020, with more than 100,000 people infected with COVID-19 and thousands dead, the World Health Organization (WHO) declared a global pandemic. Two months later, the number of infections exceeded five million and hundreds of thousands of deaths had been reported worldwide. From February 2020 onwards, in light of information regarding COVID-19 and its progression, global stock markets experienced several shock waves.

The first global alert from the WHO regarding COVID-19 was announced on January 30, 2020, and the initial reaction on the Chinese stock market, as shown on the Shanghai Composite Index (SSEC), was a negative return of 2.75%. When China's A-share market reopened on February 3, 2020, the SSEC fell by 7.72%. Accumulating the market return since February 3, 2020, we can see the return to positive terrain took approximately five months, coming on July 2, 2020. Indeed, Liu *et al.* (2020) report a negative and significant cumulative average abnormal return (CAAR) in the Chinese stock market between January 20 and

February 6, 2020. The CAAR was –6.39% for the Shanghai Stock Exchange (SHSE) and –3.78% for the Shenzhen Stock Exchange (SZSE).

The COVID-19 pandemic has generated major interest from scholars that study stock market behavior. A paper from Baig *et al.* (2020), for example, that studies both liquidity and volatility in US stock markets, shows that the increase in confirmed COVID-19 cases and deaths due to COVID-19 is linked to a significant increase in stock market illiquidity and volatility. Similarly, Albulescu (2020) finds a significant increase in the S&P 500 realized volatility. Testing the impact of the pandemic in 75 countries, Erdem (2020) reports a significant negative impact on stock markets expressed in decreasing returns and increasing volatility. Furthermore, because how COVID-19 data is processed by investors depends on the level of market freedom in the jurisdiction in which they operate, the results suggest that more market freedom is associated with lower negative returns and volatility.

Mazur *et al.* (2020) study US stock market performance at the industry level. They find that stocks representing certain economic sectors (e.g., natural gas, food, healthcare, and software) experience high positive returns, whereas equity values in petrol, real estate, entertainment, and hospitality sectors fall dramatically. Moreover, losing stocks show extreme asymmetric volatility that correlates negatively with stock returns.

In terms of the Chinese stock market, few articles have analyzed COVID-19 and its impact. The studies that have done so generally focus on stock market return behavior and the contagion effect associated with COVID-19. Al-Awadhi *et al.* (2020), for example, report that the daily growth in confirmed COVID-19 cases and number of deaths have a significant and negative impact on stock market returns in China across all companies. Topcu and Gulal (2020) document that the negative impact of the COVID-19 pandemic on emerging stock markets has gradually fallen and began to taper off in mid-April 2020. Akhtaruzzman *et al.* (2020) report that companies in China and G7 countries have shown significant increases in the conditional correlations between their stock returns, implying clear financial contagion transmission across firms and borders, with higher magnitudes of increase for financial firms. This finding is supported by Okorie and Lin (2020) who report considerable fractal contagion for market return and market volatility. Notably, they employ detrended moving cross-correlation analysis (DMCA) and detrended cross-correlation analysis (DCCA), which are less restrictive methodologies because they do not require time series processes to be stationary and directly use the moment properties of the series to establish the cross-correlation (contagion effects) in both regimes.

This study contributes to the existing literature in a number of ways. Although Wu *et al.* (2020) study the impact of COVID-19 on daily Chinese stock market returns between June 3, 2019, and October 12, 2020, they use an older methodology and conclude that herding behavior is significantly lower during the period of the COVID-19 pandemic under study. We provide new evidence regarding the impact of COVID-19 on herding behavior in the Chinese stock market. Wu *et al.* (2020) also do not implement any additional robustness checks, which are relevant when studying a longer time period. Because the existing empirical evidence is not conclusive on the presence of herding behavior in the Chinese stock market, as can be observed in Table 1, our study considers a longer time period and compares different time periods. In addition, there is no agreement in the literature on whether there is more or less pronounced herding behavior in bull markets compared to bear markets. And more research is required on herding behavior in different stock market volatility regimes (high and low). Both of these issues are investigated, and the results are presented in this study.

Both China's stock markets, the SHSE in Shanghai and the SZSE in Shenzhen, trade two types of shares: A-shares and B-shares. A-shares are very common, they are traded on both stock markets and are denominated in Chinese Renminbi (RMB). Only Chinese nationals from mainland China and Qualified Foreign Institutional Investors (QFIIs) are permitted to trade A-shares. B-shares are Chinese stocks denominated in foreign currencies. On the SHSE, B-shares are denominated in US dollars (USD); B-shares that trade on the SZSE are denominated in Hong Kong dollars (HKD). The A-share market is larger than the B-share market, measured by number of shares, market capitalization, and trade volume (Ng and Wu, 2006). Because of the size of the A-share market and the volume traded, it is more attractive for investors to exclusively trade A-shares.

We collected data on stock prices for all firms listed on the SHSE and SZSE in the period between January 30, 2001, and June 12, 2020, and employ the cross-sectional absolute deviation (CSAD) model proposed by Chang *et al.* (2000) to test for herding behavior in the Chinese stock market, with particular focus on the impact of COVID-19 on herding. To check the robustness of our results, we verify herding behavior in several different time windows, and our investigation covers periods when the stock market is trending downward and upward, as well as during periods of high and low volatility. In the context of systemic or global adverse events, such as a pandemic, stock markets become stressed and show a high degree of instability, experiencing high volatility and significant uncertainty. We therefore use rolling window regression methodology as a further robustness check for the presence of herding behavior.

We find that herding behavior becomes stronger after the COVID-19 event date (December 31, 2019 and this result holds when using different time windows. When we study potential asymmetries in returns and volatility, results show that when market returns are high, and volatility is low there is a more predominant herding behavior trend. Our results do not depend on using different time windows, and they do not change when time-varying coefficients are taken into account using rolling regressions. We include a number of variables to control for other common market shocks that might explain CSAD behavior. None of the initial results change with control variables included, and a stronger tendency towards herding behavior during the period of the COVID-19 pandemic under study and similar results for rising and falling stock markets and for high and low volatility regimes can still be observed.

This study is organized in five sections. Section 2 presents a theoretical background with empirical evidence regarding herding behavior and introduces the hypotheses. Section 3 describes the data and the methodology used to test for herding behavior. Section 4 reports the main results and provides a discussion. Section 5 presents a series of robustness checks. And Section 6 concludes and proposes future avenues of research.

2. Theoretical Background and Hypotheses

In this section we provide a brief explanation of herding behavior and summarize the empirical evidence on herding behavior from several global stock markets. We then review empirical studies on herding behavior in Chinese stock markets.

2.1. Herding behavior

Herding behavior is a social behavior that occurs when individuals subordinate their individual will, thoughts, and behaviors and imitate those of the herd-that is, the majority or group of which they form part. Herding behavior does not require a leader, just individuals coming together at the same time to act, and it can be influenced by social and economic factors. In finance, herding is the inclination of investors (or organizations) to mimic the actions of other investors following the interactive observation of each other's actions (Hirshleifer and Hong, 2003). According to Erdenetsogt and Kallinterakis (2016), herding assumes that individuals follow the behavior of others without taking their own private information or prevailing market fundamentals into account.

One group of scholars argues that herding arises from the psychological biases of investors. Devenow and Welch (1996) and Lux (1995), for example, claim that herding occurs whenever investors do not consider their prior beliefs and blindly follow the trading strategies of other investors. Another group of researchers claim that herding can also take place among rational market participants. In this view, the knowledge that the actions of informed traders may reveal inside information induces outsiders to follow the investment strategies of these informed traders (Shleifer and Summers, 1990; Chari and Kehoe, 2004; Calvo and Mendoza, 2000).

A recent bibliometric study by Choijil *et al.* (2022) that examines the literature on herding behavior in financial markets over the last 30 years reveals significant research growth in this area but does not find consensus regarding the causes of the phenomenon. When the stock market is stressed by major events such as a financial crisis due to a pandemic, the study of herding behavior is particularly fruitful (see Chiang and Zheng, 2010; Chen *et al.*, 2012; Teng and Liu 2014; Sharma *et al.*, 2015) because of the high level of uncertainty and significant market fluctuations. The studies that have focused on the presence of herding behavior during the COVID-19 pandemic differ mainly in terms of the region or countries under study: Bouri *et al.* (2021) study 49 global markets; Kizys *et al.* (2021) consider 72 countries from both developed and emerging economies; Wu *et al.* (2020) focus on China; Luu and Luong (2020) analyze Taiwan and Vietnam; Espinosa and Arias (2021a, 2021b) look at Europe and Australia; Fang *et al.* (2021) study Eastern Europe; Wen *et al.* (2021) analyze Hong Kong; and Jabeen *et al.* (2021) evaluate markets in Pakistan. Most of these studies report the presence of herding behavior in the period they study during the COVID-19 pandemic.

2.2. Herding behavior in Chinese stock markets: empirical evidence

The results of the various studies on herding behavior in the Chinese stock markets undertaken before the COVID-19 pandemic are summarized in Table 1, and it is clear that they are not conclusive. Only one study, however, reports the absence of herding behavior in this market (Demirer and Kutan, 2006). The results obtained by Fu and Lin (2010) depend on the methodology used to test for herding behavior.

Zheng, Li, and Xiaowei (2015) suggest that herding activity is more pronounced for actively traded stocks. Investors with less experience and less information show stronger herding behavior, imitate the behavior of more sophisticated peers, and make decisions based on trends. Local Chinese investors, who can only invest in A-shares, often lack both knowledge and experience in investing in stock markets compared to foreign institutional investors and these characteristics may manifest in herd behavior. Nonparametric results have suggested strong presence of herd behavior in A-share stock trading (Mahmud and Tinic, 2017).

The most common methodology used to test for herding behavior was developed by Chang *et al.* (2000). This methodology has the advantage of detecting the nonlinear behavior of returns. Wu *et al.* (2020) do not employ this methodology to test herding behavior and report a lower level of herding activity during the COVID-19 pandemic in the Chinese stock market, when compared to other time periods. Jabeen *et al.* (2021), who do not detect herding behavior during the COVID-19 pandemic, look at the stock market as a whole, but when the data is split by economic sector herding behavior is detected in some sectors.

Most of the empirical studies from around the world report herding behavior in the period they study during the COVID-19 pandemic. We therefore expect to find herding behavior in the Chinese stock markets. We also expect herding activity to be more pronounced for A-type shares because they can only be traded by local, less experienced, and less knowledgeable investors, as opposed to foreign institutional investors, which may result in a proclivity for herd behavior.

TABLE I
PREVIOUS EMPIRICAL STUDIES ON HERDING BEHAVIOR IN THE CHINESE STOCK MARKETS

Author(s)	Method	Sample	Main Result (s)
Demirer and Kutan (2006)	CH	1999-2002	Herding does not exist
Tan *et al.* (2008)	CCK	1994-2003	Herding in dual listing market shares (A and B). Herding presence in both upper and lower extremes of Rmt
Fu and Lin (2010)	CH and CCK , state space model	2004-2009	Herding does not exist. However, the tendency for herding is more dominant in market downstream.
Chiang and Zheng (2010)	CCK	1988-2009	Herding exists in both in up and down markets. It is more profound in rising markets.
Chiang *et al.* (2010)	CCK and quantile regression	1996-2007	Herding only found in A-shares but not in B-shares using CCK method. When using quantile regression herding is found for both classes of shares
Lao and Singh (2011)	CCK	1999-2009	Herding in A-Shares and stronger when market falling and volume is high.
Chiang *et al.* (2012)	CCK, using rolling regressions	1996-2007	Herding in both A-Shares and B-Shares at firm and industry level.
Chiang *et al.* (2013)	CCK, using time varying coefficients	1997-2009	Time varying coefficients lead to stronger evidence of herding behavior.
Lee *et al.* (2013)	CCK	2011-2010	Industry herding in A-shares. Herding in bull and bear markets. High Tech sector is relevant.
Yao *et al.* (2014)	CH	1999-2008	Herding is stronger in B-shares, more prevalent at industry-level, greater for largest stocks, stronger for growth stocks. Stronger under declining markets
Chen *et al.* (2015)	CCK	1994-2013	Herding exists in Chinese stock market. It is stronger during The 2008 Global Financial Crisis period.
Xie *et al.* (2015)	WCSV (Weighted Cross-Sectional Variance)	2007-2008	Herding in Chinese A-shares long lasting with a decaying trend.
Sharma *et al.* (2015)	CCK	2007-2010	Herding in up and down markets. Herding is sector-specific and time-varying.
Hou *et al.* (2017)	CCK	2007-2010	Herding depending on high frequency data.
Chong *et al.* (2017)	CCK	2000-2011	Herding in up and down markets.
Li *et al.* (2017)	CCK, using time-varying coefficients	2006-2015	Herding in turbulent periods and not in others.
Mahmud and Tinic (2017)	Non-parametric kernel regressions	2003-2014	Herding is strong in A-shares and weak in B-shares.
Kabir and Shakur (2018)	Smooth transition regression	1995-2014	Herding is present in high volatility regimes as opposed to low return scenarios.
Chen and Ru (2019)	Simulated method of moments	2010-2018	Herding behavior in both large and small capitalization stocks.
Chen (2020)	CCK	2016-2019	Herding is present and it shows an increasing tendency.
Wu *et al.* (2020)	CH	June 3 2019 Oct. 12 2020	Herding behavior is lower during the COVID-19 period. Herding is more pronounced when markets return are high and volatility is low.

Note: CH = Christie and Huang (1995); CCK = Chang, Cheng and Khorona (Chang *et al.,* 2000).

Hypothesis 1. *Herding behavior occurs in Chinese stock markets.*

The COVID-19 virus produced a scenario unprecedented in the last 100 years and caused a different type of financial crisis, characterized by stock market falls and high volatility. This leads to the following hypothesis:

Hypothesis 2. *In the period after the COVID-19 event date, we expect stronger herding behavior in Chinese stock markets.*

Another interesting phenomenon to study is herding behavior asymmetry between bear and bull markets. Investors fear potential losses (loss aversion) when a market crashes more than they delight in the potential gains when the market is booming. McQueen *et al.* (1996) suggest that this can be explained by the fact that all stocks tend to respond quickly to negative macroeconomic news. Small stocks, however, tend to have a delayed reaction to positive macroeconomic news. It could also be argued that as markets suffer losses investors may be less likely to behave in a coordinated fashion because they are reluctant to realize immediate losses and, therefore, hesitate to sell their shares as stock prices drop (Statman *et al.*, 2006).

In the case of the Chinese stock market, some authors show that there is herding when the market is down (Fu and Lin, 2010; Lao and Singh, 2011; Yao *et al.*, 2014; Chen *et al.*, 2015) and others show that herding not only occurs in bull markets but also in bear markets (Tan *et al.*, 2008; Chiang and Zheng, 2010; Lee *et al.*, 2013; Sharma *et al.*, 2015; Chong *et al.* 2017; Chen, 2020). Wu *et al.* (2020) find more pronounced herding behavior in reaction to upside market movement during the COVID-19 period they study.

Hypothesis 3. *Asymmetric herding behavior exists in the Chinese stock market during both bull and bear markets*.

A group of studies, most of which do not include Chinese stock market data in their sample, analyze herding behavior in low and high volatility market regimes. Kabir and Shakur (2018), for example, study herding behavior in Asian and Latin American markets. They find no evidence of nonlinearity across market regimes in six countries (China, India, Malaysia, Singapore, Argentina, and Brazil). They also report that investors in most of the markets, except Argentina and Brazil, display herding behavior during high volatility regimes. Lam and Qiao (2015) test herding behavior at the market and industrial level in the Hong Kong stock market and find evidence for herding activity during a bull market, when the trading volume is high, as well as in both high and low volatility regimes. Vo and Phan (2019) analyze the effect of idiosyncratic volatility on the herding behavior of investors in the Vietnamese stock market. Using established models, proposed by Christie and Huang (1995) and Chang *et al.* (2000), and index return data for the period between 2005 and 2016, they report herding behavior and find distinct herding patterns under different stock portfolios depending on the levels of market volatility. Their results are robust throughout the whole sample period. Finally, Wu *et al.*(2020), in a paper that does include Chinese stock market data, report that herding behavior is more pronounced in lower market volatility regimes caused by COVID-19.

Based on these findings, we examine potential asymmetric effects of herding behavior with respect to volatility in market return and posit the following hypothesis:

Hypothesis 4. *Asymmetric herding behavior occurs in the Chinese stock market during high and low volatility regimes.*

3. Data and Methodology

The SHSE in Shanghai and the SZSE in Shenzhen, trade two types of shares: A-shares and B-shares. A-shares are very common, they are traded on both stock markets, and are denominated in Chinese Renminbi (RMB). Only Chinese nationals from mainland China and Qualified Foreign Institutional Investors (QFIIs) are permitted to trade A-shares. B-shares are Chinese stocks denominated in foreign currencies. On the SHSE, B-shares are denominated in US dollars (USD); B-shares that trade on the SZSE are denominated in Hong Kong dollars (HKD). The A-share market is larger than the B-share market, measured by number of shares, market capitalization, and trading volumes (Ng and Wu, 2006).

The majority of herding behavior studies have focused on the A-share markets in the SHSE and SZSE, and we also focus exclusively on A-shares, which means that our results are more comparable with the existing body of work on this subject. Furthermore, A-shares have a higher market capitalization, which means that they are more representative of the market, and they also have a larger trading volume, which means we are working with liquid stocks and that helps us to test CSAD without having a bias generated by illiquid stocks.

We collected data on stock prices (A-shares) for all firms listed on the SHSE and SZSE in the period between January 30, 2001, and June 12, 2020. Tan *et al.* (2008) report that frequency of the data used to study herding behavior matters and that herding activity is more evident when using daily data than weekly or monthly data. Accordingly, we use daily stock returns data calculated as $R_{it} = 100 \times (log(P_{it}) - log(P_{it-1}))$.

The computation of the return dispersion measure in Equation (1) requires the calculation of an average market portfolio return, $R_{m,t}$. Following the literature, we use the equally-weighted average of stock returns as a proxy for $R_{m,t}$. There are 426 firms in the SHSE and 199 firms in the SZSE giving a total 5,054 observations in the selected time window.

In terms of detecting herding behavior, the return dispersion method is an approach that is frequently used (Demirer and Kutam, 2006; Tan *et al.*, 2008; Lao and Singh, 2011; Mobarek *et al.*, 2014; Yao *et al.*, 2014). Chang *et al.*

(2000) use individual stock returns and market returns, as does Christie and Huang (1995), who also propose a cross-sectional standard deviation of returns (CSSD) model to detect herding activity in the market.

Christie and Huang (1995) and Chang *et al.* (2000) claim that during normal periods rational asset pricing models predict that the dispersion in returns will increase with the absolute value of the market return because investors are trading with their own private information, which is diverse. In periods when the market exhibits extreme movements, investors tend to subdue their own beliefs and are more likely to follow the market consensus, consistent with herding behavior. During these periods, increases in dispersion in returns can be observed but at a decreasing rate, showing a nonlinear behavior in the proxy for return dispersion. Although the cross-sectional standard deviation of returns (CSSD) model proposed by Christie and Huang is an intuitive measure to capture herd behavior, the authors recognize that the measure can be considerably affected by the existence of outliers. For this reason, Christie and Huang (1995) and Chang *et al.* (2000) both propose an alternative: the cross-sectional absolute deviation (CSAD) model. They differ, however, in the way they test for herding behavior: Christie and Huang analyze extreme returns, whereas Chang *et al.* (2000) introduce a methodology that includes the entire distribution of stock market returns. Several papers suggest that the Christie and Huang (1995) testing methodology is too strict and requires a far greater magnitude of nonlinearity to find evidence of herding (Gleason, *et al.*, 2004 and Tan *et al.*, 2008).

We adopt the CSAD methodology proposed by Chang *et al.* (2000) for two main reasons. First, the COVID-19 period under study in this paper can be characterized by a major stock market turbulence and the presence of outliers. The methodology used by Christie and Huang is less appropriate, therefore, because it is less able to capture the magnitude of nonlinearity. Chang *et al.* (2000), however, observe that herding is more likely to be present during periods of relatively large price shifts and suggest that fluctuations in investor sentiment related to investment activity may be reflected in the dispersions of cross-sectional stock returns. Second, most studies of herding behavior in the Chinese stock market employ CSAD methodology and, therefore, our results can be more easily compared with existing studies.

Chang, *et al.* (2000), Gleason *et al.* (2004), and Tan *et al.* (2008) suggest using the following CSAD model to facilitate the recognition of herding behavior over the entire distribution of market return (baseline model):

$$CSAD_t = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 \left(R_{m,t} \right)^2 + \varepsilon_t, \tag{1}$$

where $CSAD_t$ is a measure of return dispersion and $R_{m,t}$ is the equally-weighted average stock return in the portfolio (market return). We compute CSAD at time t as follows:

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

where $CSAD_t$ is a measure of average absolute return dispersion from $R_{m,t}$ to measure return dispersion. $|R_{m,t}|$ is the absolute value of market return and $R_{i,t}$ is the individual stock return of stock i. β_0 is the intercept and ε_t is an error term.

Because our study is based on the CSAD model, a statistically significant and negative coefficient β_2 would indicate the presence of herding behavior in the Chinese stock market. As β_1 out to be positive, it would indicate that a nonlinear model explains CSAD. Herding behavior is present as far as CSAD increases at a decreasing rate (β_2 has to be negative), which implies a lower dispersion and indicates that investors are mimicking the investment decisions of their peers.

We extend the baseline model to assess the effect of COVID-19 on herding behavior using the following specification of Equation (1):

$$CSDA_t = \gamma_0 + \gamma_1 D^{covid}\left|R_{m,t}\right| + \gamma_2 \left(1-D^{covid}\right)\left|R_{m,t}\right| + \gamma_3 D^{covid}(R_{m,t})^2 + \gamma_4\left(1-D^{covid}\right)(R_{m,t})^2 + \varepsilon_t. \tag{2}$$

Equation (2) is a modified version of Equation (1) and is used to assess the presence of herding behavior in the Chinese stock market before and after the COVID-19 event date (December 31, 2019). Significantly negative values for γ_3 and γ_4 would indicate the presence of herding behavior before and after the COVID-19 event date. The COVID-dummy (D^{covid}) equals 1 after December 31, 2019, and 0 before that date.

Equation (1) and Equation (2) enable the evaluation of Hypothesis 1 and Hypothesis 2, respectively. We then introduce three control variables that might affect CSAD. The first control variable is the stock return from a regional stock market index, the MSCI Asia Pacific, to account for the market integration among countries in the region. The second control variable considers the integration of the Chinese stock market with the rest of the world. We proxy this potential effect by including the stock returns from a global stock market index, the MSCI all country world index. The third control variable is the return on the exchange rate, which is included because of changes to the renminbi's exchange rate regime in 2015. Thus, we extend Equation (1) and run the following model:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2\,(R_{m,t})^2 + \beta_3\,R_{mregion,t} + \beta_4\,R_{mworld,t} + \beta_5\,R_{rexchrate,t} + \varepsilon_t. \tag{3}$$

By including the control variables, Equation (2) becomes Equation (4), which is expressed as follows:

$$CSDA_t = \gamma_0 + \gamma_1 D^{covid}\left|R_{m,t}\right| + \gamma_2\left(1-D^{covid}\right)\left|R_{m,t}\right| + \gamma_3 D^{covid}(R_{m,t})^2 + \gamma_4\left(1-D^{covid}\right)(R_{m,t})^2 + \gamma_5\,R_{mregion,t} + \gamma_6\,R_{mworld,t} + \gamma_7\,R_{rexchrate,t} + \varepsilon_t. \tag{4}$$

Equation (3) and Equation (4) also enable the evaluation of Hypothesis 1 and Hypothesis 2, respectively, including the control variables.

To check the robustness of the results we use four different time windows (2005.07.21-2020.06.12; 2010.01.04-2020.06.12; 2015.01.05-2020.06.12; and 2018.01.05-2020.06.12). These subsamples let us isolate important events such as the subprime mortgage crisis in 2008-09 and the major Chinese market turbulence in 2015-16. In the first month of the 2015-16 Chinese market turbulence, A-shares on the SHSE lost more than 30% of their market value and more than half of the listed companies (more than 1,400) stopped trading their stocks to prevent higher losses. Beginning on June 12, 2015, the turbulence ended in early February, 2016 and is therefore included in the 2015.01.05-2020.06.12 window. The time window subsamples allow us to compare the results that included the Chinese market turbulence with those obtained for the 2018.01.05-2020.06.12 time window, where the crisis is excluded.

In addition, we consider two effects from the literature (Tan *et al.*, 2008; Mobarek *et al.*, 2014; Batmunkh *et al.*, 2020) that can affect herding behavior: asymmetric effects of market return, and high and low volatility regimes. Because the direction of the market return may affect investor behavior (Tan *et al.*, 2008; Mobarek *et al.*, 2014), we are interested in detecting any asymmetry in herd behavior conditional on whether the market is upstreaming or downstreaming before and after the COVID-19 event date. And we also examine the asymmetric effects of herding behavior relating to the volatility of stock markets during the same time periods. We characterize market volatility as high when the observed volatility is higher than the moving average of volatility from the previous 30 days and as low when it is below the moving average of volatility from the previous 30 days. According to previous studies, a 30-day period is the most suitable to reveal volatility effects (Chang *et al.* 2000; Tan *et al.* 2008). The volatility in market return is calculated as the standard deviation of market daily return multiplied by the square root of the 252 trading days. Finally, we analyze if the increase in herding behavior is maintained after the COVID-19 event date using rolling window regression methodology. We build windows of 100, 200, 400, and 600 days to generate series of the estimated coefficients and especially analyze β_2 in Equation (1). For robustness we reestimate the models recursively.

4. Results and Discussion

Table 2 presents the descriptive statistics for the CSAD measure and the average market return, calculated using both equal weights for each stock market. The results show that mean values (1,433 and 1.440) and standard deviations (0.677 and 0.696) of CSAD are high in both the SHSE and the SZSE. A higher mean value suggests significantly higher market variations across stock returns. A higher standard deviation may indicate that markets have unusual cross-sectional variations due to unexpected events (Chiang and

Zheng, 2010). Similar to the results in Chang *et al.* (2000), we find first order autocorrelation of CSAD in both stock markets: 0.776 for the SHSE, and 0.732 for SZSE. In order to account for this, all standard errors of the estimated regression coefficients in subsequent tests are adjusted for heteroscedasticity and autocorrelation, based on the approach suggested by Newey and West (1987). Furthermore, the unit root (Dickey-Fuller) tests indicate that the CSAD series exhibits stationarity.

TABLE 2
DESCRIPTIVE STATISTICS AND UNIVARIATE TEST OF CSAD AND MARKET RETURN OF THE SHSE AND THE SZSE

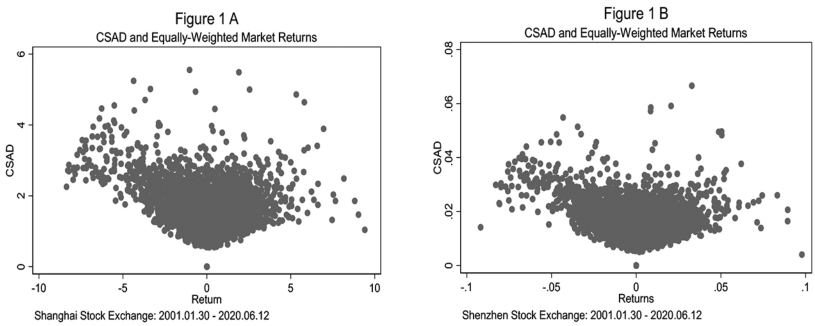
	SHSE		SZSE	
	CSAD	$R_{m,t}$	CSAD	$R_{m,t}$
N° Obs.	5054		5054	
Mean	1.433	0.201	1.440	0.028
Std. Dev.	0.677	1.72	0.696	1.677
Min	0	–8.35	0	–9.19
Max	5.553	9.41	6.661	9.78
Serial Correlation at Lag				
1	0.776	0.112	0.732	0.111
2	0.672	–0.005	0.638	–0.000
3	0.565	0.002	0.540	–0.000
4	0.510	0.042	0.463	0.028
5	0.497	0.060	0.482	0.052
20	0.362	0.013	0.350	0.020
DF-test	–16.547***	-40.954***	–16.687***	–41.3***

Table 3 reports the results of estimating the Equation (1) and Equation (2) for the SHSE and the SZSE. In Equation (1), $CSAD_t$ reaches its maximum value when $|R_{m,t}|^* = -\beta_1/(2\beta_2)$. That is, $|R_{m,t}|^* = 7.76\%$ for the SHSE and 7.33% for the SZSE. These outcomes suggest that, during large price movements in market returns that exceed the threshold level $|R_{m,t}|^*$, the $CSAD_t$ increases at a decreasing rate, as shown in Figure 1.

When $|R_{m,t}|$ increases over the range where realized average daily returns in absolute terms are less than $|R_{m,t}|^*$, the $CSAD_t$ exhibits an increasing trend. Conversely, when $|R_{m,t}|^*$ is greater than $|R_{m,t}|^*$, the return dispersion measure $CSAD_t$ starts to increase at a decreasing rate, which is captured by a significantly negative coefficient β_2. Thus, the nonlinear relationship between the market return and the return dispersion would indicate the occurrence of herding behavior. And a statistically significant and negative coefficient β_2 would indicate the presence of herding behavior. We detect herding behavior in both markets (the SHSE and

SZSE) because β_2 is significantly negative at the 1% level (–0.029 and –0.0332, respectively). This is consistent with previous empirical results from Tan *et al.* (2008), Lao and Sinh (2011), Chiang and Nelling (2013), and Yao *et al.* (2014), among others. The combined herding effect and linear relationship between $CSAD_t$ and $|Rm,|$ explain 33% on average of the total variation in $CSAD_t$. With these results, Hypothesis 1 is not rejected.

FIGURE 1
RELATIONSHIP BETWEEN THE DAILY CROSS-SECTIONAL ABSOLUTE DEVIATION $CSAD_{i,t}$ AND THE CORRESPONDING EQUALLY-WEIGHTED MARKET RETURN $R_{m,t}$



Equation (2) shows the effect of COVID-19 on herding behavior. We report a negative and statistically significant estimated coefficient (γ_3). The sizes of the coefficient capture the magnitudes of the herding behavior (Lao and Singh, 2011). Both γ_3 and γ_4 are statistically significant, but for different sizes. For the SHSE, γ_3 = –0.047 and γ_4 = –0.029, and for the SZSE, γ_3 = –0.0605 and γ_4 = –0.0315. In summary, we find herding behavior before and after the COVID-19 event date, and the results show an asymmetric herding behavior that is more pronounced in the period between December 31, 2019, and June 12, 2020, the period of the COVID-19 pandemic considered in this study. With these results, we do not reject Hypothesis 2.

Table 4 reports the results of estimating Equation (3) and Equation (4) for the SHZE and the SZSE. We find results consistent with herding behavior: β_2 is –0.027 for the SHSE and –0.031 the SZSE in Equation (3); and γ_3 is –0.054 for the SHSE and -0.039 for the SZSE in Equation (4). We also observe that regional stock return has a significant a negative impact on CSAD. When the control variables are included, the results do not change, which do not reject Hypothesis 1 and Hypothesis 2.

TABLE 3

ESTIMATES OF HERDING BEHAVIOR IN THE FULL SAMPLE PERIOD

Equation 1	β_0	β_1	β_2			R-squared		
SHSE	1.000*** (0.0129)	0.449*** (0.0142)	–0.029*** (0.00253)			0.33		
SZSE	0.975*** (0.0133)	0.487*** (0.0147)	-0.0332*** (0.00265)			0.341		
Equation 2	γ_0	γ_2	γ_2	γ_3	γ_4	R-squared	t-stat (H0:	t-stat (H0:)
SHSE	1.000*** (0.0129)	0.528*** (0.0604)	0.447*** (0.0143)	–0.047*** (0.0127)	–0.029*** (0.00256)	0.33	–60,375***	–27,983***
SZSE	0.977*** (0.0133)	0.550*** (0.0570)	0.481*** (0.0149)	–0.061*** (0.0105)	–0.032*** (0.00270)	0.343	–61,333***	–27,859***

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4
ESTIMATES OF HERDING BEHAVIOR IN THE FULL SAMPLE PERIOD
WITH CONTROL VARIABLES

Equation 3	$\beta 0$	$\beta 1$	$\beta 2$	$\beta 3$	$\beta 4$	$\beta 5$			R-squared		
SHSE	1.085***	0.438***	–0.027***	–0.121***	0.003	–0.036			0.343		
	(0.018)	(0.018)	(0.003)	(0.023)	(0.023)	(0.139)					
SZSE	1.057***	0.482***	–0.031***	–0.114***	0.003	–0.157			0.362		
	(0.018)	(0.019)	(0.003)	(0.023)	(0.024)	(0.130)					
Equation 4	$\Upsilon 0$	$\Upsilon 1$	$\Upsilon 2$	$\Upsilon 3$	$\Upsilon 4$	$\Upsilon 5$	$\Upsilon 6$	$\Upsilon 7$	R-squared	t–stat1 (H0: $\Upsilon 1=\Upsilon 2$)	t–stat1 (H0: $\Upsilon 3=\Upsilon 4$)
SHSE	1.085***	0.455***	0.437***	–0.039***	–0.027***	–0.121***	0.003	–0.030	0.343	299.5***	42.55***
	(0.018)	(0.045)	(0.018)	(0.011)	(0.003)	(0.023)	(0.023)	(0.139)			
SZSE	1.060***	0.484***	0.475***	–0.054***	–0.029***	–0.113***	0.001	–0.136	0.365	330.2***	53.11***
	(0.018)	(0.042)	(0.019)	(0.009)	(0.003)	(0.023)	(0.023)	(0.128)			

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5. Robustness

In this section, we explore whether the results presented in Section 4 change when the sample is split into several different time windows, analyze whether any change is produced by high and low market regimes, and use rolling window methodology to observe changes in herding behavior after the COVID-19 event.

5.1. Time Windows

We split the sample into four different time windows to evaluate whether or not herding activity depends on the particular time window chosen. Thus, we estimate Equation (2) for the period 2005.07.21-2020.06.12 (column 1), 2010.01.04-2020.06.12 (column 2), 2015.01.05-2020.06.12 (column 3), and 2018.01.05-2020.06.12 (column 4). Table 5.1 reports the results. Panel A shows the results for the SHSE and Panel B for the SZSE. In all cases, the results show a negative and significant γ_3, confirming herding behavior during the period of COVID-19 under study. On the other hand, because γ_3 is greater than γ_4, we can conclude that herding behavior is stronger during COVID-19. Furthermore, when we include the control variables (Equation 4) results do not change, as shown in Table 5.2.

5.2. Market Regimes

We now consider two effects from the literature that may impact herding behavior: asymmetric effects of market return and high and low volatility regimes. Accordingly, we concentrate on the results from Equation (2) and Equation (4).

Table 6.1 shows the results regarding Equation (2) for SHSE, and Table 6.2 shows the results for SZSE. In both tables, Panel A corresponds to the period 2001.01.30-2020.06.12, Panel B to the period 2010.01.04-2020.06.12, Panel C to the period 2015.01.05-2020.06.12; and Panel D to the period 2018.01.05-2020.06.12. In each panel, Columns (1) and (2) show the results for $R_{m,t} > 0$ (bull market) and $R_{m,t} < 0$ (bear market), respectively; and Columns (3) and (4) show the results for $\sigma^{HIGH} > \sigma^{MA}{}_{t-30}$ (high volatility) and $\sigma^{LOW} < \sigma^{MA}{}_{t-30}$ (low volatility), respectively.

With respect to the results showing the asymmetric effects of market return, we observe herding behavior in both bull and bear markets ($R_{m,t} > 0$ and $R_{m,t} < 0$). In a bull market, the impact is higher on the CSAD compared to a bear market across all time windows. The absolute magnitude of γ_3 for the SHSE (Table 6.1, Panel A) is 0.112 (in a bull market) and 0.078 (in a bear market), and for the SZSE (Table 6.2, Panel A) the absolute magnitude of γ_3 is 0.150 (bull market) and 0.07 (bear market). These results are consistent with Yao, Ma, and He (2014) who report that return dispersions are often lower during extreme negative market movements. In addition, $\gamma_3 > \gamma_4$ (absolute value) in the SHSE and the SZSE, which implies that herding behavior is stronger after December 31, 2019 (the COVID-19 event date). Different time windows show similar results

TABLE 5.1
TIME WINDOW ESTIMATIONS
(EQUATION 2 FOR BOTH STOCK MARKETS)

Panel A					Panel B				
SHSE	2005-2020	2010-2020	2015-2020	2018-2020	SZSE	2005-2020	2010-2020	2015-2020	2018-2020
	1	2	3	4		1	2	3	4
$\Upsilon 0$	1.082***	1.019***	0.978***	1.056***	$\Upsilon 0$	1.057***	1.003***	1.000***	1.047***
	(0.018)	(0.019)	(0.026)	(0.037)		(0.018)	(0.020)	(0.027)	(0.039)
$\Upsilon 1$	0.459***	0.513***	0.548***	0.481***	$\Upsilon 1$	0.489***	0.530***	0.533***	0.497***
	(0.045)	(0.047)	(0.051)	(0.052)		(0.039)	(0.042)	(0.044)	(0.046)
$\Upsilon 2$	0.435***	0.369***	0.482***	0.315***	$\Upsilon 2$	0.474***	0.400***	0.468***	0.319***
	(0.019)	(0.023)	(0.033)	(0.044)		(0.019)	(0.026)	(0.037)	(0.044)
$\Upsilon 3$	–0.038***	–0.045***	–0.049***	–0.041***	$\Upsilon 3$	–0.054***	–0.058***	–0.059***	–0.055***
	(0.009)	(0.011)	(0.011)	(0.010)		(0.008)	(0.008)	(0.009)	(0.008)
$\Upsilon 4$	–0.026***	–0.009**	–0.022***	–0.017*	$\Upsilon 4$	–0.028***	–0.012**	–0.019***	–0.024**
	(0.003)	(0.005)	(0.006)	(0.009)		(0.003)	(0.006)	(0.007)	(0.010)
Obs.	3,887	2,725	1,420	636	Obs.	3,887	2,725	1,420	636
R-squared	0.336	0.365	0.450	0.256	R-squared	0.359	0.351	0.403	0.237
t-stat1 ($H0{:}\Upsilon 1=\Upsilon 2$)	284.6***	155.5***	127.3***	47.39***	t-stat1 ($H0{:}\Upsilon 1=\Upsilon 2$)	316.2***	159.4***	115.3***	59.37***
t-stat1 ($H0{:}\Upsilon 3=\Upsilon 4$)	37.7***	10.22***	14.81***	8.143***	t-stat1 ($H0{:}\Upsilon 3=\Upsilon 4$)	51.79***	24.88***	24.74***	22.53***

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 5.2
TIME WINDOW ESTIMATIONS
(EQUATION 4 FOR BOTH STOCK MARKETS)

SHSE	2005-2020	2010-2020	2015-2020	2018-2020	SZSE	2005-2020	2010-2020	2015-2020	2018-2020
	1	2	3	4		1	2	3	4
$\Upsilon 0$	1.085***	1.020***	0.978***	1.054***	$\Upsilon 0$	1.059***	1.003***	0.999***	1.045***
	(0.018)	(0.019)	(0.026)	(0.038)		(0.018)	(0.020)	(0.027)	(0.040)
$\Upsilon 1$	0.456***	0.515***	0.550***	0.487***	$\Upsilon 1$	0.485***	0.533***	0.535***	0.502***
	(0.045)	(0.047)	(0.051)	(0.052)		(0.042)	(0.043)	(0.046)	(0.047)
$\Upsilon 2$	0.437***	0.373***	0.487***	0.320***	$\Upsilon 2$	0.476***	0.404***	0.475***	0.321***
	(0.018)	(0.023)	(0.033)	(0.044)		(0.019)	(0.026)	(0.037)	(0.045)
$\Upsilon 3$	–0.039***	–0.047***	–0.051***	–0.043***	$\Upsilon 3$	–0.054***	–0.060***	–0.060***	–0.056***
	(0.011)	(0.011)	(0.012)	(0.011)		(0.009)	(0.009)	(0.009)	(0.008)
$\Upsilon 4$	–0.027***	–0.011**	–0.024***	–0.019**	$\Upsilon 4$	–0.029***	–0.013**	–0.021***	–0.025**
	(0.003)	(0.005)	(0.006)	(0.009)		(0.003)	(0.006)	(0.007)	(0.010)
$\Upsilon 5$	–0.122***	–0.134***	–0.143***	–0.098*	$\Upsilon 5$	–0.114***	–0.134***	–0.140**	–0.053
	(0.023)	(0.032)	(0.053)	(0.059)		(0.023)	(0.033)	(0.056)	(0.056)
$\Upsilon 6$	0.003	0.033	0.029	0.023	$\Upsilon 6$	0.001	0.041	0.040	0.033
	(0.023)	(0.026)	(0.040)	(0.042)		(0.023)	(0.028)	(0.042)	(0.041)
$\Upsilon 7$	–0.030	0.138	0.106	0.224	$\Upsilon 7$	–0.136	–0.010	–0.056	0.113
	(0.139)	(0.142)	(0.158)	(0.217)		(0.128)	(0.127)	(0.139)	(0.200)
Obs.	3.887	2.724	1.420	636	Obs.	3.887	2.724	1.420	636
R-squared	0.343	0.372	0.455	0.262	R-squared	0.365	0.356	0.407	0.239
t-stat1 (H0: $\Upsilon 1=\Upsilon 2$)	297.8***	155.6***	127.7***	48.78***	t-stat1 (H0: $\Upsilon 1=\Upsilon 2$)	330***	157.2***	112.3***	58.94***
t-stat1 (H0: $\Upsilon 3=\Upsilon 4$)	42.50***	10.29***	14.95***	8.594***	t-stat1 (H0: $\Upsilon 3=\Upsilon 4$)	53.42***	22.52***	22.10***	22.89***

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6.1
MARKET REGIMES (EQUATION 2 FOR THE SHANGHAI STOCK EXCHANGE, SHSE)

	Panel A: Period 2001.01.30-2020.06.12				Panel B: Period 2005.07.21-2020.06.12				Panel C: Period 2010.01.04-2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$
$\Upsilon 0$	1.239***	0.813***	1.054***	0.963***	1.340***	0.881***	1.171***	1.037***	1.296***	0.832***	1.052***	0.977***
	(0.017)	(0.020)	(0.025)	(0.019)	(0.020)	(0.025)	(0.033)	(0.022)	(0.019)	(0.026)	(0.035)	(0.025)
$\Upsilon 1$	0.433***	0.803***	0.423***	0.764***	0.290***	0.747***	0.341***	0.670***	0.351***	0.788***	0.424***	0.747***
	(0.104)	(0.080)	(0.053)	(0.091)	(0.100)	(0.077)	(0.052)	(0.088)	(0.100)	(0.080)	(0.055)	(0.092)
$\Upsilon 2$	0.204***	0.669***	0.455***	0.442***	0.151***	0.705***	0.447***	0.410***	–0.016	0.644***	0.409***	0.432***
	(0.024)	(0.021)	(0.025)	(0.029)	(0.029)	(0.024)	(0.028)	(0.030)	(0.032)	(0.028)	(0.035)	(0.043)
$\Upsilon 3$	–0.112**	–0.078***	–0.030***	–0.123***	–0.073*	–0.071***	–0.021***	–0.104***	–0.090**	–0.076***	–0.031***	–0.120***
	(0.044)	(0.014)	(0.008)	(0.033)	(0.041)	(0.013)	(0.007)	(0.031)	(0.042)	(0.014)	(0.008)	(0.033)
$\Upsilon 4$	–0.009	–0.053***	–0.030***	–0.040***	0.004	–0.059***	–0.029***	–0.034***	0.053***	–0.047***	–0.015***	–0.058***
	(0.006)	(0.003)	(0.004)	(0.008)	(0.007)	(0.004)	(0.004)	(0.008)	(0.009)	(0.005)	(0.006)	(0.014)
Obs .	2,570	2,484	2,487	2,567	2,065	1,822	1,795	2,092	1,409	1,316	1,189	1,536
R-squared	0.131	0.489	0.331	0.259	0.133	0.504	0.330	0.250	0.212	0.519	0.397	0.230
t-stat1 (H0: $\Upsilon 1=\Upsilon 2$)	40.62***	530.6***	177.8***	129.4	15.77***	426.4***	123.9***	102.4***	6.696***	267.2***	77.55***	64.49***
t-stat1 (H0: $\Upsilon 3=\Upsilon 4$)	4.100**	145.4***	31.38***	16.84***	1.863	144.2***	24.45***	13.71***	18.85***	60.91***	8.984***	13.01***

	Panel D: Period 2015.01.05-2020.06.12				Panel E: Period 2018.01.05-2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$
$\Upsilon 0$	1.211***	0.802***	1.102***	0.915***	1.296***	0.867***	1.089***	0.988***
	(0.028)	(0.036)	(0.048)	(0.033)	(0.036)	(0.052)	(0.055)	(0.061)
$\Upsilon 1$	0.474***	0.812***	0.389***	0.826***	0.353***	0.759***	0.398***	0.733***
	(0.107)	(0.085)	(0.057)	(0.099)	(0.099)	(0.087)	(0.059)	(0.115)
$\Upsilon 2$	0.144***	0.760***	0.482***	0.441***	0.021	0.587***	0.337***	0.368***
	(0.044)	(0.044)	(0.047)	(0.059)	(0.054)	(0.055)	(0.056)	(0.111)
$\Upsilon 3$	–0.124***	–0.079***	–0.027***	–0.136***	–0.090**	–0.072**	–0.028***	–0.117***
	(0.045)	(0.014)	(0.008)	(0.036)	(0.041)	(0.014)	(0.008)	(0.036)
$\Upsilon 4$	0.031***	–0.059***	–0.025***	–0.050**	0.010	–0.050***	–0.020*	–0.076**
	(0.011)	(0.006)	(0.007)	(0.020)	(0.014)	(0.009)	(0.011)	(0.035)
Obs .	734	686	694	726	307	329	371	265
R-squared	0.305	0.588	0.436	0.271	0.070	0.443	0.265	0.233
t-stat1 (H0: $\Upsilon 1=\Upsilon 2$)	12.55***	161***	55.38***	46.24***	6.326***	67.48***	27.42***	20.59***
t-stat1 (H0: $\Upsilon 3=\Upsilon 4$)	8.539***	51.95***	9.123***	9.138***	2.713*	22.73***	6.125***	5.960***

TABLE 6.2
MARKET REGIMES (EQUATION 2 FOR THE SHENZHEN STOCK EXCHANGE, SZSE)

	Panel A: Period 2001.01.30-2020.06.12				Panel B: Period 2005.07.21-2020.06.12				Panel C: Period 2010.01.04-2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$
$\Upsilon 0$	1.191***	0.809***	1.018***	0.951***	1.297***	0.871***	1.122***	1.022***	1.281***	0.832***	1.031***	0.960***
	(0.018)	(0.021)	(0.026)	(0.020)	(0.020)	(0.025)	(0.031)	(0.023)	(0.022)	(0.027)	(0.036)	(0.027)
$\Upsilon 1$	0.609***	0.673***	0.479***	1.132***	0.462***	0.629***	0.412***	1.008***	0.483***	0.657***	0.471***	1.117***
	(0.113)	(0.066)	(0.043)	(0.131)	(0.108)	(0.064)	(0.042)	(0.127)	(0.109)	(0.066)	(0.045)	(0.133)
$\Upsilon 2$	0.275***	0.672***	0.497***	0.465***	0.218***	0.718***	0.494***	0.446***	0.006	0.653***	0.446***	0.468***
	(0.027)	(0.023)	(0.027)	(0.032)	(0.027)	(0.027)	(0.029)	(0.033)	(0.042)	(0.033)	(0.038)	(0.047)
$\Upsilon 3$	–0.150***	–0.070***	–0.051***	–0.380***	–0.112***	–0.066***	–0.044***	–0.337***	–0.117***	–0.069***	–0.050***	–0.374***
	(0.043)	(0.009)	(0.007)	(0.070)	(0.039)	(0.009)	(0.006)	(0.066)	(0.040)	(0.009)	(0.007)	(0.071)
$\Upsilon 4$	–0.017***	–0.051***	–0.034***	–0.041***	–0.002	–0.057***	–0.031***	–0.037***	0.059***	–0.046***	–0.018***	–0.068***
	(0.007)	(0.004)	(0.005)	(0.009)	(0.007)	(0.004)	(0.004)	(0.009)	(0.014)	(0.006)	(0.007)	(0.017)
Obs .	2,556	2,498	2,503	2,551	2,041	1,846	1,862	2,025	1,381	1,344	1,225	1,500
R-squared	0.165	0.481	0.342	0.269	0.171	0.510	0.357	0.269	0.216	0.484	0.366	0.237
t-stat1 (H0: $\Upsilon 1=\Upsilon 2$)	57.85***	440.5***	182.9***	122.4***	37.24***	374.6***	154.5	102.9***	10.08***	214.7***	89.02***	64.48***
t-stat1 (H0: $\Upsilon 3=\Upsilon 4$)	8.767***	109.5***	44.29***	21.97***	4.050***	114.2***	42.32***	19.73***	14.57***	52.67***	26.76***	19.43***

	Panel D: Period 2015.01.05-2020.06.12				Panel E: Period 2018.01.05-2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$
$\Upsilon 0$	1.259***	0.830***	1.118***	0.920***	1.289***	0.879***	1.081***	0.937***
	(0.030)	(0.038)	(0.050)	(0.036)	(0.035)	(0.054)	(0.057)	(0.066)
$\Upsilon 1$	0.514***	0.658***	0.415***	1.189***	0.472***	0.624***	0.439***	1.158***
	(0.114)	(0.069)	(0.047)	(0.143)	(0.114)	(0.071)	(0.050)	(0.172)
$\Upsilon 2$	0.093*	0.739***	0.469***	0.482***	0.023	0.551***	0.320***	0.491***
	(0.053)	(0.052)	(0.051)	(0.064)	(0.049)	(0.059)	(0.057)	(0.118)
$\Upsilon 3$	–0.125***	–0.069***	–0.044***	–0.399***	–0.115***	–0.065***	–0.047***	–0.389***
	(0.041)	(0.009)	(0.007)	(0.075)	(0.041)	(0.009)	(0.007)	(0.081)
$\Upsilon 4$	0.046***	–0.055***	–0.022**	–0.070***	0.015	–0.050***	–0.024**	–0.111***
	(0.017)	(0.008)	(0.008)	(0.022)	(0.013)	(0.010)	(0.011)	(0.040)
Obs .	722	698	717	703	299	337	380	256
R-squared	0.279	0.524	0.377	0.261	0.157	0.357	0.233	0.252
t-stat1 (H0: $\Upsilon 1=\Upsilon 2$)	10.37***	116.8***	53.38***	45***	8.844***	57.08***	39.17***	22.72***
t-stat1 (H0: $\Upsilon 3=\Upsilon 4$)	9.938***	42.81***	23.10***	16.46***	5.211***	30.57***	22.86***	11.99***

(Panel, B, C, D and E) in Tables 6.1 and 6.2. We cannot reject Hypothesis 3. And we can say, therefore, that we find that herding behavior before and after the COVID-19 event date and that herding behavior is stronger during down market regimes than up market scenarios.

One potential explanation for an asymmetry in herding activity between bull and bear markets might be the flow of positive and negative information. If the market is booming, it is possible to find more buy than sell recommendations. If investors make decisions based on these recommendations, then we should observe stronger herding behavior in bull markets than in bear markets. Another possibility is the common belief in the market that the government will intervene when markets decline significantly, which makes herding behavior less likely when markets fall. It may also be the case that investors are more focused on big companies in bull markets when they engage in herding activity. Due to loss aversion, investors may be less likely to act in a coordinated manner in a downward trending market because they are unwilling to assume immediate losses, and they therefore avoid selling their shares as market prices fall (Statman, Thorley, and Vorkink, 2006). Empirical results are consistent with more pronounced herding behavior in rising markets as opposed to falling markets. Moreover, Duffee (2001) finds that aggregate trading volume tends to be higher on days when the stock market rises than on days when it falls. Finally, Seetharam and Britten (2013) argue that this type of investor behavior may be due to quicker responses to any type of news in a down market, and because low-market investors become under confident and try to follow market fundamentals instead of trends.

The results for herding behavior under high and low volatility states are conclusive. In Table 6.1 and Table 6.2 (Panel A) the estimates for γ_3 are greater during low volatility states (in absolute terms). And these results hold across the other time windows. In addition, $\gamma_3 > \gamma_4$ (in absolute value) in both the SHSE and the SZSE. This shows that herding behavior increases after the COVID-19 event date. The difference between the γ_3 and γ_4 estimates is statistically significant in all cases. When comparing high volatility and low volatility states, it becomes clear that herding behavior is stronger in a low volatility state, regardless of the time window. We can say, therefore, that herding behavior is more pronounced in lower levels of volatility and after the COVID-19 event date, and Hypothesis 4 cannot be rejected.

Chiang *et al.* (2013) report similar results using a time-varying coefficients model. Herding is positively related to state of market return but negatively related to market volatility. Our results are consistent with more pronounced herding behavior in bull markets and in low volatility regimes before and after the COVID-19 event date. Low volatility might be associated with a higher level of agreement in the market regarding the quality of stocks; therefore, it is more likely that investors will coincide in their appraisals of investment decisions. Something similar happens with analysts. In low volatility regimes, analysts give more similar advice on which investors tend to rely, which makes herding behavior more likely.

To check the robustness of our results, we estimate Equation (4) including the control variables. The results for the SHSE are reported in the Table 7.1, and

TABLE 7.1

MARKET REGIMES (EQUATION 4 FOR THE SHANGHAI STOCK EXCHANGE, SHSE)

	Panel A: Period 2001.01.30-2020.06.12				Panel B: Period 2005.07.21-2020.06.12				Panel C: Period 2010.01.04-2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t-30}$	$\sigma^{HIGH} < \sigma^{MA}_{t-30}$
Ɣ0	1.344***	0.879***	1.173***	1.038***	1.343***	0.878***	1.172***	1.038***	1.298***	0.828***	1.050***	0.977***
	(0.020)	(0.025)	(0.033)	(0.022)	(0.020)	(0.025)	(0.033)	(0.022)	(0.019)	(0.027)	(0.035)	(0.026)
Ɣ1	0.336***	0.794***	0.341***	0.687***	0.336***	0.795***	0.341***	0.687***	0.395***	0.862***	0.431***	0.765***
	(0.095)	(0.080)	(0.049)	(0.087)	(0.095)	(0.081)	(0.050)	(0.087)	(0.093)	(0.085)	(0.053)	(0.090)
Ɣ2	0.160***	0.714***	0.449***	0.417***	0.161***	0.716***	0.450***	0.417***	0.001	0.657***	0.416***	0.438***
	(0.027)	(0.025)	(0.028)	(0.030)	(0.027)	(0.025)	(0.028)	(0.030)	(0.033)	(0.029)	(0.035)	(0.043)
Ɣ3	–0.072*	–0.076***	–0.023***	–0.114***	–0.073*	–0.076***	–0.023***	–0.114***	–0.088**	–0.084***	–0.034***	–0.128***
	(0.039)	(0.013)	(0.008)	(0.030)	(0.039)	(0.013)	(0.008)	(0.030)	(0.039)	(0.014)	(0.009)	(0.032)
Ɣ4	0.006	–0.059***	–0.030***	–0.037***	0.005	–0.059***	–0.030***	–0.037***	0.052***	–0.047***	–0.018***	–0.062***
	(0.007)	(0.003)	(0.004)	(0.008)	(0.007)	(0.004)	(0.004)	(0.008)	(0.010)	(0.005)	(0.006)	(0.015)
Ɣ5	–0.158***	0.094***	–0.112***	–0.148***	–0.160***	0.094***	–0.113***	–0.148***	–0.166***	0.087*	–0.153***	–0.135***
	(0.030)	(0.036)	(0.031)	(0.031)	(0.030)	(0.037)	(0.031)	(0.031)	(0.040)	(0.050)	(0.051)	(0.035)
Ɣ6	–0.014	–0.015	–0.005	0.022	–0.014	–0.015	–0.005	0.022	0.002	0.033	0.031	0.045
	(0.028)	(0.034)	(0.032)	(0.031)	(0.028)	(0.034)	(0.032)	(0.031)	(0.031)	(0.039)	(0.041)	(0.033)
Ɣ7	0.034	–0.117	0.128	–0.229**	0.035	–0.117	0.128	–0.229**	0.323*	0.041	0.356	–0.093
	(0.174)	(0.235)	(0.215)	(0.116)	(0.174)	(0.235)	(0.215)	(0.116)	(0.176)	(0.239)	(0.238)	(0.104)
Obs .	2,070	1,835	1,813	2,092	2,065	1,822	1,795	2,092	1,408	1,316	1,189	1,535
R-squared	0.153	0.507	0.337	0.260	0.153	0.507	0.337	0.260	0.231	0.522	0.405	0.239
t-stat1 (H0: Ɣ1=Ɣ2)	20.95***	427.5***	131.3***	108.3***	21.17***	422.6***	130.2***	108.3***	9.302***	267.9***	80.25***	67.02***
t-stat1 (H0: Ɣ3=Ɣ4)	2.274	147.8***	27.95***	16.99***	2.262	147***	28.03***	16.99***	18.78***	65.51***	10.43***	14.95***

	PanelD:Period2015.01.05–2020.06.12				PanelE:Period2018.01.05–2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH}>\sigma^{MA}_{t-30}$	$\sigma^{HIGH}<\sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH}>\sigma^{MA}_{t-30}$	$\sigma^{HIGH}<\sigma^{MA}_{t-30}$
Ɣ0	1.215***	0.799***	1.095***	0.914***	1.295***	0.865***	1.083***	0.982***
	(0.028)	(0.036)	(0.048)	(0.033)	(0.037)	(0.051)	(0.055)	(0.062)
Ɣ1	0.537***	0.898***	0.398***	0.849***	0.375***	0.891***	0.407***	0.753***
	(0.099)	(0.097)	(0.056)	(0.096)	(0.098)	(0.106)	(0.058)	(0.117)
Ɣ2	0.161***	0.778***	0.494***	0.448***	0.035	0.622***	0.347***	0.373***
	(0.047)	(0.044)	(0.048)	(0.059)	(0.064)	(0.056)	(0.058)	(0.111)
Ɣ3	–0.125***	–0.088***	–0.030***	–0.142***	–0.085**	–0.087***	–0.031***	–0.117***
	(0.041)	(0.015)	(0.009)	(0.034)	(0.039)	(0.015)	(0.009)	(0.034)
Ɣ4	0.031***	–0.059***	–0.028***	–0.053***	0.009	–0.049***	–0.025**	–0.079**
	(0.011)	(0.006)	(0.007)	(0.020)	(0.014)	(0.009)	(0.011)	(0.035)
Ɣ5	–0.234***	0.164**	–0.159*	–0.115**	–0.108	0.250**	–0.130	–0.032
	(0.073)	(0.078)	(0.083)	(0.053)	(0.081)	(0.098)	(0.086)	(0.078)
Ɣ6	0.026	–0.026	–0.003	0.095*	0.002	–0.029	–0.016	0.101
	(0.056)	(0.053)	(0.060)	(0.048)	(0.053)	(0.059)	(0.056)	(0.062)
Ɣ7	0.316	0.059	0.269	–0.081	0.521*	–0.080	0.295	0.027
	(0.194)	(0.271)	(0.258)	(0.110)	(0.305)	(0.228)	(0.300)	(0.248)
Obs .	734	686	694	726	307	329	371	265
R-squared	0.325	0.592	0.444	0.279	0.100	0.460	0.281	0.244
t-stat1 (H0: Ɣ1=Ɣ2)	16.80***	163.8***	57.91***	49.53***	7.728***	68***	29.83***	21.09***
t-stat1 (H0: Ɣ3=Ɣ4)	19.549***	55.67***	10.44***	10.89***	2.688*	24.91***	7.136***	6.525***

TABLE 7.2

MARKET REGIMES (EQUATION 4 FOR THE SHENZHEN STOCK EXCHANGE, SZSE)

	Panel A: Period 2001.01.30-2020.06.12				Panel B: Period 2005.07.21-2020.06.12				Panel C: Period 2010.01.04-2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t\text{-}30}$	$\sigma^{HIGH} < \sigma^{MA}_{t\text{-}30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t\text{-}30}$	$\sigma^{HIGH} < \sigma^{MA}_{t\text{-}30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH} > \sigma^{MA}_{t\text{-}30}$	$\sigma^{HIGH} < \sigma^{MA}_{t\text{-}30}$
ϒ0	1.301***	0.872***	1.125***	1.023***	1.301***	0.869***	1.122***	1.023***	1.284***	0.827***	1.024***	0.961***
	(0.019)	(0.025)	(0.031)	(0.023)	(0.019)	(0.025)	(0.031)	(0.023)	(0.022)	(0.027)	(0.036)	(0.027)
ϒ1	0.496***	0.651***	0.404***	1.006***	0.498***	0.653***	0.406***	1.006***	0.529***	0.720***	0.475***	1.122***
	(0.106)	(0.069)	(0.044)	(0.132)	(0.106)	(0.069)	(0.044)	(0.132)	(0.104)	(0.077)	(0.048)	(0.137)
ϒ2	0.224***	0.719***	0.494***	0.454***	0.226***	0.721***	0.497***	0.454***	0.022	0.661***	0.455***	0.472***
	(0.025)	(0.027)	(0.028)	(0.032)	(0.025)	(0.027)	(0.028)	(0.032)	(0.042)	(0.033)	(0.039)	(0.047)
ϒ3	–0.110***	–0.067***	–0.044***	–0.331***	–0.110***	–0.067***	–0.044***	–0.331***	–0.116***	–0.075***	–0.052***	–0.374***
	(0.038)	(0.009)	(0.007)	(0.073)	(0.038)	(0.009)	(0.007)	(0.073)	(0.037)	(0.010)	(0.008)	(0.078)
ϒ4	–0.000	–0.057***	–0.032***	–0.040***	–0.000	–0.057***	–0.033***	–0.040***	0.059***	–0.047***	–0.021***	–0.071***
	(0.006)	(0.004)	(0.004)	(0.008)	(0.006)	(0.004)	(0.004)	(0.008)	(0.014)	(0.006)	(0.007)	(0.016)
ϒ5	–0.117***	0.021	–0.111***	–0.124***	–0.119***	0.020	–0.113***	–0.124***	–0.160***	0.023	–0.162***	–0.112***
	(0.032)	(0.038)	(0.031)	(0.032)	(0.032)	(0.038)	(0.031)	(0.032)	(0.041)	(0.055)	(0.050)	(0.037)
ϒ6	–0.032	0.022	0.007	–0.004	–0.032	0.023	0.008	–0.004	–0.009	0.075*	0.057	0.034
	(0.030)	(0.034)	(0.030)	(0.034)	(0.030)	(0.034)	(0.030)	(0.034)	(0.033)	(0.042)	(0.039)	(0.036)
ϒ7	–0.025	–0.312*	–0.007	–0.278**	–0.025	–0.312*	–0.007	–0.278**	0.187	–0.165	0.164	–0.169
	(0.162)	(0.185)	(0.190)	(0.126)	(0.162)	(0.185)	(0.191)	(0.126)	(0.160)	(0.183)	(0.201)	(0.116)
Obs .	2,046	1,859	1,880	2,025	2,041	1,846	1,862	2,025	1,381	1,344	1,225	1,500
R-squared	0.182	0.511	0.362	0.277	0.183	0.511	0.363	0.277	0.228	0.487	0.373	0.243
t-stat1 (H0: ϒ1=ϒ2)	45.50***	364.6***	159.8***	107.4***	46.16***	362.3***	160***	107.4***	13.20***	205.2***	88.17***	65.28***
t-stat1 (H0: ϒ3=ϒ4)	4.214**	113***	41.42***	19.30***	4.231***	113.1***	41.91***	19.30***	14.93***	53.71***	24.99***	18.17***

	PanelD:Period2015.01.05–2020.06.12				PanelE:Period2018.01.05–2020.06.12			
	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH}>\sigma^{MA}_{t-30}$	$\sigma^{HIGH}<\sigma^{MA}_{t-30}$	$R_{m,t}>0$	$R_{m,t}<0$	$\sigma^{HIGH}>\sigma^{MA}_{t-30}$	$\sigma^{HIGH}<\sigma^{MA}_{t-30}$
ϒ0	1.263***	0.827***	1.110***	0.917***	1.292***	0.872***	1.074***	0.924***
	(0.030)	(0.038)	(0.049)	(0.036)	(0.036)	(0.054)	(0.057)	(0.066)
ϒ1	0.574***	0.729***	0.414***	1.201***	0.448***	0.746***	0.441***	1.171***
	(0.107)	(0.091)	(0.051)	(0.146)	(0.102)	(0.105)	(0.051)	(0.174)
ϒ2	0.110**	0.750***	0.482***	0.486***	0.016	0.580***	0.327***	0.499***
	(0.055)	(0.052)	(0.052)	(0.064)	(0.053)	(0.061)	(0.057)	(0.116)
ϒ3	–0.125***	–0.076***	–0.046***	–0.407***	–0.104***	–0.078***	–0.048***	–0.402***
	(0.039)	(0.011)	(0.008)	(0.081)	(0.039)	(0.012)	(0.007)	(0.080)
ϒ4	0.046***	–0.055***	–0.025***	–0.071***	0.016	–0.050***	–0.027**	–0.114***
	(0.017)	(0.008)	(0.009)	(0.022)	(0.014)	(0.010)	(0.011)	(0.039)
ϒ5	–0.202***	0.060	–0.170**	–0.076	0.009	0.126	–0.107*	0.093
	(0.075)	(0.088)	(0.075)	(0.059)	(0.072)	(0.111)	(0.065)	(0.090)
ϒ6	–0.008	0.051	0.032	0.119**	–0.017	0.056	0.028	0.143
	(0.057)	(0.057)	(0.052)	(0.060)	(0.041)	(0.061)	(0.045)	(0.089)
ϒ7	0.187	–0.217	0.060	–0.146	0.326	–0.149	0.263	–0.077
	(0.169)	(0.204)	(0.216)	(0.120)	(0.273)	(0.234)	(0.245)	(0.319)
Obs .	722	698	717	703	299	337	380	256
R-squared	0.292	0.527	0.384	0.267	0.166	0.369	0.242	0.276
t-stat1 (H0: ϒ1=ϒ2)	14.42***	111.7***	52.25***	44.56***	10.06***	48.70***	38.27***	22.71***
t-stat1 (H0: ϒ3=ϒ4)	10.38***	40.97***	19***	15.28***	4.834***	27.59***	21.91***	12.90***

Table 7.2 shows the results for the SZSE. In most of the time windows, herding behavior is stronger in down markets compared to up markets. In terms of volatility states, however, herding is stronger in all time windows when the market exhibits low volatility.

5.3. Rolling Window Analysis

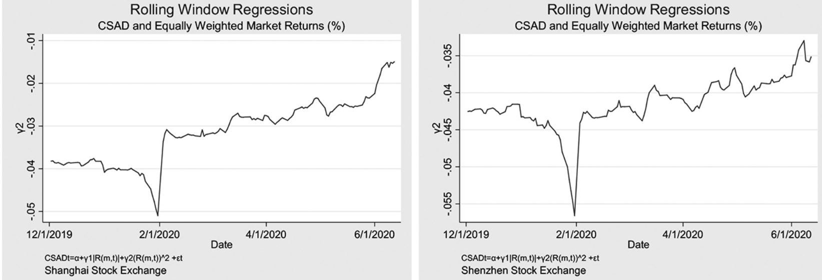
Now we analyze if the increase in herding behavior holds after the COVID-19 event date, using rolling window regression methodology. We build windows of 100, 200, 400, and 600 days to generate series of the estimated coefficients, particularly looking to analyze β_1 and β_2 from Equation (1). For robustness we re-estimate the models recursively. The results turned out to be similar.

Figure 2 shows the evolution of β_2 from Equation (1) for the SHSE and SZSE during the period between December 01, 2019, and June 12, 2020. Every coefficient is statistically significant at 5% and even at lower levels of statistical significance. The average R^2 is 0.25 (min 0.21, max 0.30) for the SHSE and 0.19 (min 0.17, max 0.23) for the SZSE. We find that herding behavior increases after December 31, 2019 (the COVID-19 event date). As bad news about the pandemic continued to be announced (COVID-19 cases and deaths), herding activity decreased with the same intensity as it increased. This could indicate that in the face of events that create an extreme perception of systemic gravity, investors participating in a market rely on their own decisions to a greater extent. Finally, we explore the behavior of β_2 in Equation (1) over a five-year period. We find that herding behavior during this period shows similar patterns in terms of a decrease in magnitude in different previous periods. As shown in Figure 3, (a) identifies the period in which diplomatic relations between China and Panama began (immediately after the breakdown of diplomatic relations between Panama and Taiwan); (b) is the period that encompasses the high-point for China-US relations, inferring that the COVID-19

FIGURE 2

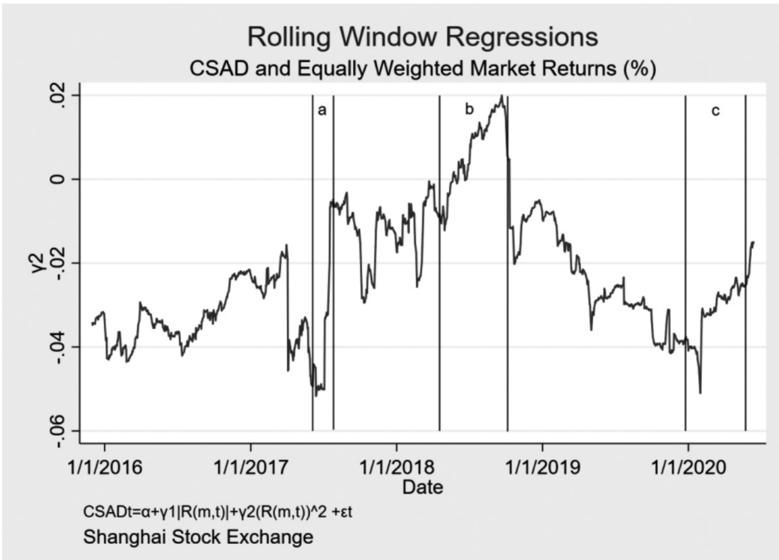
ROLLING WINDOW REGRESSION (RWR) FOR SHSE AND SZSE.

RWR to $CSAD_t = \alpha + \beta_1 \left| R_{m,t} \right| + \beta_2 \, (R_{m,t})^2 + \varepsilon_t$



pandemic is a new factor that influences the behavior of stock markets; and (c) is the period after the COVID-19 announcement. WHO's declaration that COVID-19 was a pandemic.

FIGURE 3
ROLLING WINDOW REGRESSION OVER SHSE



6. Conclusions

The results reported in this study confirm the existence of herding behavior in the Chinese stock market by using the cross-sectional absolute deviation (CSAD) model on stock return data in the period between January 30, 2001, and June 12, 2020. We consider A-share stock prices for all firms traded on the SHSE and SZSE. We show that herding behavior occurred during the entire period.

We include three control variables (regional stock return, world stock return, and exchange rate) to see if herding behavior is still observable in both stock markets. The results clearly show that herding activity is observable even when the controls are included and that the size of the coefficient estimates do not change significantly.

We split the sample according to the market return level (to identify bull and bear markets) and we show that there is asymmetric behavior, revealing stronger herding behavior in an up market. Moreover, we show that herding behavior is more pronounced during the period of COVID-19 under study. In terms of market volatility, we find that lower levels of volatility are associated with more pronounced herding behavior.

Our results show more pronounced herding behavior occurs in bull markets and in low volatility regimes (before and after the COVID-19 event date). More pronounced herding activity in a low volatility market might be associated with a higher level of agreement in the market regarding the quality of stocks; in this scenario, it is more likely that investors will coincide in their appraisals of investment decisions. Something similar happens with analysts, who give more similar advice in low volatility markets on which investors tend to rely, which makes herding behavior more likely. On the other hand, in stock markets with high volatility and negative returns, investors will gather more information to make decisions and try to avoid losses. Moreover, analysts in the market will not agree on investment decisions because there is a high uncertainty regarding the future of the economy and, therefore, the future of the stock market.. Finally, we cannot affirm that herding behavior is good or bad for market, as the reasons for the behavior might be rational or irrational.

To check the robustness of our results, we split the sample into a series of different time windows. The results show stronger herding behavior in the stock market after December 31, 2019 (the COVID-19 event date). However, as further bad news about the COVID-19 pandemic continued to be announced (COVID-19 cases and deaths), herding behavior decreases with the same intensity as it increased. It is clear that herding activity is weaker when the market is low (bear market) and in a high volatility state. It is likely that in situations with extreme perception of systemic gravity, investors may have a greater degree of trust in their own decisions, as opposed to the collective beliefs of market participants. As a robustness check, we use time-varying coefficients using rolling regressions.

This paper contributes to the literature on herding behavior in stock markets by examining four hypotheses related to Chinese stock markets and how herding behavior changes after the COVID-19 event date. We controlled for other variables to confirm the presence of herding behavior in our results and they did not change: herding behavior is still present during the period of COVID-19 under study. Indeed, our results are distinct and opposite to those obtained by Wu *et al.* (2020).

This article is not absent of limitations. First, similar to other studies on herding behavior, we are able to identify herding but not able to associate it with one or more alternative explanations for the behavior. Second, Equation (2) is regularly used in the literature to isolate potential herding behavior during COVID-19; however, it is impossible to discern if herding increases during the time period under study or if the movement comes from a common shock. This is a common limitation in all studies that employ CSAD methodology. We control by three relevant variables (regional market return, world market return, and exchange rate return) to mitigate this limitation as far as possible.

In terms of avenues of future research, as previous studies in herding behavior have come to different conclusions, it might be useful to explore other methodologies, such as nonparametric kernel regressions and smooth transition regressions, to test for herding behavior. Furthermore, the date of the COVID-19 event could be identified endogenously, which would be particularly interesting if used in conjunction with a cross-country study. Finally, once there is universal agreement regarding the end of the COVID-19 pandemic, it will be necessary to repeat these studies on the presence of herding behavior in stock markets using data from a time period that covers the pandemic as a whole.

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