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Sectoral Herding and Volatility in the Chinese Stock Market: Lessons from COVID-19

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Abstract

This study investigates the Chinese stock market's herd mentality and volatility both before and after the COVID-19 outbreak. Using the GARCH (1,1) and return dispersion (CSAD) models, the study examined how market volatility and investor behavior differ across economic sectors. Due to the market meltdown and instability caused by the COVID-19 pandemic, the results showed a significant rise in herd behavior and volatility following the outbreak. To control cross-sector herding and volatility in times of crisis, the research shows that sector-specific variations in these phenomena are necessary. The study highlights shortcomings, such as failing to consider more comprehensive factors like regional and global influences, and recommends that these areas be addressed in subsequent studies.

Keywords:
COVID-19, Diversification, Efficient, Herding, Market Hypothesis, Volatility

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1. Introduction

The Chinese stock market was the first market to experience unprecedented economic uncertainty and havoc after the COVID-19 outbreak. The economy is continually struggling with the effects of the ongoing pandemic, trying to recover from fear and damage. Economic growth was significantly affected by containment and restrictions. After a slowdown to 2.6% in 2022, China experienced a rebound in economic growth, with an increase of 5.2% in 2023 and 5.0% in 2024. In the context of a financial crisis, the Chinese stock market experienced a notable decline, and return volatility increased during the pandemic's initial phase.

Due to fear and instability, investors' confidence has been adversely affected. This highlights a behavioral finance perspective: psychological biases, such as copying other decisions rather than fundamentals, are a primary source of herd behavior and market volatility. As irrational investor behavior intensifies during financial crises, the examination of herd behavior becomes more important. Consequently, investors need new strategies for portfolio diversification and hedging purposes (Assaf et al., 2023). The financial crisis resulted in price inefficiency, extreme volatility, and unpredictability; furthermore, the spread of herd behavior among investors during the crisis was lightning-fast (Demirer et al., 2019; IMF, 2023).

While numerous studies exist on herding and volatility, there is currently no consensus regarding their origins, intensity, or similarities, and, to the best of our knowledge, there is a lack of sectoral analyses of volatile markets before and after COVID-19. There are different characteristics of COVID-19 compared to previous crises, essentially stemming from a compulsory hibernation of productive capacity in many economic sectors that remained mostly intact, waiting to recover after lockdowns. This paper explores herding and volatility at the sectoral level to identify driving factors and common features of herding and volatility before and after COVID-19. A method is presented to assess the impact of COVID-19 on investor sentiment and the resulting excessive volatility in the country at the epicenter.

Investors herd when they follow the market trend rather than their own expectations (Chauhan et al., 2020). Investors' uniform behavior is the result of similar beliefs and ideas widespread in the financial markets (Ghorbel et al., 2022). Investors' herd behavior causes returns to deviate from their fundamentals and, sooner or later, creates chaos in stock markets (Javaira and Hassan, 2015). The literature establishes that herd behavior intensity increases during adverse market conditions, thereby spiking volatility in the stock market. The COVID-19 pandemic boosted investors' irrational behavior and caused extreme volatility in the financial markets. All Chinese economic sectors have been affected, but with varying intensities. For instance, the real estate sector experienced a massive 20% decline, whereas the healthcare sector posted positive returns (IMF, 2023). Therefore, sectoral analysis is key to understanding the dynamics of the Chinese stock market after the COVID-19 outbreak.

Classical models, supported by research studies and risk-and-return theory, are unable to explain excessive price movements and herd behavior (Wang et al., 2023). Behavioral finance provides a theoretical foundation for understanding how irrational decisions and imitation can fuel market volatility, especially during crises. Behavioral finance has emerged as a field, claiming that excessive volatility results from many investors following others' decisions. During periods of chaos, it is not uncommon for less informed investors to mimic the actions of other investors (Chang et al., 2020; Litimi et al., 2016). The financial markets have been significantly affected by the COVID-19 pandemic, leading to greater volatility and uncertainty. Investors are now relying more on general market sentiment rather than conducting their own individual analyses (Ampofo et al., 2023). Blasco et al. (2012) provide empirical evidence on the link between herding and volatility. Recent research discusses the COVID-19 financial crisis, with Ferreruela and Mallor (2021) claiming that existing herding and volatility vanish during the crisis and re-emerge afterwards.

This validates the behavioral finance theory that herd behavior is driven by market sentiment, which leads to temporary shifts in investor behavior (Espinosa-Méndez and Arias, 2021). COVID-19 has intensified herd behavior in financial markets as a short-term phenomenon. Therefore, this paper investigates whether herding is a short-term phenomenon and explores its origins, as well as those of volatility, across different economic sectors in the Chinese stock market.

In addition to a description of what happened during COVID-19 in terms of the financial crisis, what was special about COVID-19 that affected herding and volatility, and how different economic sectors were affected and how they faced its effects, relative to other crises, are worth knowing.

In this paper, no differences were found between the before- and after-COVID-19 periods across all economic sectors. Although all sectors exhibited a similar reaction, the prevalence of herding and volatility is more noticeable on a sector-by-sector basis than when considered in aggregate.

This observation indicates that crises stemming from productive capacity hibernation do not uniformly impact or impose a challenging slow recovery across economic sectors, as has occurred in other financial crises. Based on our current knowledge, this particular phenomenon was previously unknown. Our findings also revealed that herding and volatility are strongly present, which calls for effective reforms and improved information efficiency.

This study provides useful insights into herd behavior and volatility, offering new knowledge to the literature that could be generalizable through further empirical research in other countries and using data from similar COVID-19 financial crises. Research findings provide insight into a volatility component not associated with investors' behavior across all economic sectors, which is fruitful for forecasting procedures, hedging strategies, and portfolio diversification. The authors observe a significant lack of studies that focus on both volatility and herding behavior of investors, specifically in the context of sectoral versus aggregate analyses in the Chinese stock market. Consequently, this paper seeks to address this gap in the existing literature and advance our understanding of investor behavior across these distinct economic sectors.

The paper proceeds with part two for the literature review, part three for the data and methodology, part four for the analysis and results, and part five for the concluding remarks.

2. Theoretical foundations

2.1. Herding in equity markets

To address herd behavior, many theories have examined herd formation in financial markets. For instance, some describe herd behavior as most evident and damaging during the financial crisis (Chiang & Zheng, 2010). In contrast, others conclude that herd behavior intensifies during periods of lower uncertainty (Hudson et al., 2020). Herd behavior is difficult to define, and researchers have not agreed on a single definition. Welch (1992) defines herding as "investors who imitate the actions of other investors intentionally and ignore their own private information". Herding occurs when a group of investors reaches consensus, influenced by economic and social factors. Investors choose the herd when sufficient information is unavailable to construct an optimal portfolio, and their main objective is to protect their investments from uncertainties, market risk, and non-parametric results (Lee et al., 2021).

Chang et al. (2000) claimed that during the financial crisis, investors ignore the available private information and follow the market consensus. Due to herd behavior, individual investors' returns tend to move in tandem with market returns, leading to high volatility and making it difficult to reap the benefits of diversification. Investors' aggregate behavior influences other investors' decisions and contributes to market inefficiency. The literature on herding behavior explains several associated risks, like price volatility, asymmetric effects in returns, speculation, market bubbles, errors in stock prices, imbalance between market variables, and market crashes (Sihombing et al., 2021). Herding promotes volatility and disturbs market trading, requiring regulators and policymakers' immediate attention to stabilize the stock market (Demirer and Kutan, 2006).

Several studies have examined herd behavior in the Chinese stock market, but only after the COVID-19 pandemic. For instance, Espinosa Méndez and Maquieira (2023) claimed that the Chinese stock market experienced strong herd behavior after COVID-19, with herd behavior dominance during low volatility and high returns. Chang et al. (2000) noted herding when investors sold their oil stocks due to fear and uncertainty after the COVID-19 crisis. By contrast, Wu et al. (2020) concluded that herding intensity decreased after COVID-19. Yuan (2021) looked at herding at the sectoral and aggregate levels, but findings fail to generalize the presence of herding across economic sectors before COVID-19. So,

H1. COVID-19 influences herd behavior across economic sectors.

2.2. Volatility in equity markets

Asian stock markets experienced sharp declines and extreme volatility during the COVID-19 outbreak. A highly volatile market has weakened investors' confidence and created doubts (Mishra and Mishra, 2021). Fear of a devastating virus has increased the likelihood of abrupt price movements, market crashes, and financial crises. Significant empirical evidence of investors' fear and anxiety led to unprecedented volatility (Vuong et al., 2022). Stock market volatility is a barometer of risk; therefore, volatility is a key factor for stock market performance (Zaremba et al., 2020). Exploring the causes, timing, and magnitude of volatility is essential for understanding and navigating instability and financial turmoil. In addition, social media plays a pivotal role in spreading pandemic-related rumors and creating fear, thereby risking the financial system and destabilizing financial markets.

Some notable empirical studies have examined the effects of COVID-19 and how the pandemic led to greater uncertainty and significant setbacks for the Chinese economy. Li et al. (2022) stated that high trading activity significantly contributes to high volatility, causes substantial negative sentiment, and leads investors to take "flights to safety". Research argues that excessive stock market volatility results from the association between information asymmetry and investors' sentiment (Gao et al., 2022b; Li et al., 2022). Choi (2021) found that aggregate market index analysis yields homogeneous results and obscures critical information needed for future decisions. In addition, earlier studies have examined how volatility has passed through the stock market during health crises; however, no study has examined extreme volatility across economic sectors.

This paper also examines volatility in the Chinese stock market to anticipate potential threats to the financial system and its stability. The Chinese stock market is a promising and large emerging market, but it has imposed some restrictions on foreign investment and is described as a segmented market (Wang et al., 2022). Historically, the Chinese stock market has been vulnerable, generating highly volatile abnormal returns during economic crises (Li et al., 2022; Ramelli and Wagner, 2020; Wu et al., 2020). Identifying the drivers of stock market volatility after COVID-19 provides stakeholders with insights to address issues and control the further financial impact of pandemic crises. Previous research provides concrete evidence that fear and volatility across economic sectors are uneven. According to Mensi et al. (2017), the economic sectors of finance, technology, energy, and telecommunications are the largest contributors to stock market volatility. Zhang and Giouvris (2022) analyzed cross-sectional economic sectors' volatility before and after COVID-19, suggesting that volatility varies across economic sectors in the long run. Relying on the literature discussed above, the following research question arises.

H2. COVID-19 influences volatility across economic sectors.

3. Data and methodology

Daily closing prices from January 1, 2015, to December 31, 2024, for all companies listed on the Shanghai Stock Market were obtained from Thomson Reuters Data Stream and subdivided into 10 economic sectors according to the Thomson Reuters Business Classification (TRBC). TRBC is a useful tool for investors when selecting investment portfolios across developed and emerging markets. The pre-COVID-19 period was defined as January 2015 to December 2019, and the post-COVID-19 period as January 2020 to December 2024. The time series data, comprising both aggregate and sectoral components, were tested for stationarity using the Dickey–Fuller (ADF) unit root test.

3.1. Herd behavior detection

When the stock market is under stress, investors copy other investors' actions and overlook information available to them. Such behavior reduces the cross-sectional variation among the stocks and causes herding in the equity market (Christie and Huang, 1995). Cross-Sectional Standard Deviation (CSSD) model can check the presence of herd behavior in the stock market using the following equation for each economic sector/market:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(r_{i,t}-r_t)^2}{N-1}} \qquad (1)$$

where $CSSD_t$ is the cross-sectional standard dispersion of returns among all companies in the same sector/market on a given day t, $r_{i,t}$ is the stock return for the company i on day t, r_t is the sector/market average stock return on a given day t, and N is the total number of companies in the sector/market.

However, Chang et al. (2000) put forward a new model based on the Capital Asset Pricing Model (CAPM), denoted by followers as the CCK model. This model captures investors' herd behavior through a nonlinear association between Cross-Sectional Absolute Deviation (CSAD) and market returns. For example, when a large number of investors form a herd, returns cluster around a single point. However, if investors take an anti-herding stance, returns are dispersed (Sheikh et al., 2025). Tan et al. (2008) argue that the CCK model is better at detecting herd behavior than the CSSD model. Therefore, this paper adopts the CSAD model to check herd behavior in the Chinese stock market, using the following equation:

$$CSAD_t = \alpha + \gamma_1|r_t| + \gamma_2 r_t^2 + e_t \quad (2)$$

with $CSAD_t$ given by the following equation:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} | r_{i,t} - r_t| \quad (3)$$

where $CSAD_t$ is the mean of the cross-sectional absolute return of all companies in a sector/market, r_t is the sector/market average stock return on a given day t, $r_{i,t}$ is the stock return for the company i on day t, N is the total number of companies in the sector/market, α is a constant, the bottom cross-sectional absolute return of all companies in a sector/market, γ_1 and γ_2 are coefficients to be estimated.

The coefficients γ_1 and γ_2 represent the linear and nonlinear relationships, respectively, between the sectoral return and the cross-sectional absolute return of all companies within a sector. If γ_2 is negative and statistically significant, indicating that herd behavior exists in that economic sector/market. During periods of financial crisis and uncertainty, large price movements should occur in the stock market, thereby boosting herd behavior. Similarly, unequal rates of fluctuation between $CSAD$ and sector/market returns show a severe presence of herd behavior (Chang et al., 2000).

3.2. GARCH(1,1) Effect

The autoregressive conditional heteroskedasticity (GARCH (1,1)) model is employed to capture volatility in the Chinese stock market before and after the COVID-19 pandemic. The GARCH(1,1) model is used to forecast and assess volatility in time series. EGARCH and TGARCH models are used to capture persistent volatility and the leverage effect. Thus, the GARCH(1,1) model performs better at capturing sudden volatility clustering, which is vital for the before-and-after COVID-19 evaluation. The so-called random coefficient problem in the GARCH (1,1) model can be addressed by calculating variations across different sample periods. The baseline idea of the GARCH (1,1) model is “large price movements followed by large price movements and low price movements followed by low price movements”. To check the presence of volatility in the stock market in the aggregate and sectoral context, the following GARCH (1,1) model was set:

Conditional Mean Eq

$$\mathrm{R_t} = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t \quad (4)$$

Where: $\varepsilon_t \sim N(0, \sigma_t^2)$

Conditional Mean Eq

$$\sigma_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 \quad (5)$$

In the conditional mean equation, $\mathrm{R_t}$ are the returns of stocks, as per the Efficient Market

Hypothesis (EMH), R_t has mean-reversion behavior; therefore, returns are highly volatile and unpredictable. Equation No.5 represents the conditional variance equation, where σ_t^2 depends on the squared lag values σ_{t-1}^2 and μ_{t-1}^2 is the GARCH (1,1) term. Investors' financial decision-making depends on risk and returns; the GARCH(1,1) model is used to estimate risk (volatility) and return, with risk (volatility) derived from the mean equation and return from the variance equation. Therefore, this study employed the GARCH (1,1) model to assess volatility across all stock market sectors during both stable and financial crisis periods. The AR(1) model is selected to analyze the conditional mean equation based on AIC and BIC; it is simple and fits well across all sectors.

4. Empirical analysis and discussion

4.1. Descriptive statistics

Descriptive statistics of r_t and $CSAD_t$ for each sector and at the aggregate market level, before and after COVID-19, are presented in Tables 1 and 2. The descriptive statistics of the CSAD and sectoral returns before and after COVID demonstrate persistent distributional patterns. In both sub-periods, most sectoral returns exhibit negative skewness, suggesting an asymmetric distribution and a greater likelihood of negative returns. The values of the Kurtosis coefficients exceed 3 in most sectors (except healthcare), indicating leptokurtic distributions; these results are well documented in the financial literature.

Comparison of the sub-periods reveals that the post-COVID period exhibits higher mean returns and greater cross-sectional dispersion, particularly in the telecom and technology sectors. This suggests that the stock market faces greater uncertainty and risk following the pandemic shock. The ongoing presence of Non-normal return distributions in both sub-periods supports the use of the CSAD to capture herding behavior, as traditional models assume a normal distribution and cannot detect underlying return behavior. The minimum CSAD values are reported as zero due to rounding to three decimal places.

Table 1. Descriptive statistics before COVID-19

Sector	Variable	Mean	Median	SD	Kurt.	Skew.	Min	Max
Cyclical Consumer	r_t^{cc}	-0.025	0.002	0.563	5.573	-1.218	-3.389	2.026
	$CSAD_t^{cc}$	0.548	0.545	0.202	2.904	-0.453	0.000	1.351
Energy	r_t^{en}	-0.026	0.000	0.638	4.286	-1.124	-3.422	1.990
	$CSAD_t^{en}$	0.575	0.545	0.289	1.035	0.514	0.000	1.709
Financials	r_t^{fin}	-0.005	0.000	0.409	6.896	-0.514	-2.469	2.368
	$CSAD_t^{fi}$	0.405	0.382	0.188	3.867	0.856	0.000	1.415
Healthcare	r_t^{hc}	-0.011	0.000	0.571	3.150	-0.655	-3.100	2.167
	$CSAD_t^{hc}$	0.559	0.552	0.225	1.871	-0.175	0.000	1.537
Industrials	r_t^{in}	-0.019	0.003	0.576	5.590	-1.203	-3.458	2.169
	$CSAD_t^{in}$	0.551	0.545	0.215	2.303	-0.202	0.000	1.411
Materials	r_t^{ma}	-0.018	0.000	0.572	4.672	-1.066	-3.265	2.074
	$CSAD_t^{ma}$	0.551	0.544	0.212	2.554	-0.235	0.000	1.357
Non-Cyclical	r_t^{nc}	-0.019	0.000	0.548	4.089	-0.853	-3.263	2.116
	$CSAD_t^{nc}$	0.566	0.554	0.234	3.080	0.209	0.000	1.811
Technology	r_t^{it}	-0.003	0.000	0.741	3.243	-0.722	-3.931	2.397
	$CSAD_t^{it}$	0.661	0.653	0.265	2.335	-0.081	0.000	1.912
Telecom	r_t^{tc}	0.041	0.029	0.956	1.602	-0.486	-4.360	2.749
	$CSAD_t^{tc}$	0.697	0.541	0.551	0.402	0.949	0.000	2.773
Utilities	r_t^{ut}	-0.016	0.000	0.499	6.346	-1.224	-2.986	1.899
	$CSAD_t^{ut}$	0.450	0.439	0.205	1.836	0.388	0.000	1.267
Aggregate	r_t	-0.016	0.003	0.532	5.452	-1.085	-3.158	2.079
	$CSAD_t$	0.548	0.541	0.204	3.576	-0.220	0.000	1.429

Table 2. Descriptive statistics after COVID-19

Sector	Variable	Mean	Median	SD	Kurt.	Skew.	Min	Max
Cyclical Consumer	r_t^{cc}	0.005	0.000	0.581	7.391	-1.343	-4.600	2.117
	$CSAD_t^{cc}$	0.714	0.740	0.238	3.758	-1.483	0.000	1.787
Energy	r_t^{en}	0.014	0.000	0.676	4.077	-0.760	-4.672	2.043
	$CSAD_t^{en}$	0.709	0.698	0.324	0.813	0.027	0.000	1.950
Financials	r_t^{fin}	-0.013	0.000	0.543	6.796	-0.662	-4.240	2.926
	$CSAD_t^{fi}$	0.522	0.517	0.216	1.559	-0.156	0.000	1.235
Healthcare	r_t^{hc}	0.003	0.000	0.650	1.740	-0.288	-2.958	2.581
	$CSAD_t^{hc}$	0.733	0.743	0.299	10.577	0.477	0.000	3.538
Industrials	r_t^{in}	0.007	0.023	0.572	6.919	-1.283	-4.418	1.880
	$CSAD_t^{in}$	0.656	0.686	0.233	2.317	-1.208	0.000	1.443
Materials	r_t^{ma}	0.016	0.012	0.598	5.303	-1.081	-4.288	1.995
	$CSAD_t^{ma}$	0.721	0.751	0.268	1.699	-0.928	0.000	1.495
Non-Cyclical	r_t^{nc}	0.007	0.000	0.572	5.120	-1.018	-3.851	1.858
	$CSAD_t^{nc}$	0.708	0.721	0.274	1.911	-0.563	0.000	1.837
Technology	r_t^{it}	-0.009	0.000	0.778	3.898	-0.695	-5.122	2.303
	$CSAD_t^{it}$	0.757	0.758	0.288	5.427	-0.234	0.000	2.887
Telecom	r_t^{tc}	0.247	0.255	0.783	3.330	-0.719	-4.571	2.681
	$CSAD_t^{tc}$	0.891	0.933	0.472	-0.505	0.167	0.000	2.391
Utilities	r_t^{ut}	0.006	0.000	0.618	4.478	-0.762	-4.227	2.334
	$CSAD_t^{ut}$	0.547	0.535	0.260	1.512	0.357	0.000	1.732
Aggregate	r_t	0.004	0.003	0.550	6.589	-1.249	-4.158	1.748
	$CSAD_t$	0.713	0.747	0.238	3.694	-1.506	0.000	1.771

1303 observations

During the COVID-19 period, the financial sector had the lowest mean return, while the telecom sector had the highest. A similar pattern is observed for CSAD mean return: the financial sector has the lowest, and the telecom sector the highest. Risk is estimated using the standard deviation; the telecom sector has the highest risk among all sectors, indicating it is more volatile than other sectors of the Chinese stock market (Chiang and Zheng, 2010). The skewness values indicate that the Gaussian distribution is not present in all sectors, and the returns of all sectors are left-skewed. Kurtosis coefficient values for all sectoral returns are higher than 3, except for healthcare, indicating that sectoral returns are leptokurtic, with a thick-tailed distribution.

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4.2. Herd behavior

Tables 3 and 4 present the sectoral and aggregate regression results of the CSAD model to capture herd behavior in the Chinese stock market. The R-squared values for all sectoral and aggregate regressions are acceptable and vary across sectors. The γ2 coefficient is significant and negative for all sectors except the healthcare sector and aggregate data sets before the COVID period. The healthcare and aggregate data sets are positive and significant, which indicates reverse herding. During reverse herding, investors make irrational decisions, ignore fundamental values, and increase return dispersion. However, the γ2 coefficient demonstrates that the nonlinear association between CSAD and squared mean return is present in all sector samples after the COVID-19 pandemic. The negative sign indicates that herd behavior is present in the stock market, and the CSAD coefficient decreases rather than increases, corresponding to a high value of r_t^2. The results confirm our research question Q1: herd behavior is spotted in all sectors and aggregate data sets, except for healthcare and aggregate data sets before the COVID-19 period. The findings of this study are consistent with those of Chang et al. (2000), Espinosa Méndez and Maquieira (2022), Sheikh et al. (2025), Wu et al. (2020), and Yuan (2021).

Table 3. Herd behavior – sectoral and aggregate before COVID-19

Sectors	γ_1	γ_2	α	R^2
Materials	0.388***	-0.055***	0.417***	0.328
	(0.031)	(0.015)	(0.010)	
Cyclical Consumer	0.370***	-0.052***	0.425***	0.329
	(0.029)	(0.013)	(0.009)	
Financials	0.544***	-0.070***	0.271***	0.537
	(0.030)	(0.019)	(0.007)	
HealthCare	-0.050***	0.118***	0.520***	0.199
	(0.013)	(0.010)	(0.007)	
Industrials	0.356***	-0.046***	0.429***	0.297
	(0.031)	(0.014)	(0.010)	
Non-Cyclical	0.430***	-0.059***	0.420***	0.321
	(0.036)	(0.019)	(0.011)	
Technology	0.427***	-0.083***	0.483***	0.278
	(0.033)	(0.013)	(0.013)	
Utilities	0.408***	-0.049***	0.328***	0.360
	(0.032)	(0.016)	(0.009)	
Energy	0.473***	-0.068***	0.393***	0.301
	(0.040)	(0.017)	(0.014)	
Telecom	0.882***	-0.203***	0.264***	0.289
	(0.061)	(0.023)	(0.030)	
Aggregate	-0.102***	0.099***	0.519***	0.298
	(0.012)	(0.008)	(0.006)	

***, ** and * denote significance at <0.01, <0.05 and <0.1, respectively. Standard deviation in parentheses.

This model explains that herding occurs in the market when investors follow the average market opinion. These findings confirm the presence of the Bandwagon Effect (tendency to rally on public opinion) in all sectors of the market and violate the assumptions of the efficient market hypothesis by indicating anomalies in the stock market during the period of crisis (Lee et al., 2021). These results also confirm that during the period of COVID-19, investors feel confident by copying the actions of other investors and reduce uncertainty (Mishra and Mishra, 2023). The empirical findings imply that COVID-19 has generated a market bubble that stimulates cross-sector herding in the stock market. Resultantly, herd behavior of investors caused extreme volatility in all sectors of the market and affected the returns of optimal portfolios (Bukhari et al., 2021). During the period of chaos and extreme uncertainty, investors panicked and were forced towards herd behavior instead of following their own beliefs (Sihombing et al., 2021). In this situation, market efficiency is compromised, and investors will not be able to achieve desired goals by portfolio diversification across sectors (Bukhari et al., 2022). The panic and irrational behavior of investors create a vicious cycle that spreads across all sectors of the market.

Table 4. Herd behavior – sectoral and aggregate after COVID-19

Sectors	γ_1	γ_2	α	R^2
Materials	0.485***	-0.129***	0.562***	0.205
	(0.037)	(0.016)	(0.014)	
Cyclical Consumer	0.412***	-0.109***	0.584***	0.181
	(0.037)	(0.013)	(0.012)	
Financials	0.460***	-0.099***	0.383***	0.318
	(0.028)	(0.013)	(0.009)	
HealthCare	0.600***	-0.163***	0.512***	0.266
	(0.047)	(0.025)	(0.016)	
Industrials	0.429***	-0.108***	0.522***	0.210
	(0.032)	(0.013)	(0.012)	
Non-Cyclical	0.451***	-0.104***	0.559***	0.180
	(0.041)	(0.019)	(0.014)	
Technology	0.355***	-0.045***	0.590***	0.244
	(0.031)	(0.011)	(0.014)	
Utilities	0.499***	-0.112***	0.376***	0.293
	(0.034)	(0.015)	(0.012)	
Energy	0.505***	-0.122***	0.518***	0.191
	(0.041)	(0.017)	(0.017)	
Telecom	0.639***	-0.175***	0.612***	0.145
	(0.059)	(0.023)	(0.028)	
Aggregate	0.419***	-0.095***	0.581***	0.196
	(0.035)	(0.015)	(0.012)	

***, ** and * denote significance at <0.01, <0.05 and <0.1, respectively.Standard errors in parentheses

The study has highlighted uncorrelated sectors in the stock market, which are useful for investors when selecting a balanced portfolio (basket). Further, the findings of this study provide useful insights for all stakeholders to take necessary remedial measures to overcome the negative effects of herd behavior during financial turmoil.

4.3. Volatility

Results for volatility across sectors and the aggregate, before and after COVID-19, are presented in Tables 5 and 6 and Figures 1 and 2. Before estimating the GARCH (1,1) effect, we check stationarity in all data streams and employ the Augmented Dickey-Fuller (ADF) test. Results show that all data streams are stationary at the level, and the null hypothesis is rejected. The GARCH (1,1) effect indicates that volatility is present in only 3 sectors: healthcare, telecom, and utilities; all other sectors and aggregate data streams show stability before COVID-19. Our results confirm that the magnitude of volatility varies across the sectors and the aggregate market sample. However, after COVID-19, returns remain highly volatile, and the GARCH(1,1) effect is evident across all sectoral and aggregate data sets. COVID-19 is highly harmful to all sectors, and volatility is more pronounced afterwards. This supports our research question that the magnitude of volatility differs across sectors and aggregate data streams. Study findings are consistent with previous studies that volatility significantly increased during the period of COVID-19 (Gao et al., 2022a; Zhang and Giouvris, 2022).

Table 5. Volatility – sectoral and aggregate data sets (Before COVID-19)

Sectors	β_0	β_1	ADF
Materials	-0.00558	0.319***	-28.134
	(0.033)	(0.011)	
Cyclical Consumer	0.0014	0.406***	-26.485
	(0.026)	(0.015)	
Financials	-0.0109	0.169***	-27.436
	(0.024)	(0.005)	
HealthCare	0.153***	0.282***	-27.974
	(0.050)	(0.012)	
Industrials	-0.0137	0.336***	-27.353
	(0.031)	(0.011)	
Non-Cyclical	-0.0137	0.331***	-28.220
	(0.020)	(0.011)	
Technology	0.0406	0.288***	-28.490
	(0.035)	(0.010)	
Utilities	0.0364	0.529***	-27.888
	(0.035)	(0.021)	
Energy	0.283***	0.685***	-26.330
	(0.062)	(0.042)	
Telecom	0.204***	0.206***	-27.17
	(0.041)	(0.007)	
Aggregate	-0.0101	0.286***	-28.062
	(0.027)	(0.009)	

***, ** and * denote significance at <0.01, <0.05 and <0.1, respectively.
Standard errors in parentheses.

Table 6. Volatility – sectoral and aggregate data sets (After COVID-19)

Sectors	β_0	β_1	ADF
Materials	0.182***	0.280***	-27.070
	(0.044)	(0.015)	
Cyclical Consumer	0.238***	0.356***	-28.658
	(0.052)	(0.022)	
Financials	0.257***	0.232***	-26.962
	(0.050)	(0.013)	
HealthCare	0.298***	0.312***	-22.237
	(0.058)	(0.023)	
Industrials	0.294***	0.243***	-27.044
	(0.048)	(0.014)	
Non-Cyclical	0.184***	0.297***	-26.089
	(0.046)	(0.016)	
Technology	0.118***	0.291***	-25.296
	(0.041)	(0.014)	
Utilities	0.122***	0.530***	-28.406
	(0.043)	(0.027)	
Energy	0.118**	0.541***	-22.356
	(0.046)	(0.028)	
Telecom	0.303***	0.277***	-27.419
	(0.049)	(0.015)	
Aggregate	0.208***	0.245***	-27.025
	(0.044)	(0.013)	

***, ** and * denote significance at <0.01, <0.05 and <0.1, respectively.

The results of the COVID-19 period are understandable, as all sectors were affected by an unprecedented pandemic that disrupted market trading, and sectoral volatility is strongly associated with the COVID-19 outbreak. Chinese financial market faced serious financial turmoil and remained sensitive after the outbreak of the pandemic. About 5 years of data (from Jan 2020 to Dec 2024) for the Chinese stock market show the far-reaching impact of COVID-19 on sectoral and aggregate returns. Our findings also suggest that investor sentiment has produced more sectoral volatility, especially after COVID-19 (Gao et al., 2022a). The results provide a clear picture to investors that risk has increased due to extreme volatility and herd behavior in the Chinese stock market after the pandemic (Bukhari et al., 2021; Gao et al., 2022b). Based on the paper's findings, investors can develop new investment strategies to hedge against risks posed by the COVID-19 pandemic across all sectors of the stock market.

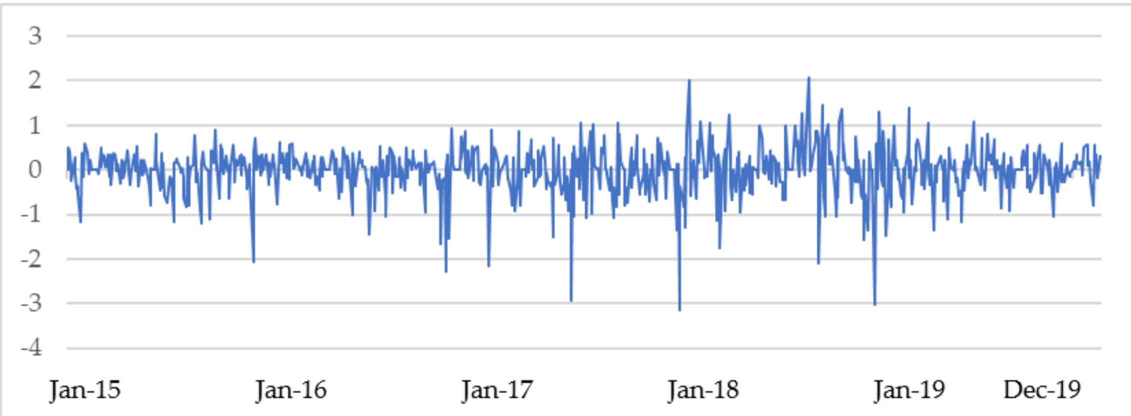

Figure 1. Aggregate returns before COVID-19

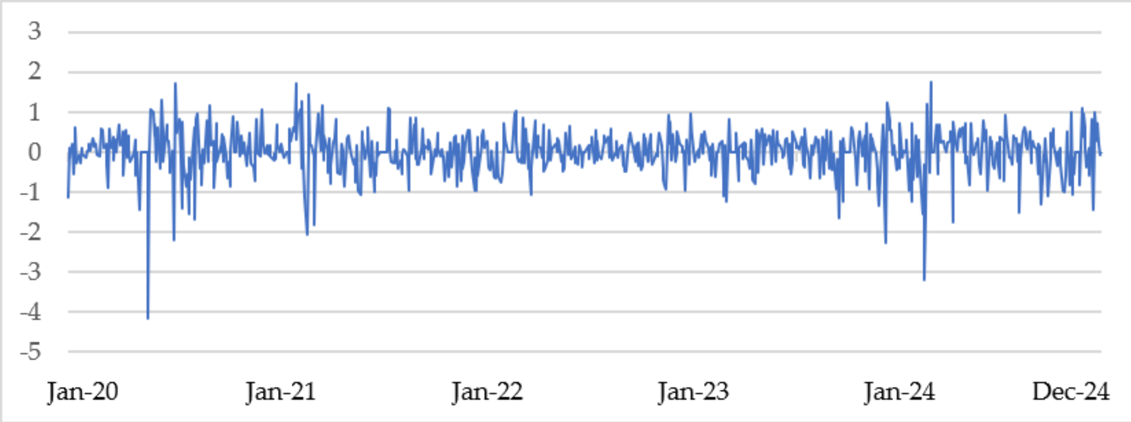

Figure 2. Aggregate returns after COVID-19

The outcomes of this study provide a comprehensive understanding of the root causes of panic and market chaos after COVID-19. The effects of volatility can be minimized by increasing information efficiency for investors during periods of chaos. These findings are valuable for the participants regarding expected future crises in the market/sector. After analyzing these results, fund managers can explore the causes and effects of sector-level volatility to develop comprehensive investment strategies that deliver productive results.

4.4. Robustness test

To ensure the robustness of our findings, we split the data into 10-year windows (2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, and 2024) to verify the presence of herd behavior and volatility. The results for each year are calculated to assess robustness and are presented in Tables 7 and 8. The overall findings from robust testing are not substantially different from the results already reported in (3-6). Chinese stock market experienced extreme volatility and herd behavior after the COVID-19 outbreak. This corroborates our main empirical findings and supports the reliability of our results.

Table 7. Robustness Testing – Herd Behavior

Years	γ_1	γ_2	α	R^2
2015	-0.119***	0.159***	0.498***	0.409
	(0.024)	(0.018)	(0.010)	
2016	-0.125***	0.210***	0.510***	0.417
	(0.027)	(0.023)	(0.011)	
2017	-0.133***	0.242***	0.489***	0.421
	(0.028)	(0.030)	(0.010)	
2018	-0.101***	0.082***	0.527***	0.358
	(0.020)	(0.012)	(0.011)	
2019	-0.070***	0.097***	0.525***	0.213
	(0.020)	(0.014)	(0.012)	
2020	0.159***	-0.028***	0.309***	0.198
	(0.035)	(0.011)	(0.014)	
2021	0.330***	-0.056***	0.555***	0.186
	(0.049)	(0.019)	(0.018)	
2022	0.509***	-0.135***	0.539***	0.286
	(0.066)	(0.031)	(0.024)	
2023	0.561***	-0.188***	0.595***	0.243
	(0.072)	(0.037)	(0.028)	
2024	0.574***	0.193***	0.598***	0.301
	(0.075)	(0.039)	(0.029)	

***, ** and * denote significance at <0.01, <0.05 and <0.1, respectively. Standard errors in parentheses.

Table 8. Robustness testing – Volatility

Years	β_0	β_1	ADF
2015	0.141*	0.346***	-27.646
	(0.097)	(0.022)	
2016	-0.0119*	0.440***	-26.835
	(0.077)	(0.028)	
2017	0.137*	0.134***	-27.747
	(0.081)	(0.012)	
2018	-0.032	0.386***	-28.850
	(0.044)	(0.021)	
2019	1.071***	0.116***	-26.325
	(0.125)	(0.016)	
2020	-0.021	0.367***	-27.856
	(0.046)	(0.022)	
2021	-0.031	0.281***	-28.732
	(0.084)	(0.032)	
2022	0.214**	0.310***	-27.585
	(0.097)	(0.039)	
2023	0.235**	0.337***	-28.525
	(0.098)	(0.042)	
2024	0.215	0. 324***	-27.805
	(0.088)	(0.040)	

***, ** and * denote significance at <0.01, <0.05 and <0.1, respectively. Standard errors in parentheses.

5. Conclusion

This paper investigated sectoral herding and volatility in the Chinese stock market, using data from Jan 2015 to Dec 2024 (before and after the pandemic). We employed Chang et al. (2000) model to check for herd behavior and an AR (1) was used to examine volatility. Li et al. (2022) claim that AR (1) is reliable in capturing the volatility and fear among the participants of the stock market. The impact of the pandemic was massive, and the stock market's sudden crash triggered fear and unprecedented instability. Our results showed that cross-sectoral herding and volatility have increased during the pandemic. The Chinese stock market was highly sensitive during COVID-19 compared with the pre-COVID-19 period and experienced excessive volatility. However, sectoral and aggregate herding and volatility exhibit distinct features across market conditions. It provides an opportunity for all investors to select a balanced portfolio across sectors when a COVID-19 crisis arises. Nevertheless, investors should not pursue high returns during excessive volatility and herding (Wu et al., 2020).

This paper contributes to the literature in several ways, as it examines herding and volatility at the sectoral and aggregate levels under different market conditions, providing useful insights into optimal portfolio selection. The results showed that herding activity is stronger during periods of high volatility; however, low volatility has not weakened herd behavior.

The robustness of the results also confirms that the stock market was semi-stable and efficient before COVID-19; however, the pandemic has had a devastating effect on the Chinese stock market. As a result, policymakers must be more concerned about uncertainty and instability in the market. Regulators should intervene and support advanced systems that can detect volatility clustering and enable pre-emptive measures against herd behavior. In addition, policymakers should develop information transparency requirements so that all listed companies disclose relevant information during periods of crisis and uncertainty. Timely and accurate information prevents irrational decision-making and reduces herding and market trends. Cross-sector herding and volatility during both periods, which require comprehensive strategies to mitigate the effects of future crises alike.

The main research limitation was that herding is a complex phenomenon, and it is difficult to disassociate herding from other investors' behavioral patterns. Future studies can examine the cross-sector contagion effects of volatility and herding across Asian stock markets, incorporating macroeconomic variables and diagnostic tests.

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