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Examining Herding Behaviour and Its Impact on Stock Market Volatility: Insights from Asian Economies

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Abstract

Objective: This study empirically investigates herding bias in six key Asian countries—Indonesia, Singapore, Taiwan, China, Hong Kong, and India—across different periods (pre-, during, and post-COVID-19). It analyzes herding behaviour during COVID and non-COVID periods, exploring its impact on volatility and examining asymmetry during bearish and bullish market conditions.
Design/Methods/Approach: The investigation employs the Cross-Sectional Absolute Deviation (CSAD) model with a polynomial regression to scrutinize herding behaviour. A GARCH (1,1) volatility model is also established to assess the relationship between herding and volatility. The sample includes daily stock returns from the mentioned countries from January 2, 2019, to September 30, 2023.
Findings: The study reveals the presence of herding behaviour in China and Singapore. In Indonesia and China, herding is evident, specifically during and after the COVID period. The research confirms that herding influences volatility and exhibits asymmetry. Herding is more pronounced during bearish market conditions in China, Indonesia, and Taiwan.
Originality/Value: This study contributes to the existing literature by providing empirical insights into herding behaviour comparing in Asian markets, while others research usually only focus on one country. This study further distinguishes itself by examining post-pandemic periods, a unique aspect as most studies typically focus only on pre- and during-COVID periods. Including volatility and asymmetry aspects enriches understanding the nuanced relationship between herding and market conditions.
Practical/Policy implication: Investors should remain cautious of short-term herding-induced volatility, leveraging stability for consistent profits. Recognizing limited diversification during market losses is crucial. Additionally, governments and regulators should focus on enhancing market transparency and investor education, investing in robust market infrastructure to mitigate the impact of excessive herding.

Keywords: Behavioural finance, CSAD, Herding, Volatility

JEL Classification: A1, G4

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I. Introduction

In finance, investors face two possibilities when making investment decisions: achieving favourable outcomes or facing adverse results. In the case of unfavourable outcomes, two scenarios can unfold. First, the decision may have been sound, but unforeseeable factors of misfortune played a role. Second, the decision itself might have been flawed, an outcome that could have been avoided(Ross et al., 2019). Therefore, studying behavioural finance is essential to avoid the latter possibility and ensure informed decision-making.

Investors can sometimes act irrationally, influenced by emotions or cognitive biases rather than relying solely on logic and facts(Ross et al., 2019). Investors may exhibit behavioural biases, such as herding behaviour, for mimicking the majority's actions or following the crowd without independent analysis (Burton and Shah, 2013). Herding leads market participants to make financial decisions not based on fundamental principles but rather on the decisions of other investors, systematically ignoring early warning signals (Bekiros et al., 2017).

Herding is considered irrational behaviour as it contradicts the basic assumptions of the Efficient Market Hypothesis (EMH). It posits that all investors act rationally and efficiently and utilize available information to make investment decisions. This behaviour can create imbalances between stock prices and their intrinsic values, contrary to the assumption that stock prices reflect all available information. Investors can suffer adverse consequences due to a lack of theoretical understanding of the stock market and behavioural biases (Chhapra et al., 2018).

The world faced economic turmoil and challenges during the COVID-19 pandemic. COVID-19 significantly impacted financial markets and investment behaviour in the Chinese stock market (Wu et al., 2020a). Herding behaviour is more prevalent during COVID-19 (Fei and Zhang, 2023). On the other side, Sukmadilaga et al.(2023) suggest that herding is not the primary factor influencing stock price movements before and after COVID-19, and Zhang and Giouvris (2022) found that COVID-19 as non-economic crises do not strengthen herding behaviour as economies crises do. The latest research focuses on the periods before and during COVID-19, with none incorporating the post-COVID era into their investigations. It is also unclear whether herding behaviour is stronger during COVID-19 than before or after this period.

Research on herding behaviour in financial markets spans various regions, including China and Iran, examined by Fei and Zhang (2023) and Nouri-Goushki and Hojaji (2023), respectively. While Zhang and Giouvris (2022) covered BRICS nations and Bekiros et al. (2017) focused on the United States, there is a gap in exploring other Asian countries. The impact of herding on stock price volatility remains debated. Fei and Zhang (2023) found increased herding during bullish phases. Papadamou et al. (2021) notion that herding is more intense during the bullish market conditions. This contrasts with Vidal-Tomás et al. (2019) and Chong et al. (2017), who argue for more pronounced herding in bearish conditions. (Filip and Pochea, 2023) also assert that herding is a persistently occurring phenomenon in the stock market, observed under extremely positive and negative sentiment conditions.

This research explores herding behaviour and its impact on stock market volatility in Asian stock markets during the COVID-19 and post-COVID-19 periods. Asia was chosen due to numerous emerging countries with the highest number of listed companies compared to other emerging country groups. As of 2023, Asia is home to more than 14,000 listed companies. Herding is analyzed using the Cross-Sectional Absolute Deviation (CSAD) variable introduced by Chang et al. (2000), employing polynomial regression, an adaptation of (Fei and Zhang, 2023) research, which established a model to investigate asymmetry or volatility concerning herding behaviour in the market through stock returns. Furthermore, we use the GARCH (1,1) model to estimate how herding behaviour influences stock price volatility. The sampled countries in this research are Indonesia, India, Singapore, China, Hongkong, and Taiwan, selected based on their representative trend patterns in stock prices over the past five years.

The research findings indicate significant herding behaviour tendencies in Singapore's stock market. Additionally, herding behaviour was observed in China and Indonesia both during and after the COVID-19 period and in Taiwan during the post-COVID-19 phase. Moreover, the analysis revealed that herding behaviour in China, Singapore, and Taiwan significantly influences stock price volatility, highlighting the substantial impact of herding on market stability. The study revealed an interesting finding about herding behaviour, which is not symmetrical. The phenomenon is more prominent in China, Singapore, and Indonesia, particularly during bearish market trends. This indicates that investors tend to act differently depending on the market direction, often following the crowd and making similar decisions during market uncertainty or negative sentiment periods. These results demonstrate the tendency of investors to engage in herding behaviour and its impact on their investment decisions.

This research offers a primary contribution by focusing on one aspect of behavioural finance: herding, especially during the COVID-19 pandemic and its aftermath. This is distinct from previous studies that often explored several aspects of behavioural finance through qualitative research without in-depth analyses of each behaviour. Additionally, this research analyzes herding behaviour over a more extended and up-to-date sample period, encompassing both the COVID-19 and post-COVID-19 periods, unlike previous research that typically examined before and after COVID-19. This study offers a more comprehensive insight into the role of investor behaviour in shaping global market dynamics during critical periods.

The structure of this paper is as follows: Section 1 Introduction, Section 2 provides a literature review and hypotheses Development. Section 3 explains the Method. Section 4 presents the research results and discussion. The last is section 5, which offers the conclusion.

2. Literature Review and Hypotheses Development

Behavioural finance is defined as the study of how psychology influences the behaviour of financial practitioners and its subsequent effects on the market, helping to explain why and how markets may not be efficient (Sewell, 2007). Tversky and Kahneman (1974) revealed that people do not employ statistical methods in their decision-making but rely on a set of heuristic principles.

Herding behaviour, as defined by Hirshleifer and Hong Teoh (2003), involves reciprocal imitation, leading to the convergence of actions. Herding is investors' tendency to follow one another into and out of the same stocks. Herding is an individual's inclination to mimic a large group's actions (Sias, 2002). Herd instincts are often motivated by observing financial market booms and busts and tend to be highly aggregative, typically summarized by a single-agent model representing the herd (Burton and Shah, 2013). Fei and Zhang (2023) state that herding triggers the formation of investment decision groups based on shared basic information. Investors follow one another's trading decisions, disregarding their own beliefs. The traditional financial theory emphasizes that prices adjust in an orderly fashion, making herding behaviour in finance difficult.

There is a diverse debate in the literature regarding the impact of herding behaviour on market volatility. Some studies support the notion that herding can increase market volatility. Wermers (1999) found that institutional herding in investments can increase short-term volatility. Herding also intensifies during bullish markets and can influence market volatility (Papadamou et al., 2021). Conversely, some studies show contrasting results. Chen et al. (2012) found that institutional investors use contrarian strategies during financial crises to stabilize stock prices. Vidal-Tomás et al. (2019) indicated that herding is more likely to occur during bear markets than bull markets. Therefore, the influence of herding on market volatility remains a subject of debate and depends on different market contexts.

Research conducted during the COVID-19 pandemic has yielded varied findings regarding herding behaviour. Nouri-Goushki and Hojaji (2023) found that the COVID-19 pandemic triggered the formation of herding behaviour, exacerbated by market volatility. Other research indicated that herding behaviour was more prominent when the market experienced rising prices, low trading volumes, and lower volatility due to COVID-19 (Wu et al., 2020a). Meanwhile, Fang et al. (2017) found that herding behaviour during COVID-19 was more apparent and had a significant impact across economic sectors. Studies by Espinosa-Méndez and Arias (2021), using stock data from France, Germany, Italy, and the U.K., showed that COVID-19 increased herding behaviour in the stock market, with investors tending to follow market winners due to uncertainty and fear of extreme situations. Fei and Zhang (2023) also stated that herding behaviour in the Chinese stock market was more pronounced during the COVID-19 pandemic, and this herding behaviour had a negative impact on stock market volatility. Based on these references, we propose the first hypothesis:
H_1: Herding behaviour is observed in Asia before, during, and after the COVID-19.

In the context of relevant literature, several studies have highlighted the impact of herding on the stock market, emphasising market stability and volatility. For instance, research by Zhang and Giouvris (2022) and Fei and Zhang (2023) indicates that herding behaviour can potentially disrupt stock market stability and investment efficiency. Furthermore, the findings from this research suggest that herding behaviour has a negative effect on stock market volatility, depicting the significant influence of herding behaviour on market dynamics. In the specific context of the COVID-19 pandemic, research also indicates that the sensitivity of market volatility to herding behaviour changed during this period, as observed in the study by Zhang and Giouvris (2022). Additionally, it should be noted that high market volatility can amplify herding behaviour, especially in the Chinese market. This finding is reinforced by the research of Bekiros et al. (2017), who highlight the critical role of various volatility measures in influencing the relationship between herding and the stock market. Therefore, gaining a deeper understanding of the impact of herding behaviour on stock market volatility becomes essential. Based on this foundation, the second hypothesis in this study is proposed.
H_2: Herding behaviour impacts stock market price volatility in Asia.

Herding behaviour occurs when investors tend to follow the actions of other investors in both Bullish and Bearish market conditions. Gleason et al. (2004) found that herding behaviour is more prevalent during Bearish market conditions. This is attributed to the heightened uncertainty during Bearish market conditions, leading investors to follow the actions of others to mitigate risks. Tan et al. (2008) discovered similar results, indicating that herding behaviour is more pronounced during bearish market conditions, particularly during periods of high volatility. Fei and Zhang (2023) Therefore, the third hypothesis is formulated as follows:
H_3: Asymmetric herding behaviour exists when facing bullish and bearish market conditions.

3. Method

3.1 Data

This study employs secondary data obtained from Thomson Reuters Refinitiv. The sample period is divided into three segments. The pre-COVID period covers January 2, 2019, to January 29, 2020. The COVID period aligns with the announcement and conclusion of the COVID pandemic by the WHO, spanning from January 30 to May 5, 2023. Meanwhile, the post-COVID period encompasses May 6, 2023, to September 30, 2023.

We collected closing price, volume, and index volatility data from stocks in four countries. Indonesia, Singapore, India, China, Hong Kong, and Taiwan are the four selected countries. The chosen stocks comprise all stocks listed on the stock exchanges of these four countries, except for India, where only those listed on the National Stock Exchange of India are considered. From Indonesia, there are 908 stocks, Singapore has 686 stocks, India has 2494 stocks, Hong Kong sample has 1127 stocks, China's sample has 1350 stocks, and Taiwan has 2127 stocks.

This study analyzes differences during the COVID and non-COVID periods. To ensure the representativeness of the research sample, companies that went public during or after the COVID period are excluded from the sample. Stocks are traded five days a week, excluding holidays, resulting in varying numbers of observations for each country. Indonesia has 1142 days, Singapore has 1176 days, India has 1286 days, China has 1153 days, Hongkong has 1168 days, and Taiwan has 1165 days. These days collectively cover the period from January 2, 2019, to September 30, 2023.

3.2 Methodology

The detection of herding behaviour employs the excess stock return approach, utilizing the method introduced by Chang et al. (2000). Chang identified herding behaviour using the Cross-Sectional Absolute Deviation (CSAD) method.

Initially, daily stock return on a trading day t is expressed as $R_{i,t,}$ calculated by daily percentage price change. It is calculated by subtracting the previous day's price $P_{i,t-1,}$ from the current day's price $P_{i,t}$ and dividing the result by the previous day's price. This is written as follows:

$$R_{i,t} = (P_{i,t} - P_{i,t-1}) / (P_{i,t-1}) \tag{1}$$

The average cross-sectional spread of N stock returns (Rm,t) is calculated by taking the average of all individual stock returns on day t, following the method adapted from Nouri-Goushki and Hojaji (2023).

$$R_{m,t} = \frac{\sum \mathrm{Ri,t}}{N} \tag{2}$$

Where $R_{i,t}$ represents the observed stock return of firm i at time t, and N is the number of companies in the market portfolio.

Next, we follow Chang et al. (2000) definition of CSAD and assume that there are N stocks in the market, where the stock return on trading day t is represented as $R_{i,t,}$ and $R_{m,t}$ is the rate of return of the average market portfolio at time t. Stock return is calculated in logarithmic form. Subsequently, the absolute deviation spread of the return decreases on trading day t is calculated.

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |\, R_{i,t} - R_{m,t}| \tag{3}$$

CSAD is not the herding variable itself. To measure the presence of herding, we need to examine the relationship between CSAD and the market return. The model used is no longer linear but instead employs one of the non-linear regression methods, namely polynomial regression.

$$CSAD_t = \beta_0 + \beta_1 |R_{m,}| + \beta_2 R_{mt}^2 + \epsilon_t \tag{4}$$

Herding is the behaviour of individuals following the crowd, causing investors to make decisions in line with the majority in the stock market. The returns generated will converge with the market return, resulting in a smaller CSAD value. Therefore, if β_2 is found to be negative and significant, it indicates the presence of herding behaviour.

To examine the impact of herding on stock market volatility during COVID-19, a model adapted from Fei and Zhang (2023) is utilized.

$$\sigma_t^m = \gamma_0 + \gamma_1 CSAD_{m,t-1} + \gamma_2 R_{m,t-1} + \gamma_3 V_{m,t-1} + \varepsilon_t \tag{5}$$

The current market volatility (σ_t^m) is influenced by the previous period's market return and the previous period's CSAD. $V_{m,t-1}$ the daily circulation market value, or volume trading, is calculated with a one-period lag. When γ_1 has a positive and significant value, it indicates that a decrease in CSAD (meaning increased herding behaviour) leads to a reduction in stock volatility. A negative result implies the opposite interpretation.

Subsequently, an examination of the impact of herding behaviour on stock volatility is conducted. Therefore, it is necessary first to determine the method for calculating stock volatility. In this study, stock volatility is computed using the GARCH (1,1) estimation method. By employing GARCH, daily volatility is forecasted based on past volatility. GARCH is suitable for application when data exhibit heteroskedasticity, displaying varying volatility over time. GARCH (1,1) has been empirically proven to significantly enhance stock return volatility (Molnár, 2016) (Huang et al., 2015).

In behavioural finance theory, market volatility is typically higher during a market decline (Bearish) than a market upswing (Bullish). However, the same might not necessarily hold for herding behaviour. Testing is required to examine whether there exists asymmetric behaviour in herding. The examination involves regression analysis utilizing dummy variables. Regression estimation is employed following the polynomial regression equation for the initial herding estimation. Dummy variables are added to address the need to capture potential asymmetries or distinct behavioural patterns between bullish and bearish market conditions, enhancing the model's ability to comprehensively analyze and explain herding dynamics in different market scenarios. These variables assign a value of 1 or 0 to a subject, depending on whether the subject possesses specific characteristics. In this context, the characteristic of the Dummy variable is defined as follows:

D = 1, when $R_m < 0$

D = 0, when $R_m \geq 0$

Hence, the regression formula will be transformed into:

$$CSADt = \alpha + \beta_1(1 - D)R_{m,t} + \beta_2 DR_{m,t} + \beta_3 R_{mt}^2 + \varepsilon_t \quad (6)$$

The coefficient β_1 indicates the influence of return on herding behaviour when the market is Bullish. Meanwhile, the coefficient indicates the influence of the market return when the market is Bearish or declining. If the value is positive, it implies that Rm decreases CSAD, indicating an increase in herding behaviour.

Descriptive statistics will be generated using Microsoft Excel for each country's variables, Rm and CSAD, providing key insights into their respective characteristics. R Studio will construct the volatility model, assumption testing, and herding and asymmetry models, ensuring a comprehensive analytical approach. Additionally, R Studio will facilitate data visualization, specifically illustrating the relationship between CSAD (Y-axis) and Rm (Y-axis). These visualizations will enhance the interpretative framework, enabling a deeper comprehension of the interplay between herding behaviour and market returns.

4. Results

4.1 Stationarity Testing

Table 1 displays the results of the stationarity testing for the variables Rm and CSAD across each country. Stationarity tests were conducted due to the time series nature of the data, which may lead to spurious regression, autocorrelation, and heteroskedasticity in data analysis. In the Augmented Dickey-Fuller (ADF) test, the unit root value is a parameter that determines whether a time series data is stationary or not. A data series is considered stationary if its mean, variance, and autocorrelation remain constant over time (Enders, 2015).

The results indicate that the ADF values for the Rm and CSAD variables in all six countries have p-values less than 1% at the significance level. This suggests that the data is stationary. Consequently, data processing can proceed without needing differencing to achieve stationarity.

Table 1. Stationarity test

	Variable	**ADF**	**p-value**	**remarks**
China	CSAD	-8.2650	0.0100	Stationer
	Rm	-7.5280	0.0100	Stationer
Indonesia	CSAD	-8.8566	0.0100	Stationer
	Rm	-7.8590	0.0100	Stationer
Singapura	CSAD	-6.9883	0.0100	Stationer
	Rm	-7.2240	0.0100	Stationer
Taiwan	CSAD	-9.3170	0.0100	Stationer
	Rm	-1.2635	0.0100	Stationer
Hongkong	CSAD	-8.2130	0.0100	Stationer
	Rm	-5.1660	0.0100	Stationer
India	CSAD	-8.7370	0.0100	Stationer
	Rm	-6.1142	0.0100	Stationer

* This table summarizes stationarity tests for herding variable (CSAD) and market return (Rm) in six sample countries using data from January 2, 2019, to September 30, 2023. Analyzed in R-studio, the Augmented Dickey-Fuller (ADF) test yields p-values, indicating stationarity at a 1% significance level

4.2 Descriptive Statistics

Several descriptive statistics were calculated for the main variables, namely CSAD and Rm (market return), across the five countries.

Table 2 presents low values for each country's CSAD and Rm variables, as both are measured in the form of standard deviation and percentage return. Descriptive statistics depict the centrality of data (mean and median) and its dispersion (standard deviation, kurtosis, skewness, and range). Differences in the mean and median values of market returns between countries reflect variations in average daily stock price changes, indicating the level of market risk or systemic risk. This systemic risk, which cannot be mitigated through diversification, is reflected in the high values of Rm.

The analysis of data dispersion indicates that skewness and kurtosis for the CSAD and Rm variables are relatively high in each country. This can be explained by the volatile nature of daily data reflecting stock price volatility. Over more than 1000 days, daily data clarifies the volatility, demonstrating significant fluctuations in both variables. This insight into the daily data highlights substantial volatility, underscoring the inherent risk and market dynamics associated with both CSAD and Rm variables across the observed countries.

Table 2. Descriptive result

Descriptive	CSAD _id	Rm_ id	CSAD _sg	Rm_ sg	CSAD _in	Rm_ in	CSAD_ tw	Rm_ tw	CSAD _cn	Rm_ cn	*CSAD _hk*	*Rm_ hk*
Mean	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Standard Error	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mode	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
StDev	0.8	0.8	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.3	0.0
Sample Variance	0.6	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
Kurtosis	184.3	183	112.9	15.0	-1.3	11.2	133.8	87.7	-1.0	3.8	537	2.9
Skewness	13.2	13.1	7.0	-1.1	-0.6	1.5	10.1	6.4	-0.2	0.2	22.1	-0.2
Range	12.3	13.2	0.4	0.2	0.0	0.1	1.8	1.9	0.0	0.1	9.1	0.2
Min	0.0	-0.9	0.0	-0.1	0.0	0.0	0.0	-0.5	0.0	-0.1	0.0	-0.1
Maxi	12.3	12.3	0.4	0.1	0.0	0.1	1.8	1.3	0.0	0.1	9.1	0.1
Sum	120.2	72.3	23.9	0.2	17.6	-0.8	29.1	3.6	14.8	0.2	58.4	0.5
Count	1154	1154	1196	1196	1174	1174	1152	1152	1153	1153	1168	1168

* The table provides descriptive statistics for the stock sample from January 2, 2019, to September 30, 2023, across six sample countries, focusing onherding (CSAD) variables and market return (Rm). Country abbreviations follow the ISO 3166-1 alpha-2 standard, representing international two-letter codes for respective countries worldwide: "_id" for Indonesia, "_sg" for Singapore, "_in" for India, "_tw" for Taiwan, "_cn" for China, and "_hk" for Hong Kong.

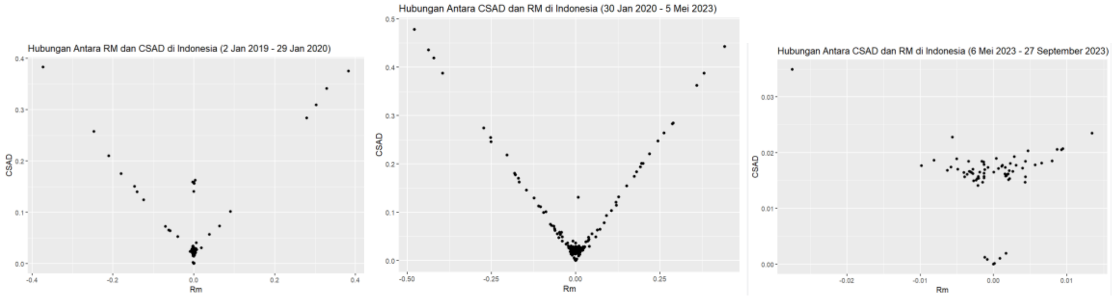
4.3 Scatter Plot

The visualization of the relationship between CSAD and market return (Rm) is examined using scatter plots. Scatter plots are generated for all countries across three periods: pre-COVID, COVID, and post-COVID. These scatter plots are meticulously created for each country, subdividing the visual representation into six distinct panels corresponding to the sample countries: Indonesia, Singapura, India, Taiwan, Hongkong, and China.

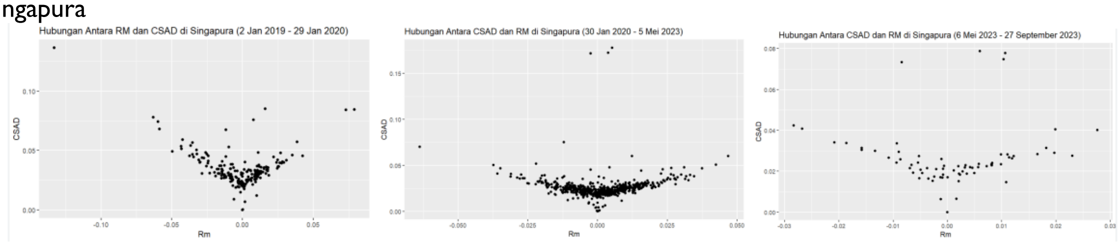
Figure 1 illustrates that the relationship between CSAD and Rm is non-linear, suggesting a violation of the Capital Asset Pricing Model (CAPM) assumptions. CAPM assumes a linear positive relationship between individual returns and market returns, and a non-linear relationship can be interpreted as a departure from this assumption. Analysis of all five panels also indicates that no country exhibits a linear pattern in the plot between CSAD and Rm, affirming the non-linear nature of this relationship. This finding aligns with the quadratic model proposed by Chang et al. (2000) in modelling CSAD and Rm. Consequently, adopting a non-linear model may be more efficient in accurately depicting the true relationship between CSAD and Rm.

Figure 1 depicts the relationship between CSAD and market return (Rm). The author utilized R Studio to generate the visual, organizing panels based on the analyzed countries. Each panel comprises data for the periods before, during COVID-19, and after COVID-19. The thicker points in the 'during COVID' pattern indicate a higher density of time series data during the COVID period compared to the non-COVID periods.

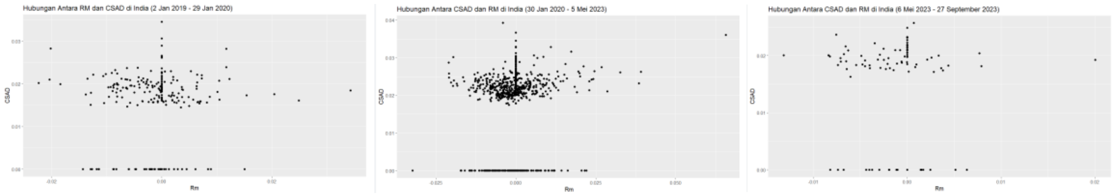
Panel Indonesia



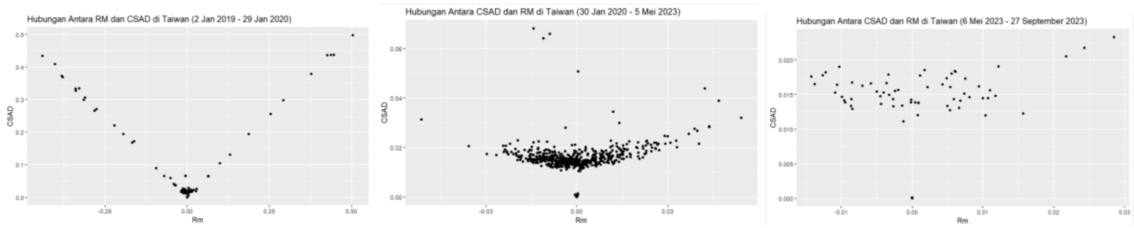
Panel Singapura



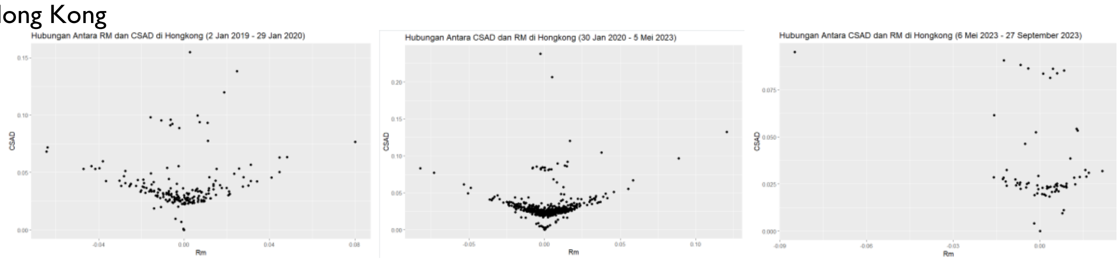
Panel India



Panel Taiwan



Panel Hong Kong



Panel China

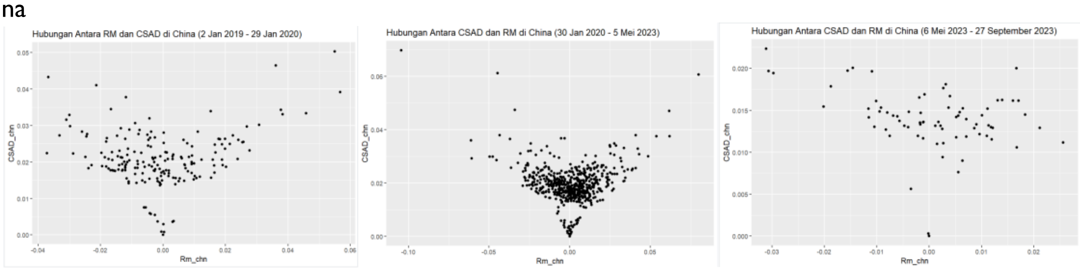


Figure 1. Scatter Plot between CSAD and Rm

Table 3. Herding behaviour regression results during precovid, covid, and post-covid

Country	Coefficient	Pre-Covid	Covid	Post-Covid
Hongkong	β_0	0.0246***	0.0167	-0.0871
		(0.0026)	(0.0166)	(0.1949)
	β_1	0.3351	3.8559*	28.0057
		(0.5292)	(1.8499)	(29.5953)
	β_2	6.4923	-52.4731	-520.0369
		(19.5286)	(36.1681)	(939.9949)
Taiwan	β_0	0.0071***	0.0082**	0.0044***
		(0.0006)	(0.0025)	(7.62E-04)
	β_1	0.9599***	0.8091***	1.7990***
		(0.0108)	(0.1765)	(2.01E-01)
	β_2	0.0536**	0.1403	-48.0400***
		(0.0176)	(0.1373)	(9.62E-01)
China	β_0	0.0071***	0.0063***	0.0037***
		(0.0006)	(3.36E-04)	(6.44E-04)
	β_1	0.9599***	1.2220***	1.5590***
		(0.0107)	(5.39E-02)	(1.66E-01)
	β_2	0.0535**	-16.7400***	-44.4100***
		(0.0175)	(1.46E+00)	(7.51E+00)
Indonesia	β_0	0.0156***	0.0092***	0.0055***
		(0.0015)	(3.45E-04)	(8.47E-04)
	β_1	0.9723***	0.9980***	2.9210***
		(0.0125)	(1.52E-03)	(3.27E-01)
	β_2	0.0033*	-5.46E-6*	-74.5900***
		(0.0017)	(1.35E-04)	(1.51E-01)
Singapura	β_0	0.0109***	0.0093***	0.0052**
		(0.0009)	(9.15E-03)	(1.8E-03)
	β_1	1.4055***	1.8480***	3.7890***
		(0.0813)	(1.67E-01)	(4.68E-01)
	β_2	-4.5851***	-24.3800***	-103.4000***
		(0.9734)	(5.21E-00)	(2.02E-01)
India	β_0	0.0115***	0.0144***	0.0126***
		(7.95E-04)	(0.0005)	(0.0013)
	β_1	0.6439**	0.3159**	0.3889
		(2.29E-01)	(0.1085)	(0.5629)
	β_2	-16.2000	-1.5369	-0.7419
		(1.10E+01)	(3.2972)	(40.7357)

* The table displays the results of Regression Equation Number 4 using polynomial regression to address non-linear characteristics. Coefficients β_0, β_1, and β_2 represent regression coefficients, with standard errors in parentheses. Significance denoted by symbols: ***, **, and *, indicating 1%, 5%, and 10% levels.

4.4 Herding Behaviour Testing

CSAD is not an indicator that characterizes herding behaviour. The presence or absence of herding behaviour is observed through the relationship between the CSAD variable and the market return variable. Testing uses a polynomial regression with CSAD as the dependent variable and market return (Rm) as the independent variable.

The significance of the regression results is assessed, as depicted in Table 3. This table presents the coefficients of the second-order polynomial regression along with their corresponding standard errors enclosed in parentheses. The asterisks in the output signify that the test results provide substantial evidence, with p-values less than 0.05, indicating statistical significance. This suggests that the coefficients of the quadratic regression model are statistically different from zero, supporting the conclusion of the model's significance.

The coefficient examined to determine the presence of herding is the coefficient β_2. Specifically, that is the coefficient on the squared term of Rm (sqr_Rm). If this coefficient is negative and significant, it indicates herding in the respective country during the tested period. A negative coefficient suggests an inverse relationship between herding and market return. When the market return is high, the CSAD value tends to be low. In this context, a low CSAD implies low variability in individual returns, indicating a herding pattern where individuals follow the market.

Based on Table 3, herding is identified when the β_2 value is both negative and significant. Among the six countries, only India and Hong Kong show no evidence of herding during the pre-COVID, COVID-19, and post-COVID periods. The remaining four countries exhibit herding behaviour. In Taiwan, herding is only found in the post-COVID period. In Indonesia and China, herding is observed during the COVID period and persists in the post-COVID period. No herding is found in the pre-COVID period for both countries. In Singapore, herding is identified across all three periods: pre-

COVID, during COVID, and post-COVID. This analysis suggests variations in herding behaviour across countries and periods, providing valuable insights into the dynamics of investor behaviour in response to market conditions.

Among the six countries, only India and Hong Kong are found to have completely no herding behaviour during the pre-COVID, COVID-19, and post-COVID periods. This aligns with the findings of Ganesh et al. (2017), asserting the absence of herding in India even during crisis periods. This phenomenon is attributed to several regulatory reforms that enhance investor protection, reducing their vulnerability to herding effects. In 2011, the Indian government established the Securities Exchange Board Insider Trading Regulation (SEBI), prohibiting trading based on insider information. In 2017, SEBI also prohibited unhealthy market practices such as market manipulation, front-running, and back-dating.

Additionally, the Investor Education and Protection Fund (IEPF) educates investors on enhancing their capability for independent analysis. According to Ganesh, many investors in India also come from Foreign Institutional Investors (FIIs), which are foreign institutional investors investing in the Indian stock market. FIIs have broader resources than domestic retail investors, possess a long-term orientation, and contribute to rational behaviour.

Satish and Padmasree (2018), Bharti and Kumar (2022), and Garg and Gulati (2013) also state that in India, herding is not detected even during crisis periods. Stock market investors in India conduct independent analyses and make investment decisions without a tendency to imitate the behaviour of other investors. Chathurika and Tennekoon (2022) also summarize that most studies yield that herding is not observed in India. The dominance of institutional investors in India leads to investment decisions based more on fundamental analysis and long-term strategies, thereby reducing the inclination for herding. However, Bharti and Kumar (2022) state that during the COVID-19 conditions, herding was found to be significant in India but was successfully controlled by the government. Policies to control the pandemic, including a USD 266 billion stimulus and SEBI regulations, effectively reduced uncertainty and information asymmetry that could lead to herding.

Research by Laih and Liau (2013) supports that herding is not observed in Hong Kong. Herding is more prevalent in developing countries where individual investors dominate the market, while institutional investors are more abundant in Hong Kong. However, different results are presented by Wen et al. (2022) and Jiang et al. (2022), indicating that mild herding was observed from August 2019 to January 2020. Then, it weakened in the subsequent months until July 2020. The Hong Kong Monetary Authority (HKMA) implemented policies to enhance financial institutions' liquidity, encouraging banks to use their liquidity buffers more flexibly and reducing the scale of issuance of exchange fund bills. This resulted in a more stable market, as herding tends to emerge when stock market conditions exhibit idiosyncratic volatility.

The remaining four countries exhibit herding behaviour. In Taiwan, herding is only found during the post-COVID period. P.-J. Chen (2016) asserts that herding is evident in Taiwan due to a lack of experience and access to various sources of information. Shinn-Juh Lin (2017) and Y.-C. Chen et al. (2021) also state that herding in Taiwan varies over time and is present during the post-2008 period or after the 2008 financial crisis. There is also a conditional correlation between beta and herding. Wang and Huang (2019) suggest that herding has decreased in Taiwan due to increased government transparency regarding listed companies in the country. Luu and Luong (2020) found that, in general, no herding was observed in the Taiwanese market during the pandemic. Herding was identified solely within the food and beverage industry. According to Huang et al. (2015), herding in Taiwan intensifies in response to idiosyncratic volatility in the stock market. In 2023, there was heightened tension between Taiwan and China, increasing uncertainty in Taiwan's financial markets. Investors may feel the need to safeguard their investments against potential military conflicts. Behaving in a herding manner or following more knowledgeable investors could be considered as an option to mitigate potential losses.

In Indonesia and China, herding is found during the COVID period and persists into the post-COVID period. During the pre-COVID period, herding was not observed in both countries. Herding behaviour is observed in China and Indonesia during the COVID-19 and post-COVID pandemic. This aligns with the early theory suggesting that individuals are inefficient in processing new information during periods of heightened uncertainty (Keynes, 2018). The uncertainty escalated with the occurrence of COVID-19. In the post-COVID period, the effects of the pandemic recovery have not fully materialized, compounded by global events in 2023, such as the geopolitical tensions between Ukraine and Russia, a slowdown in global economic growth, the collapse of major banks in the U.S., and concerns about high inflation in several countries. These factors are also worrying for investors.

In Indonesia, herding aligns with the findings of Malini and Sakliana (2022) and Rizal and Damayanti (2019), who assert the presence of herding in Indonesia. Arisanti and Asri (2018) also state herding behaviour in Indonesia, especially when there are underpriced stocks of newly listed IPOs and Sharia-compliant stocks. Nabil et al. (2017) and Miranti (2021) empirically prove that herding did not exist in Indonesia before COVID-19 but emerged afterwards. Herding behaviour is significantly absent during the pre-COVID period, as indicated by the significant and positive value of β_2. When the market conditions are stable, investors may be more confident in their portfolios, leading them to conduct independent analyses and not follow others.

According to Yuan's (2021) research, herding is present in China. Fei and Zhang (2023) found that in the CSI index stocks, herding behaviour was not observed during the pre-COVID period but is evident during the COVID period. Zhang and Giouvris (2022) state that China exhibits the highest level of herding compared to other BRICS countries. Before the pandemic, herding behaviour had not emerged. During the pandemic, the economic conditions of the country became fluctuating. Chong et al. (2017) explain that herding behaviour in China is caused by analyst recommendations, short-term investors, and risk. Zhuang et al. (2022) also agree that individual investors in China tend to easily follow investment behaviour based on the decisions of a specific group, especially when there is a particular sentiment; they lack confidence in their independent analyses. Herding tendencies in the Chinese stock market escalated amid the COVID-19 pandemic compared to the preceding period, aligning with Keynes (2018) initial herding theory. According to this hypothesis, individuals exhibit inefficiencies in processing new information during heightened uncertainty, as observed during the COVID-19 pandemic.

In Singapore, herding is identified in three periods: pre-COVID, COVID, and post-COVID. Arjoon et al. (2020) state that herding is evident in Singapore with spurious and intentional behaviour. Herding is observed in Singapore before, during, and after COVID. The herding behaviour does not differ during this health crisis. This implies that herding behaviour in Singapore persists whether the economy is rising or falling during a health crisis. This is also consistent with the research by Jiang et al. (2022), which detects herding in Singapore both when the market is up and down.

On the other hand,Kumar et al. (2021) state that herding in Singapore is more prevalent during periods of high volatility in a stock. Arjoon et al. (2020) also find that herding is pronounced at the market level and in each size portfolio.

4.5. Calculation of Daily Stock Volatility

After examining the presence of herding behaviour in each country, the next step is to investigate whether this herding behaviour influences market volatility. However, before conducting this analysis, the first step is to construct the volatility variable using GARCH (1.1). This method will assist in understanding how market volatility fluctuates over time and whether herding behaviour significantly impacts fluctuations (Dowd, 2002).

Table 4. Best arima order result

No	Country	ordo ARIMA	AIC
1	China	(0. 1. 0)	431.44
2	Indonesia	(1. 1. 1)	-9068.43
3	Singapura	(5. 1. 0)	-5368.16
4	Taiwan	(3. 1. 1)	-191.18
5	Hongkong	(0. 1. 0)	-6532.91
6	India	(1. 1. 1)	-7350.31

* The table summarizes the results of the auto. The Arima formula was applied to stock price variables in R Studio, presenting the optimal Arima order (Ar, dif, ma). The AIC values, indicating model fit, are also included.

Table 4 presents the values of AIC and the optimal ARIMA order that will be used in constructing the GARCH (1.1) volatility model. Based on Table 4, it is evident that each country has a unique optimal order and AIC value. The AIC value is typically used to determine the best order. The model with the lowest AIC is considered the best in terms of the trade-off between data fit and model complexity.

Table 5. GARCH (1.1) processing result

No	Country	Mu	Omega	Alpha	Beta
1	China	19.4978	0.0115***	0.3214***	0.6721***
		(0.0505)	(0.0023)	(0.0410)	(0.0389)
2	Indonesia	4.64E-03	1.86E-06	0.1178***	0.7839***
		(1.07E-03)	(3.42E-02)	(1.58E-02)	(1.65E-02)
3	Singapura	1.88E-02	8.33E-6	0.1294***	0.8718***
		(3.34E-03)	(2.96E-02)	(2.31E-02)	(1.49E-02)
4	Taiwan	4.00E-02	1.52E-6	0.0667***	0.9411
		(1.43E-02)	(2.24E-02)	(3.27E-03)	(1.84E-02)
5	Hongkong	0.8296	2.43E-05	0.7461***	0.2735***
		(0.0001)	(0.0000)	(0.0830)	(0.0697)
6	India	1.08E-03	1.83E-06	0.0598***	0.9274***
		(1.25E-03)	(3.48E-06)	(1.22E-02)	(1.00E-02)

* This table presents the parameter outcomes of the GARCH (1.1) model, where omega, alpha 1, and beta 1 individually represent the contributions of each model component to market volatility. The significance levels are denoted by symbols: ***. **and *represent statistical significance at 1%. 5% and 10% levels, respectively.

Applying the GARCH (1.1) model yields results as shown in Table 5, indicating high Beta values for China, Indonesia, Singapore, Taiwan, and India, while Hong Kong has a lower Beta value. This suggests that the stock market responds well to short-term market movements and volatility in Singapore. However, for the other five countries, volatility is expected to stabilize in the long term, and stock data is not as responsive to market movements as in Singapore.

4.6 Herding impact on market volatility

After examining the presence of herding behaviour in each country, the next step is to evaluate its impact on market volatility. This is accomplished through multiple linear regression, with the volatility variable as the dependent variable and CSAD as the independent variable. The model also incorporates volume and return variables to control for the volatility effects, following the approach used by Fei and Zhang (2023).

Table 6. Regression results of CSAD influence on stock market volatility

Country	γ_0	γ_1	γ_2	γ_3
China	3.6710***	28.0406***	-4.4542	-0.7623***
	(0.2356)	(7.3799)	(5.9980)	(0.1436)
Indonesia	0.0108***	0.0006	-0.0006	-0.0904**
	(0.0005)	(0.0012)	(0.0012)	(0.0315)
Singapura	0.0258***	0.0472**	-0.0047	-0.0098***
	(0.0009)	(0.0183)	(0.0298)	(0.0028)
Taiwan	0.0111***	-0.0060*	0.0007	-0.1017**
	(0.0005)	(0.0024)	(0.0027)	(0.0315)
Hongkong	0.0018	0.0002	0.0021	0.0482
	(0.0005)	(0.0005)	(0.0126)	(0.0022)
India	0.0069	0.0133	-0.0957	0.0187
	(0.0005)	(0.0219)	(0.0333)	(0.0018)

* The table provides the results for Regression Equation 5, illustrating the regression relationship between volatility and herding behaviour (CSAD). The coefficients γ_0, γ_1, γ_2 and γ_3 represent the regression coefficients. The number in parenthesis is a standard error. Significance levels are indicated by symbols: ***. **and *denote statistical significance at 1%. 5% and 10% levels, respectively.

The modelling results are presented in Table 6. It is observed that the γ_1

CSAD value is positive and significant. The positive and significant γ_1 value indicates that high CSAD values (indicating low herding behaviour) can lead to high market volatility. The regression is conducted on the full sample period of the six sampled countries. The results reveal that only China, Singapore, and Taiwan exhibit significantly influenced volatility due to herding behaviour in these countries. The other three countries, Indonesia, Hong Kong, and India, show no evidence that herding behaviour affects volatility. China has the largest CSAD coefficient, indicating that the negative herding effect is more pronounced in China than in Singapore or Taiwan.

Herding behaviour significantly influences stock volatility in China. Singapore, and Thailand. Y.-C. Chen et al. (2018) and Shen (2018) state that herding behaviour in stock investment strongly contributes to stock volatility in China, especially during the stock market crash 2015. Herding affects stock price volatility. When herding behaviour is stronger, stock prices experience higher volatility. Conversely, when herding behaviour in stock investment decreases, the stock market also experiences reduced volatility (Wu et al., 2020b). Zhang and Giouvris (2022) also confirm that high volatility in the stock is related to high levels of herding behaviour in China. Y.-C. Chen et al. (2018) also conclude that herding behaviour greatly influences stock price volatility, especially during financial crises.

However, this research yields positive γ_1 coefficients in China and Singapore, indicating that herding behaviour negatively affects volatility. When CSAD decreases (indicating high herding behaviour), stock volatility decreases, suggesting that herding behaviour can suppress stock volatility (Fei and Zhang, 2023). This aligns with Wermers (1999), asserting that herding behaviour can expedite the price-adjustment process. Many investors engaging in similar trades based on the same market information or sentiment cause rapid price movements, facilitating price adjustments. Dasgupta et al. (2011) state that when conducted by large institutional investors, herding can stabilize the market if the herding behaviour persists over time because the institution significantly impacts overall market movements.

In the Taiwan stock market, the γ_1 coefficient exhibits a contrary negative and significant value. This contradicts the findings in China and Singapore, where lower CSAD values (indicating increased herding) lead to higher volatility. This aligns with Chen et al.'s (2021) research, which asserts that herding is a key transmitter in the Taiwan stock market and correlates with betas, causing volatility. Tan et al. (2008) also state that foreign investors engage in herding, following positive feedback and causing an increase in stock prices in Taiwan. However, there are contradictory results. Hsieh (2013) argues that institutional investor herding speeds up the price-adjustment process and is more likely to be driven by correlated private information, while individual herding is most likely driven by behaviour. Herding, where investors collectively act in unison, following the market together, can lead to dramatic price movements, either increasing or decreasing dramatically, thereby elevating the risk of volatility.

4.7. Asymmetric Herding Behaviour in Bull and Bear Markets

In the next stage, the regression results of CSAD (Cross-Sectional Absolute Deviation) with Rm (market return) as the independent variable will be explored, along with the use of a dummy variable with a value of 1 when Rm is negative and 0 when Rm is positive. The selection of this dummy variable aims to understand how investor behaviour changes when the stock market experiences a directional change, either towards positive conditions (bull market) or negative conditions (bear market).

Table 7. Testing asymmetry in herding behavior during bull and bear market conditions

Country	λ_0	λ_1	λ_2	λ_3
China	0.0016 (1.33E-03)	0.7023*** (2.81E-02)	-0.7060*** (2.98E-02)	2.85E-4*** (6.14E-05)
Indonesia	0.0107 (4.24E-04)	0.9976*** (2.18E-03)	-0.9834*** (4.56E-03)	9.29E-5** (1.97E-04)
Singapura	0.0116 (0.0006)	1.1852*** (0.0660)	-1.1105*** (0.0581)	-0.9396*** (1.2909)
Taiwan	0.0071 (0.0016)	0.9816*** (0.0530)	-0.9582*** (0.4410)	0.0169*** (0.0578)

* The table provides the results for Regression Equation Number 6. The coefficients λ_0, Λ_1, Λ_2 and λ_3 represent the polynomial regression coefficients with dummy variables. Λ_2 capturing conditions during the bearish period (denoted as dummy D) and representing conditions during bullish periods (denoted 1-D). The number in parenthesis is a standard error. Significance levels are indicated by symbols: ***. **and *denote statistical significance at 1%. 5%, and 10% levels. Respectively.

In Table 7, λ_2 represents the condition when the market is experiencing Bearish, while λ_1 R_m represents the opposite, namely when the market is in a Bullish condition. The result indicates that herding behaviour is stronger when the market is in a Bearish condition or experiencing a decline. This case is consistent across the four countries exhibiting herding. Significant values for λ_1 and λ_2 are observed but have different signs. The distinct positive and negative signs respond to how the market reacts to the rise or fall of market returns.

The positive sign for variable λ_1 implies that when the market faces a Bullish condition, the value of CSAD will increase positively. This suggests that when the market is Bullish. CSAD will be high, indicating low herding behaviour. Conversely, the significant negative values for λ_2 imply that CSAD decreases (herding strengthens) when the market is Bearish.

Herding behaviour has exhibited asymmetric characteristics in responding to the market under bearish and bullish conditions. In the case of China, the variable λ_1 has a positive value, indicating that when the market faces bullish conditions, the CSAD value will increase positively. This suggests that when Rm is high in a bullish market, CSAD will also be high, signifying reduced herding behaviour. When market news or sentiments turn positive (bullish), investors may feel more confident and tend to invest or buy stocks more independently. They perceive the market as positive, resulting in less similarity in herding behaviour among investors.

Conversely, when the market is in a bearish condition, the CSAD value decreases, indicating increased herding behaviour. Herding behaviour intensifies during bearish market conditions, confirming the previous findings during the COVID testing. During the Covid period, stock market performance tends to decline or experience bearish trends, strengthening herding behaviour. In bearish conditions, investors become pessimistic and concerned about their independent analyses, providing more incentive to mimic others to avoid losses. This research aligns with studies by Vidal-Tomás et al. (2019), Yao et al. (2014), and Luo and Schinckus (2015). They found that investors exhibit more herding behaviour during bearish conditions for A-shares. Lin et al. (2013) also state that securities analysts tend to herd behaviour by recommending selling stocks rather than buying during bearish market conditions to avoid losses, potentially triggering other investors to follow these recommendations.

This result differs from Fei and Zhang (2023) study, which found that investors in China exhibit more herding during Bull Market conditions. When the market is Bullish, investors tend to be optimistic and exchange information more frequently, leading to herding behaviour. The finding that herding behaviour is stronger during Bull markets is also supported by Papadamou et al. (2021) and Lee et al. (2013), who found that herding is more pronounced during Bullish periods. The discrepancies in research findings reflect the complexity of herding behaviour and its impact on market dynamics, with no consensus on whether this behaviour is more prevalent during market upswings (bull markets) or downturns (bear markets).

The analysis results for China provide intriguing insights into investor herding behaviour under Bullish and Bearish market conditions. The findings indicate that when the Chinese market experiences Bullish conditions, investors tend to exhibit less structured behaviour (low herding). Conversely, herding behaviour tends to increase when the market is in a Bearish state. However, these findings are not unique to China alone. Similar analyses were conducted for other countries, such as Indonesia. Singapore and Taiwan, and the results align with the findings in China. This suggests asymmetry in investor herding behaviour across various countries when facing different market conditions (Chiang and Zheng, 2010). While in these countries. Bullish market conditions result in lower herding behaviour. When the market turns Bearish, investor herding behaviour tends to intensify. These findings provide valuable insights into how investors in different countries respond to changes in market conditions that can influence their investment dynamics.

5. Conclusions

This study uncovers herding behaviour in four of the six sampled Asian countries, namely China, Indonesia, Taiwan, and Singapore. However, herding is not observed in India and Hong Kong. In particular, herding is identified in Indonesia and China during both the COVID and post-COVID periods, while in Taiwan, it is only evident during the post-COVID period. However, herding is not observed in India and Hong Kong, as the empirical evidence does not support its presence in these two regions.

Herding behaviour predominates during the COVID-19 period compared to the pre-COVID period, indicating market reactions during crises. The early herding theory posits that individuals are inefficient in processing new information during heightened uncertainty (Keynes, 2018). During the COVID-19 and post-COVID-19 periods, increased uncertainty leads individuals to follow other investors due to inefficiencies in processing new information.

Herding has an impact on stock price volatility. In China and Singapore, herding behaviour dampens stock price volatility, expediting stabilization due to a consistent movement pattern. Conversely, stronger herding behaviour in Taiwan increases stock price volatility, making the stock market more extreme and volatile. Additionally, using a dummy variable representing bearish market conditions with a value of 1 and 0 for other conditions, this research demonstrates that herding behaviour exhibits asymmetry. Herding becomes stronger during bearish market conditions. Investors tend to be pessimistic and follow herd movements during bearish markets to avoid losses. Conversely, investors are more confident in their independent analyses during bullish markets.

The research findings indicating stronger herding behaviour in China, Indonesia, Taiwan, and Singapore during the COVID-19 pandemic have significant implications for investors and governments. Investors need to exercise caution in making investment decisions by understanding the potential occurrence of herding behaviour in various countries. For instance, herding behaviour has been identified in Indonesia. Investors should be more attuned when stock prices experience volatility, avoiding being swayed by other investors' opinions, as this volatility might be a result of herding behaviour. Investors should strengthen their fundamental analysis when selecting stock portfolios. While herding can suppress stock price volatility, investors should be aware that, in the short term, volatility due to herding may still occur. Investors can capitalize on this by not being overly influenced by minor price fluctuations. They can leverage the stability generated by herding to achieve more consistent gains. Investors who understand that herding can mitigate volatility may find it easier to identify fundamental investment opportunities. They can focus on the fundamentals of companies or assets, seek intrinsic value, and make investment decisions with greater composure. Herding knowledge is crucial for investors, as it indicates limited diversification opportunities in the stock market, especially during market losses (Demirer et al., 2010).

These findings provide impetus to strengthen transparency and investor education at the government and regulatory levels. Governments can enhance market transparency and provide better educational literacy to investors regarding the risks and impacts of herding behaviour. Transparency in information will facilitate investors in conducting fundamental analysis and avoiding specific herd behaviours. Additionally, investments in robust market infrastructure, such as fast-responding electronic trading systems to mitigate potential bubbles resulting from excessive herding, can be considered to minimize their impact. Governments and regulators may also contemplate policies or preventive actions to address the potential bearish market conditions. Maintaining economic stability and preventing bearish markets can reduce the risk of herding, as this research suggests that herding tends to increase during bearish markets. Government actions during crises can mitigate investor tendencies toward herding (Zaremba et al., 2020).

This study is subject to several research limitations. Herding was examined solely using the CSAD approach, while other herding approaches, such as the state space model, were not considered. Additionally, the research is constrained to the six sampled countries and does not differentiate between institutional and individual investors. Furthermore, the study provides a general overview of herding in a country's stock market without categorizing stocks into various industrial sectors.

To address these limitations, future research could incorporate alternative herding approaches, such as the state space model, to provide a more comprehensive understanding of herding dynamics. Additionally, exploring the distinctions in herding behaviour between institutional and individual investors could contribute valuable insights. Further investigations may also consider a more granular analysis by categorizing stocks into different industrial sectors to unveil sector-specific herding patterns. Expanding the scope of the study in these ways would enhance the robustness and applicability of findings in understanding herding behaviour across diverse market conditions.

Author Contribution

Author 1: conceptualization, writing original draft, data curation, formal analysis, investigation, methodology, visualization, writing review and editing.
Author 2: review and editing, writing review and editing, supervision.

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Conflict of Interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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