“The impact of COVID-19 on investor herding in Indonesia: Evidence from LQ-45 index before, during, and after the pandemic”

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THE IMPACT OF COVID-19 ON INVESTOR HERDING IN INDONESIA: EVIDENCE FROM LQ-45 INDEX BEFORE, DURING, AND AFTER THE PANDEMIC

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Abstract

Herding behavior, in which investors follow overall market trends rather than conducting independent analysis, has significant implications for market efficiency, volatility, and liquidity conditions, particularly in emerging markets like Indonesia. This study aims to investigate the presence and dynamics of herding behavior in Indonesia's LQ-45 index during three distinct periods: pre-pandemic (2019), pandemic (2020–2021), and post-pandemic (2023). The sample comprises 22 firms consistently listed on the LQ-45 index, with daily data collected from 2019 to 2023. A time-series regression based on the Cross-Sectional Absolute Deviation (CSAD) model measured herding intensity, while a Granger causality test assessed the relationship between herding behavior and market liquidity. The results indicate that herding behavior intensified significantly during the pandemic, evidenced by a strong negative γ_2 coefficient (–0.0124, $p = 0.0026$) and an adjusted R^2 of 0.1902, the highest across all periods. In contrast, the pre-pandemic period showed relatively weak herding behavior under more stable market conditions, while the post-pandemic phase demonstrated a return to more independent decision-making. The Granger causality test confirmed a bidirectional relationship between market liquidity and herding during the crisis, while such causality was absent after the pandemic. In the pre-pandemic period, herding influenced liquidity ($p = 0.014$), while no significant causal relationships were found afterward. Overall, herding behavior increased during the pandemic but returned to more independent decision-making in the post-pandemic phase.

Keywords behavioral finance, COVID-19, CSAD, herding, investment, liquidity, volatility

JEL Classification G41, G15, G12, C22

INTRODUCTION

Financial markets are significantly influenced by investor behavior, particularly during periods of uncertainty and economic distress. One of the most widely studied phenomena in behavioral finance is herding behavior, where investors irrationally follow the actions of others rather than relying on independent analysis. This behavior can distort asset prices, increase volatility, and reduce market efficiency. While herding has been widely documented in global markets, its manifestations in emerging economies like Indonesia remain less understood, largely due to distinct market dynamics, regulatory structures, and the dominant role of retail investors. In markets such as Indonesia, where information asymmetry and sentiment-driven trading are prevalent, herding behavior may have more profound effects on price formation and liquidity. The LQ-45 Index, which comprises the 45 most liquid and high-capitalization stocks on the Indonesia Stock Exchange, offers an ideal setting to examine such investor behavior. The COVID-19 pandemic serves as a critical stress event that disrupted normal trading patterns and increased uncertainty, provid-

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ing a unique window to study behavioral shifts under crisis conditions. Despite considerable research, there is no consensus on how herding evolves under varying economic circumstances. Some studies find that uncertainty and panic intensify herding, while others suggest that reduced liquidity during crises may actually limit herding behavior. These mixed findings point to a broader scientific problem that this study seeks to address: How does the intensity and pattern of herding behavior evolve in emerging markets across different economic regimes, such as stable, crisis, and recovery – and what is its relationship with key market microstructure variables such as liquidity and trading volume? This problem is not merely academic; it has critical implications for market stability, investor protection, and regulatory effectiveness. Unchecked herding can amplify systemic risk, reduce market efficiency, and undermine investor confidence, especially in markets where structural vulnerabilities are more pronounced. Therefore, a deeper understanding of this phenomenon is essential for designing better-informed regulatory interventions and enhancing financial resilience in emerging economies. By addressing this gap, the study contributes to ongoing discourse in behavioral finance and financial market microstructure, offering insights that are particularly relevant for policymakers, institutional investors, and scholars focused on post-crisis financial reform in emerging markets.

1. LITERATURE REVIEW

Financial markets are affected by both rational decision-making and behavioral biases. Among these biases, herding behavior is one of the most extensively studied phenomena in behavioral finance. It occurs when investors mimic the decisions of others rather than relying on their independent analysis, often leading to excessive volatility and price deviations from fundamental values. In emerging markets, where financial literacy and institutional influence are relatively lower, herding behavior tends to be more pronounced, exacerbating inefficiencies and market instability.

1.1. Herding behavior in financial and emerging markets

Herding behavior in finance is a powerful phenomenon where individuals tend to follow the actions of larger groups. This often leads to irrational decision-making, as people are swayed by the collective actions of others rather than relying on their analysis (Ahmad & Wu, 2022). This phenomenon occurs when investors follow the crowd rather than relying on their analysis or insights, especially in situations of uncertainty or when information is ambiguous. This finding complements the work of Komalasari et al. (2022), who emphasized that information asymmetry significantly drives herding behavior in Indonesian markets, leading to inefficiencies in decision-making.

Empirical studies have demonstrated herding behavior during periods of economic instability. For instance, herding intensifies during financial crises, contributing to extreme price swings and volatility (Bekiros et al., 2017; Chang et al., 2020; Dixit, 2024). Similarly, there was evidence of herding in major Asian stock markets during the COVID-19 pandemic, as investors responded collectively to market shocks and policy interventions (Vidya et al., 2023). These studies highlight the importance of understanding herding behavior, especially in crisis periods, to assess its impact on market stability and efficiency.

Herding behavior is more prevalent in emerging markets due to lower levels of financial literacy, greater information asymmetry, and the dominance of retail investors (Bogdan et al., 2022; Vo & Phan, 2019). Unlike developed markets, where institutional investors are stabilizing, emerging markets often experience excessive price movements influenced by speculative trading and external shocks.

Research on herding behavior in Indonesia's capital market has shown similar trends. Information asymmetry significantly contributes to herding behavior, leading to inefficient investment decision-making (Awad et al., 2025). Additionally, Southern European markets revealed that herding behavior was evident before and after financial crises, but not during the crisis itself, suggesting that market sentiment plays a key role in shaping investor actions (Ben Ameur et al., 2024; Ferreruela

& Mallor, 2021). Understanding these regional differences is crucial for designing effective market regulations that mitigate systemic risks (Zhang et al., 2024).

The Efficient Market Hypothesis (EMH) posits that stock prices reflect all available information, making it impossible to achieve above-average returns consistently (Fama, 1970). EMH is categorized into three levels: 1) Weak-form efficiency – Stock prices reflect all past market data; 2) Semi-strong form efficiency – Prices incorporate all publicly available information; 3) Strong-form efficiency – Prices reflect all information, including insider knowledge. However, behavioral finance challenges the assumptions of EMH, arguing that psychological factors, cognitive biases, and social influences drive investor behavior (Banerjee et al., 2018; Shefrin & Statman, 2000). In addition, investors frequently deviate from rational decision-making due to emotional biases, leading to market anomalies such as speculative bubbles and panic-driven selloffs (Moustafa & El-Shal, 2025; Ritter, 2003). Herding behavior contradicts the Efficient Market Hypothesis (EMH) by indicating that stock prices may not always reflect fundamental values, particularly during crises.

Three versions of an efficient market are categorized according to the availability of information to investors: weak, semi-strong, and strong. In the weak version, stock prices already reflect all information that has been available in the market, such as historical prices, trading volume, and short-term interest rates. Thus, investors can easily react to what is formed in the market using information that can be freely obtained and at no cost. In contrast, in the semi-strong version, all publicly available data related to a company's prospects must be reflected in market prices. The data in this case include the data used in the weak version, plus the company's fundamental data, management quality, income predictions, balance sheet information, and accounting practices. The strong version argues that all information related to the company, including insider information, must be reflected in market prices.

Market efficiency itself is determined by the influence of relevant information considered in investment decision-making based on the distribution of information (Beaver et al., 1989). Researchers have found that, in addition to considering investment prospects, investors often consider psychological factors, emotions, and even the psychological influences of those around them when making decisions. Behavioral finance is financial behavior influenced by psychological phenomena (Bansal, 2025; Shefrin & Statman, 2000).

Behavioral finance is based on different assumptions and interactions from various sciences and emotional involvement. The characteristics and psychological factors that investors use in decision-making allow them to optimize returns while considering related risks. This creates inaccurate probability distributions to predict future returns. When distributions become apparent, investors tend to make suboptimal decisions. In behavioral finance studies, it is mentioned that investors tend to act irrationally. The actions of these investors are affected by the lack of complete information in the market. As we know, information is crucial before investors make investment decisions. However, what often happens in the capital market is the existence of information asymmetry. The presence of information asymmetry can make the market inefficient and lead some investors to incur losses. Herding behavior is behavior caused by information asymmetry (Li, 2020; Lowry et al., 2023).

Market liquidity, which is the ability to buy or sell assets without significantly impacting their prices, is crucial in influencing herding behavior. High liquidity markets provide smoother price adjustments, reducing the impact of collective trading behavior. Conversely, in low liquidity markets, investor panic can exacerbate price swings, intensifying herding tendencies (Fei & Liu, 2021; Levine & Schmukler, 2006).

Herding is more pronounced in illiquid markets, as price discovery becomes inefficient and investors rely on prevailing market sentiment (BenSaïda, 2017; Cai et al., 2019). Institutional trading contributes to herding, particularly in stocks with lower trading volumes. These findings underscore the importance of liquidity management in mitigating herding-induced volatility (Lakonishok et al., 1992).

The concept of herding behavior through a decision-making scenario, such as selecting a res-

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taurant, a restaurant with high foot traffic appears more appealing to potential customers (Bikhchandani & Sharma, 2000). This behavior, termed herding, is also applicable in financial markets, particularly stock exchanges (Gurung et al., 2024). Herding behavior among investors frequently aligns with market sentiment or follows advice from financial experts. Herding is a situation where individuals emulate the actions of others, even when alternative courses of action may be advised based on personal information (Banerjee, 1992; Zhou, 2024).

Empirical evidence is essential to substantiate herding behavior in practice, as it cannot be fully explained through theoretical analysis (Hwang & Salmon, 2004). Researchers suggest that herding behavior affects the Capital Asset Pricing Model (CAPM), influencing stock price fluctuations and impacting returns and risk. In asset pricing contexts, if market participants tend to conform to prevailing sentiments, asset prices can diverge from their fundamental values. Consequently, investors may engage in inefficient trading practices. When market participants exhibit herding behavior and adhere to trends, it exacerbates the volatility of stock returns (Bikhchandani & Sharma, 2000; Cai et al., 2019; Xing et al., 2025).

Trading volume, a key measure of market activity, is often used as a proxy for investor sentiment and speculative behavior. It has a strong relationship between trading volume and herding behavior, indicating that abnormal volume surges are often driven by collective investor actions rather than fundamental analysis (Lakonishok et al., 1992). Herding was prevalent in industries with higher trading volumes, particularly during periods of economic uncertainty (Litimi et al., 2016). This aligns with studies by Espinosa-Méndez and Arias (2021), who reported heightened herding in European stock markets during the COVID-19 pandemic, driven by panic-induced trading activity.

Trading volume refers to the total quantity of shares traded in the stock market for a specific stock at a given time. It is a critical factor that influences stock price movements and is a key indicator used in predicting stock price trends. In financial literature, trading volume is widely recognized as an alternative measure for market liquidity (Levine & Schmukler, 2006). As a liquidity indicator, trading volume plays an integral role in price formation and stock performance evaluation. In cases of herding behavior, stock prices deviate from equilibrium and move toward the market average, leading to higher trading volumes (BenSaïda, 2017).

The first empirical study to examine the influence of trading volume on herding behavior was conducted by Lakonishok et al. (1992). This study analyzed the relationship between herding and stock prices using ownership data from 769 tax-exempt funds in the U.S. The findings revealed that herding behavior was weaker among smaller stocks, while only limited herding was observed in larger stocks, which are predominantly owned and traded by institutional investors.

There was a close relationship between herding and trading volume in the U.S. equity market. The study found herding behavior on high- and low-volume trading days by using dummy variables for the top and bottom 10 percent of abnormal trading days. Using the Granger Causality Test, the researchers found a significant bilateral relationship between herding and trading volume, indicating that trading volume triggers herding behavior, and vice versa (BenSaïda, 2017).

Trading volume potentially influences herding in different U.S. sectors, compared to the overall stock market (Litimi et al., 2016). Using the CSAD model, the results showed that herding behavior due to trading volume occurred in only three of the 12 sectors analyzed. The study modified the CSAD model by incorporating trading volume as an independent variable, revealing that trading volume prompted herding in five sectors and across the entire U.S. stock market.

The closing price refers to the final price at which a stock is traded when the stock market closes. The closing price represents the final price at which a stock is traded on a given trading day, marking the official end of trading for that session. It is a key indicator in the financial markets because it reflects the most recent valuation of a stock based on supply and demand during that day.

The COVID-19 pandemic created extreme market conditions that amplified herding behavior across global financial markets. Research indicates that during the early phase of the pandemic, investors responded irrationally to market shocks, resulting in heightened market volatility and sudden price fluctuations. Significant herding behavior in major Asian stock exchanges, as investors followed market trends rather than conducting independent assessments (Vidya et al., 2023). European capital markets exhibited intensified herding during COVID-19, as investors responded collectively to lockdown measures and economic uncertainty (Espinosa-Méndez & Arias, 2021). Furthermore, an analysis of 72 stock market indices worldwide confirmed that herding behavior was more pronounced in developing economies, where government and regulatory interventions significantly influenced market movements (Kizys et al, 2021). In the context of Indonesia, herding behavior was evident in the LQ-45 Index, where panic selling and liquidity concerns led to extreme price fluctuations. This study builds on prior research by investigating the persistence of herding behavior beyond the pandemic period, providing insights into whether investor sentiment has stabilized or remains influenced by crisis-induced behavior.

While existing studies have extensively examined herding behavior during financial crises, few have explored its persistence across different economic phases (pre-crisis, crisis, and post-crisis). Moreover, limited research has focused on the relationship between herding behavior, market liquidity, and trading volume in Indonesia's stock market, particularly in the context of LQ-45 stocks.

Accordingly, this study aims to investigate herding tendencies in the LQ-45 index of the Indonesian Stock Exchange across the pre-pandemic, pandemic, and post-pandemic phases. By mapping how herding intensity evolved before, during, and after the COVID19 shock, and by quantifying its interaction with liquidity and volume, this study adds a behavioral dimension to ongoing debates on market efficiency in emerging economies. The findings offer practical insights for investors seeking to calibrate risk, for regulators charged with containing destabilizing cascades, and for policymakers designing safeguards to bolster the robustness of Indonesia's capital markets in the face of future crises.

2. METHODOLOGY

2.1. Data collection and sources

The data collected are secondary, meaning they are obtained indirectly through intermediary sources, such as stock prices of companies listed in the LQ45 Index during the periods of pre-Covid-19 (2019), during COVID-19 (2020-2021), and post-COVID-19 (2023). Time series data are employed in this study to capture trends over time, enabling a deeper analysis of the changing patterns in stock returns, market behavior, and liquidity across different periods.

Daily closing prices and trading volumes were taken from the 22 firms that remained in the LQ45 Index throughout 20192023, which were retrieved from the Indonesia Stock Exchange website (www.idx.co.id). After eliminating non-trading days and synchronizing tickers, the final panel contains 948 trading-day observations (January 2019 – December 2023), which were split into three subsamples: pre-pandemic (2019), pandemic (20202021), and post-pandemic (2023). From this data, stock returns, return dispersion, and market liquidity are calculated to gain insights into the market's dynamics. The analysis is primarily conducted using Microsoft Office Excel 2019 and R-Studio software to process and analyze the time series data.

2.2. Variables and measurement

2.2.1. Cross-Sectional Absolute Deviation (CSAD)

To detect herding behavior, the study applies the CSAD model developed by Chang et al. (2000). The CSAD formula is given by:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{n}\left|R_{it} - R_{mt}\right|, \quad (1)$$

where R_{mt} represents the weighted average market return at time t, R_{it} is the return of individual stock i at time t, and N is the number of stocks in the index. The presence of herding behavior is detected when the relationship between CSAD and market returns R_{mt} becomes non-linear, indicating that investors are likely following the crowd rather than relying on individual assessments. The non-linear relationship is captured in the following equation:

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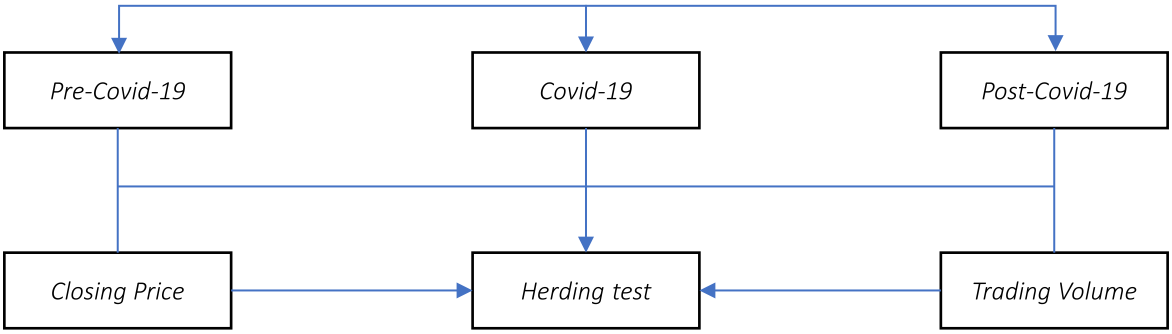

Figure 1. Framework analysis

$$CSAD_t = \gamma_0 + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \varepsilon_t. \quad (2)$$

A significantly negative γ_2 indicates herding behavior.

2.2.2. Market liquidity

In addition to herding detection, market liquidity is measured using a modified version of the illiquidity ratio (Amihud, 2002). This approach assesses the sensitivity of stock prices to trading volumes. The liquidity formula is expressed as:

$$Liq_{it} = -log\left(1 + \left(\frac{|R_{it}|}{P_{it} Vo_{it}}\right)\right), \quad (3)$$

where R_{it} represents the return of stock iii at time t, P_{it} is the adjusted closing price of stock i, and Vo_{it} is the trading volume. To compute market-wide liquidity, the average liquidity across all stocks is calculated using the formula:

$$Liq_{mt} = \frac{1}{N} \sum_{i=1}^{N} L_i q_{it}. \quad (4)$$

2.2.3. Empirical models

2.2.3.1. Time-series regression

To examine herding across different market phases, the CSAD model is estimated separately for each sub-period: pre-pandemic, pandemic, and post-pandemic. Newey-West standard errors are employed to correct for autocorrelation and heteroskedasticity in the residuals.

1. Liquidity-herding interaction

To test whether herding behavior is sensitive to market liquidity conditions, the following augmented regression model is estimated:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \gamma_3 D_1 R_{mt}^2 + \gamma_4 D_2 R_{mt}^2 + \varepsilon_t, \quad (5)$$

where $D1$_t and $D2$_t are dummy variables representing the upper and lower 25% tails of the liquidity distribution, respectively. This helps assess whether herding is more pronounced under extreme liquidity conditions. This equation helps to identify whether herding behavior is influenced by liquidity conditions, with specific attention given to the tails of the liquidity spectrum. Moreover, the Granger causality test elucidates the intricate interplay between herding behavior and market liquidity, confirming a significant bidirectional relationship that emphasizes the reciprocal influence of these variables, particularly during periods of heightened market uncertainty. This complex relationship is essential for understanding investor behavior in emerging markets, where external shocks, such as the COVID-19 pandemic, significantly impact trading dynamics and market stability.

2. Granger causality test

Finally, to explore the dynamic relationship between herding behavior and market liquidity, a Granger causality test is conducted. The test determines whether past values of liquidity help predict CSAD and vice versa, indicating a bidirectional relationship. The optimal lag length is selected using the Akaike Information Criterion (AIC).

2.2.3.2. *Software and tools*

All data preprocessing and analysis are performed using Microsoft Excel 2019 for preliminary calculations and R-Studio (with packages such as plm, lmtest, and tseries) for econometric modeling and statistical testing.

3. RESULTS

This analysis investigates herding behavior in financial markets by assessing the relationship between market returns (R_{mt}), cross-sectional absolute deviation ($CSAD_t$), and market liquidity across different periods: pre-pandemic (2019), pandemic (2020-2021), and post-pandemic (2023) and the full sample. The descriptive statistics are summarized in Table 1, providing key insights into the behavior of market returns and $CSAD_t$.

The descriptive statistics indicate significant variability in both market returns (R_{mt}) and cross-sectional absolute deviation ($CSAD_t$), particularly during the pandemic period (2020–2021). The mean return (R_{mt}) across all periods remains close to zero, reflecting overall market stability in the long run. However, the highest standard deviation (1.795) is recorded during the pandemic period, signaling heightened market volatility.

Furthermore, $CSAD_t$ exhibits greater dispersion during the pandemic period, with the highest mean (1.567) and standard deviation (0.632) among all periods. This suggests that investor uncertainty was at its peak during the crisis. In contrast, the post-pandemic period (2023) shows reduced market volatility and a lower $CSAD_t$ mean (1.233), indicating a relative stabilization in investor behavior.

The regression analysis provides compelling evidence of herding behavior in financial markets. A significant positive relationship is evident be-

Table 1. Descriptive statistics

Source: Output R-studio.

Variables	Min (%)	Max (%)	Median (%)	Mean (%)	Std. Dev (%)	Obs (unit)
Pre-pandemic						
Rm_t	–3.294	2.424	0.046	0.007	0.944	242
$CSAD_t$	0.670	2.533	1.310	1.343	0.329	242
Pandemic						
Rm_t	–8.623	13.908	–0.021	–0.007	1.795	473
$CSAD_t$	0.312	7.817	1.418	1.567	0.632	473
Post-Pandemic						
Rm_t	–2.513	2.407	0.040	0.015	0.729	237
$CSAD_t$	0.578	2.813	1.145	1.233	0.401	237
Full Sample						
Rm_t	–8.623	13.908	0.018	0.002	1.401	948
$CSAD_t$	0.312	7.817	1.310	1.428	0.536	948

Table 2. Regression result of herding

Source: Output R-Studio.

Variable	Full sample		Pre-Pandemic		Pandemic		Post-Pandemic	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
γ_0	1.175***	$<0.002\text{x}10^{-13}$	1.193***	$<0.002\text{x}10^{-13}$	1.265***	$<0.002\text{x}10^{-13}$	1.049***	$<0.002\text{x}10^{-13}$
$\gamma_1(\lvert R_m \rvert)$	0.308***	$<0.002\text{x}10^{-13}$	0.279**	0.004	0.294***	$3.59\text{x}10^{-15}$	0.377**	0.006
$\gamma_2(Rm^2)$	–0.014***	$0.002\text{x}10^{-2}$	–0.064	0.067	–0.014***	0.0007	–0.042	0.265
Adj R-sq		0.203		0.06537		0.1902		0.121
F-stat		121.4		9.428		56.42		16.93
Prob.		$< 2.2\text{x}10^{-16}$		0.0001		$< 2.2\text{x}10^{-16}$		$1.379\text{x}10^{-7}$

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tween market returns ($|R_m|$) and $CSAD_t$ across the full sample ($\gamma_1 = 0.308$, $p < 0.002\text{x}10^{-13}$), suggesting that as market returns become more extreme, cross-sectional dispersion decreases. This tendency is particularly marked during the pandemic, where the coefficient for $|R_m|$ ($\gamma_1 = 0.294$, $p < 3.59\text{x}10^{-15}$) indicates pronounced herding among investors.

Moreover, the negative coefficient for squared returns (Rm^2) in the full sample ($\gamma_2 = -0.014$, $p < 0.002\text{x}10^{-2}$) further confirms this herding tendency, indicating that as market returns increase in extremity, $CSAD_t$ declines. In contrast, evidence of herding during pre-pandemic and post-pandemic periods is less pronounced, with coefficients for squared returns often not statistically significant, indicating a lower likelihood of herding behavior among investors in more stable market conditions. There is a significant non-linear relationship between market returns ($|R_m|$) and $CSAD$, supporting herding behavior. The relationship is stronger during the pandemic period. The Evidence is based on positive γ_1 ($|R_m|$) and negative γ_2 (R_m^2) coefficients in regression models across most periods, particularly the pandemic.

3.1. Regression analysis of herding behavior

The regression analysis results confirm the presence of herding behavior across different periods. **Pre-pandemic:** The regression coefficient for market returns (γ_1) was significant, but the squared returns coefficient (γ_2) was not, suggesting a more fundamental-driven market with less evidence of herding. **During the pandemic:** Herding behavior was strongly present, as indicated by a significantly negative γ_2 coefficient. Investors tended to follow collective trends rather than making independent investment decisions. **Whereas in the post-pandemic:** the significance of γ_1 persisted, but γ_2 was no longer statistically significant, indicating that while herding tendencies declined, residual effects of collective decision-making remained.

The introduction of market liquidity into the regression model reveals its significant effects on herding behavior. However, the results do not fully align with the previously mentioned impact of liquidity dummy variables. In the post-pandemic period, low liquidity conditions (D_1) are significantly associated with reduced herding behavior ($\gamma_3 = -0.209$, p = 0.009). Meanwhile, high liquidity conditions (D_2) do not exhibit a significant relationship with herding behavior ($\gamma_4 = 0.0005$, p = 0.991). In the pre-pandemic period, neither low liquidity (D_1, $\gamma_3 = 0.040$, $p = 0.463$) nor high liquidity (D_2, $\gamma_4 = 0.014$, $p = 0.620$) significantly influences herding behavior, suggesting that market liquidity played a less prominent role before the pandemic. Post-pandemic, market liquidity plays a crucial role in herding behavior. Notably, low liquidity tends to decrease the likelihood of individuals following the crowd.

The results from Tables 4 and 5 suggest a significant difference in herding behavior during pandemic periods compared to more stable market environments. The split regression models were used due to potential multicollinearity issues, which arise when two or more independent variables are highly correlated, potentially distorting the estimated coefficients.

During the pandemic period, the coefficients for market returns (γ_1) are markedly high (0.2757 and

Table 3. Regression of market liquidity (Pre-pandemic and Post-pandemic)

Source: Output R- Studio.

Variable	Pre-Pandemic		Post-Pandemic	
	Coefficient	p-value	Coefficient	p-value
γ_0	1.198***	<0.02 x 10^{-13}	1.036***	<0.02 x 10^{-13}
$\gamma_1(\|R_m\|)$	0.258*	0.011	0.457**	0.001
$\gamma_2(Rm^2)$	−0.062.	0.075	−0.064	0.188
$\gamma_3(D_1)$	0.040	0.463	−0.209**	0.009
$\gamma_4(D_2)$	0.014	0.620	0.0005	0.991
Adj R-sq		0.06003		0.141
F-stat		4.848		10.51
Prob.		0.0008934		7.787 x 10^{-8}

Table 4. Regression of market liquidity (Pandemic and Full sample, part I)

Source: Output R-Studio.

Variable	Crisis		Full sample	
	Coefficient	p-value	Coefficient	p-value
γ_0	1.268***	<0.02 x 10^{-13}	1.1779***	<0.02 x 10^{-13}
γ_1 ($\lvert R_m \rvert$)	0.2757***	<0.02 x 10^{-13}	0.292***	1.78 x 10^{-10}
γ_2 (Rm^2)	–0.0124**	0.0026	–0.0129***	0.00007
γ_3 (D_1)	0.0407*	0.044	0.0385	0.0186
Adj R-sq	0.1954		0.2066	
F-stat	39,21		83.18	
Prob.	< 2.2 x 10^{-16}		< 2.2 x 10^{-16}	

Table 5. Regression of market liquidity (Crisis and Full sample, part II)

Source: Output R-Studio.

Variable	Pandemic		Full sample	
	Coefficient	p-value	Coefficient	p-value
γ_0	1.263***	<0.02x10^{-13}	1.1769***	<0.02x10^{-13}
γ_1 ($\lvert R_m \rvert$)	0.282***	<0.02x10^{-13}	0.292***	1.78x10^{-10}
γ_4 (D_2)	–0.013***	0.0005	–0.013	7.68x10^{-6}
Adj R-sq	0.1935		0.2046	
F-stat	57.63		122.8	
Prob.	< 2.2x10^{-16}		< 2.2x10^{-16}	

0.282, $p < 0.02 \times 10^{-13}$), confirming strong herding tendencies in times of uncertainty and market stress. This effect remains consistent in the full sample ($\gamma_1 = 0.292$, p = 1.78×10^{-10}), reinforcing the idea that investors tend to follow collective behavior during volatile market conditions.

Moreover, the negative coefficient of squared returns (γ_2) in both the pandemic (–0.0124, p = 0.0026) and full sample (–0.0129, $p = 0.00007$) periods further supports the presence of herding behavior, as extreme market movements are associated with lower dispersion in returns.

Regarding liquidity effects, the dummy for low liquidity (D_1, $\gamma_3 = 0.0407$, $p = 0.044$) during the pandemic period suggests a moderate impact on herding behavior. However, in the full sample, the effect of D_1 ($\gamma_3 = 0.0385$, $p = 0.0186$) remains significant but slightly lower. In contrast, the dummy for high liquidity (D_2, $\gamma_4 = -0.013$, $p = 0.0005$) in the pandemic period suggests that higher liquidity conditions mitigate herding behavior, a pattern also observed in the full sample ($\gamma_4 = -0.013$, $p = 7.68 \times 10^{-6}$). Market liquidity significantly influences herding behavior during the post-pandemic period. Low liquidity reduces herding behavior post-pandemic. High liquidity does not significantly affect herding behavior after the pandemic. The evidence based on γ_3 ($D1$) is significantly negative in the post-pandemic phase, indicating low liquidity reduces herding. γ_4 (D2) is insignificant in the pre-pandemic period, showing high liquidity has limited impact.

Post-pandemic data show that in high-liquidity conditions, herding behavior was less pronounced, suggesting that market stability was improving. the pandemic, low liquidity conditions were associated with stronger herding tendencies, aligning with theories that investors tend to follow group behavior when faced with uncertainty and limited market depth.

Table 6. Granger causality (p-value)

Source: Output R- Studio

Hypothesis	Full sample	Pre-Pandemic	Pandemic	Post-Pandemic
Liqm does notcause CSAD	< 2.2 x 10^{-16}	0.892	< 2.2 x 10^{-16}	0.203
CSAD does notcause Liqm	1.812 x 10^{-12}	0.014	1.783 x 10^{-10}	0.678

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The Granger causality test results presented in Table 6 reveal a bidirectional relationship between CSAD and market returns (R_m). Specifically, in full the sample and pandemic periods, the null hypothesis that CSAD does not Granger cause R_m is rejected at the 5% significance level (p = < 2.2 x 10^{-16}), indicating that market liquidity significantly influences herding behavior. Likewise, the hypothesis that R_m does not Granger cause CSAD is also rejected in the full sample (p = 1.812x 10^{-12}) and pandemic period (p = 1.783x 10^{-10}), suggesting that herding behavior impacts market liquidity.

However, in the pre-pandemic and post-pandemic periods, the results differ. During the pre-pandemic period, there is no significant causality from Liqm to CSAD (p = 0.892), while CSAD does Granger cause Liqm (p = 0.014). This suggests that before the pandemic, herding behavior played a role in driving market liquidity, but liquidity did not significantly influence herding behavior. In the post-pandemic period, neither direction shows significant causality (p = 0.203 for Liqm → CSAD and p = 0.678 for CSAD → Liqm), indicating a weakened relationship between liquidity and herding behavior after the pandemic. These findings highlight the dynamic relationship between market liquidity and herding behavior, with strong bidirectional causality observed during the full sample and pandemic periods, but weaker or no causality in the pre- and post-pandemic periods**.** The Granger causality tests examined the bidirectional relationship between market liquidity and herding behavior**. Bidirectional causality (Pandemic period):** The test confirmed that herding behavior influenced market liquidity, and vice versa, during the crisis. This highlights a feedback loop in which collective trading intensified liquidity fluctuations. **Pre-pandemic:** Herding behavior influenced liquidity, but liquidity did not significantly affect herding. **Post-pandemic:** No significant causality was found in either direction, indicating a normalization of market dynamics. The study provides important insights into the economic behavior of investors under varying market conditions**.** The increased herding during the pandemic supports behavioral finance theories, which suggest that investors exhibit irrational collective behavior during periods of uncertainty. The results challenge the Efficient Market Hypothesis (EMH), as herding-induced price movements indicate deviations from fundamental values, particularly during crises. There is a bidirectional causality between market liquidity and herding behavior during the pandemic period. In the pre-pandemic period, only herding behavior caused market liquidity. In the post-pandemic period, there is no significant causality in either direction. The evidence is based on Granger causality tests, which show significant bidirectional relationships in the pandemic and full sample but weaker or absent relationships before and after the crisis.

4. DISCUSSION

This study presents new evidence on the dynamics of herding behavior among LQ-45 stocks in Indonesia, both before, during, and after the COVID-19 pandemic. The findings reveal that herding intensified significantly during the pandemic, consistent with behavioral finance theory, which suggests that heightened uncertainty and emotional trading can override rational decision-making (Shefrin & Statman, 2000b). In contrast, herding behavior was weaker during stable periods, supporting the Efficient Market Hypothesis (Fama, 1970), which assumes that investors process information efficiently under normal conditions.

The results align with Vidya et al. (2023) and Espinosa-Méndez and Arias (2021), who documented increased herding during crises in Asian and European markets. However, the observed post-pandemic decline in herding differs from Vo and Phan (2019), who found that herding tended to persist after financial shocks. This difference may be attributed to Indonesia's relatively swift economic recovery and effective regulatory interventions that restored investor confidence.

Market liquidity emerged as a key determinant of herding behavior. The bidirectional causality between liquidity and herding indicates that herding can both influence and be influenced by liquidity conditions, particularly in emerging markets. This finding corroborates BenSaïda (2017), who observed that herding is more pronounced in illiquid markets with higher information asymmetry. During the pandemic, liquidity shocks and government interventions such as short-selling restrictions may have amplified collective trading patterns, echoing the observations of Kizys et al. (2021) in other emerging economies.

Behaviorally, the findings suggest that during crisis periods, even informed investors may act irrationally due to fear, uncertainty, and social pressure. This supports the notion that investor sentiment plays a crucial role in price formation under stress (Bhutto et al., 2025). Post-pandemic, the weakening of herding behavior indicates a gradual return to more rational investment strategies, although residual collective tendencies persist due to risk aversion and lingering uncertainty.

From a theoretical standpoint, these results demonstrate that market behavior in Indonesia oscillates between rational efficiency and behavioral bias depending on the level of uncertainty. The coexistence of these dynamics suggests that neither EMH nor behavioral finance fully explains investor behavior in emerging markets; rather, a hybrid approach may be more appropriate.

Practically, understanding these dynamics is vital for policymakers and investors. Regulators should monitor liquidity fluctuations and investor sentiment during periods of market stress to prevent excessive herding that could destabilize prices. For investors, recognizing periods of high herding intensity could help improve timing strategies and risk management.

Finally, while this study offers insights into herding behavior across different market phases, future research should explore the differential roles of institutional and retail investors, as well as sectoral variations in herding intensity, to provide a more comprehensive understanding of market dynamics in Indonesia.

These findings highlight that during crisis periods, even sophisticated investors may exhibit herding behavior, contradicting traditional finance theories that assume rational decision-making. Instead, the results align with behavioral finance theories (Bhutto et al., 2025; Shefrin & Statman, 2000b).

Post-pandemic gradual stabilization occurred when market conditions improved, and herding behavior weakened, although it did not completely disappear. The γ_2 coefficient remained negative but was no longer statistically significant, suggesting that investors started to regain confidence and make more independent decisions. The residual herding behavior persisted caused by: a) Lingering risk aversion: Investors remained cautious, with some continuing to rely on market trends rather than fundamental analysis; b) External economic uncertainties: Global inflation concerns, geopolitical tensions, and macroeconomic policies continued to influence investor sentiment, leading to cautious trading behavior; c) Institutional influence: Large institutional investors played a stabilizing role post-pandemic, yet their collective actions still influenced market trends, indirectly promoting some degree of herding behavior.

These findings are consistent with Vo and Phan (2019), who found that herding behavior tends to persist in the aftermath of financial crises before gradually fading as market confidence is restored. Market liquidity conditions influence herding behavior, as investors react to liquidity constraints by following dominant market trends. These results are consistent with Levine and Schmukler (2006), who demonstrated that low liquidity environments often exacerbate herding behavior due to the increased cost of trading and information asymmetry.

The results indicate that herding behavior intensified during the COVID-19 pandemic, aligning with findings from studies by Vidya et al. (2023) and Espinosa-Méndez and Arias (2021), who observed increased herding in Asian and European stock markets during times of extreme uncertainty. However, unlike some previous studies, such as Vo and Phan (2019), who reported herding behavior continuing after a crisis, this study suggests a decline in herding behavior in the post-pandemic period. This decline indicates a stabilization of the market. The role of market liquidity in influencing herding behavior has also been widely discussed in the literature. The findings also align with BenSaïda (2017), who found that herding is more prevalent in illiquid markets where price discovery is inefficient. Several factors contribute to the observed herding behavior in LQ-45 stocks across different periods: **1) Investor psychology and**

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market uncertainty: During the pandemic, fear-driven trading led investors to follow the majority rather than rely on individual analysis. The reduction in herding post-pandemic suggests a gradual return to rational decision-making, as investor confidence stabilized and economic uncertainty declined. **2) Market liquidity and trading volume:** The study shows that market liquidity plays a crucial role in shaping herding behavior. During the pandemic, low liquidity conditions intensified herding, as investors faced higher transaction costs and relied on market trends rather than fundamental analysis. Post-pandemic, increased liquidity reduced herding behavior, supporting the argument that deeper markets allow for better price discovery and reduced reliance on collective decision-making. **3) Regulatory and policy interventions:** Government interventions, such as trading halts and short-selling restrictions, may have influenced investor behavior during the pandemic. The easing of these interventions post-pandemic allowed markets to function more efficiently, contributing to the observed decline in herding behavior. This study provides valuable insights into herding behavior in the Indonesian stock market; several areas warrant further investigation: Future research should examine whether herding behavior returns in future economic crises or remains permanently subdued in the post-pandemic period. A deeper investigation into the role of institutional versus retail investors in driving herding behavior would be beneficial.

CONCLUSION

This study aimed to analyze the existence and evolution of herding behavior among LQ-45 Index stocks on the Indonesia Stock Exchange before, during, and after the COVID-19 pandemic, and to examine the influence of market liquidity and uncertainty on the intensity of herding behavior across these periods.

By investigating 22 firms consistently listed on the LQ-45 Index across 948 trading days, this study employed a time-series regression based on the Cross-Sectional Absolute Deviation (CSAD) model with Newey-West standard errors, complemented by a Granger causality test. The results revealed that herding behavior intensified significantly during the pandemic, as indicated by a strong negative γ_2 coefficient (–0.0124, $p = 0.0026$) and the highest adjusted R^2 value (0.1902). This reflects a heightened reliance on collective sentiment amid crisis-driven uncertainty.

In contrast, the pre-pandemic period showed relatively weak herding behavior under more stable market conditions, while the post-pandemic phase demonstrated a return to more independent decision-making, suggesting gradual market normalization. This shift reflects how investor behavior is heavily influenced by broader economic sentiment and uncertainty, particularly in the LQ45 Index of the Indonesian Stock Exchange. The study also found that market liquidity played a critical role in influencing herding dynamics. During the pandemic, low liquidity conditions exacerbated herd behavior, whereas the recovery of liquidity in the post-pandemic period helped reduce collective trading tendencies.

The findings confirm that herding behavior was significantly present during the pandemic period, characterized by heightened market volatility, panic-driven trading, and reduced reliance on individual analysis. In contrast, herding behavior was weaker in the pre-pandemic period when market conditions were more stable. After the pandemic, although some residual herding effects remained, investor behavior gradually returned to more independent decision-making, suggesting market normalization. This study reinforces the critical role of behavioral biases in financial markets, particularly during times of economic uncertainty. Understanding how herding behavior evolves across different market conditions provides valuable insights for investors, policymakers, and regulators seeking to enhance market efficiency and stability.

AUTHOR CONTRIBUTIONS

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