

# “Herding behavior in the UAE stock markets during COVID-19: Evidence using the CSAD approach”

<b>AUTHORS</b>	Suchi Dubey  Mayank Joshipura  Mariam Joseph Sebastian  Anjleen Kaur Thiara  Ashish Dwivedi  Tripti Singh 
<b>ARTICLE INFO</b>	Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara , Ashish Dwivedi and Tripti Singh (2026). Herding behavior in the UAE stock markets during COVID-19: Evidence using the CSAD approach. <i>Investment Management and Financial Innovations</i> , 23(1), 186-200. doi: <a href="https://dx.doi.org/10.21511/imfi.23(1).2026.14">10.21511/imfi.23(1).2026.14</a>
<b>DOI</b>	<a href="http://dx.doi.org/10.21511/imfi.23(1).2026.14">http://dx.doi.org/10.21511/imfi.23(1).2026.14</a>
<b>RELEASED ON</b>	Thursday, 05 February 2026
<b>RECEIVED ON</b>	Friday, 18 April 2025
<b>ACCEPTED ON</b>	Friday, 21 November 2025
<b>LICENSE</b>	 This work is licensed under a <a href="#">Creative Commons Attribution 4.0 International License</a>
<b>JOURNAL</b>	"Investment Management and Financial Innovations"
<b>ISSN PRINT</b>	1810-4967
<b>ISSN ONLINE</b>	1812-9358
<b>PUBLISHER</b>	LLC "Consulting Publishing Company "Business Perspectives"
<b>FOUNDER</b>	LLC "Consulting Publishing Company "Business Perspectives"



NUMBER OF REFERENCES

**63**



NUMBER OF FIGURES

**2**



NUMBER OF TABLES

**3**

© The author(s) 2026. This publication is an open access article.



## BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"  
Hryhorii Skovoroda lane, 10,  
Sumy, 40022, Ukraine  
[www.businessperspectives.org](http://www.businessperspectives.org)

**Type of the article:** Research Article

**Received on:** 18<sup>th</sup> of April, 2025  
**Accepted on:** 21<sup>st</sup> of November, 2025  
**Published on:** 5<sup>th</sup> of February, 2026

© Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara, Ashish Dwivedi, Tripti Singh, 2026

Suchi Dubey, Ph.D., Associate Professor, Finance Faculty, Department of Management, Symbiosis International University, UAE; Symbiosis International (Deemed) University, Pune, India.

Mayank Joshipura, Ph.D., Vice-Dean-Research & Professor (Finance), School of Business Management, SVKM's NMIMS Deemed to be University, Mumbai, India.

Mariam Joseph Sebastian, Master's degree, Independent Scholar, Manipal Academy of Higher Education, Dubai Campus, UAE.

Anjleen Kaur Thiara, Master's degree, Independent Scholar, Manipal Academy of Higher Education, Dubai Campus, UAE.

Ashish Dwivedi, Ph.D., Professor, Operations and Decision Sciences Faculty, Jindal Global Business School, OP Jindal Global University, India.

Tripti Singh, Ph.D., Assistant Professor, Design Discipline, Indian Institute of Information Technology, Design and Manufacturing, India. (Corresponding author)

Suchi Dubey (UAE), Mayank Joshipura (India), Mariam Joseph Sebastian (UAE), Anjleen Kaur Thiara (UAE), Ashish Dwivedi (India), Tripti Singh (India)

# HERDING BEHAVIOR IN THE UAE STOCK MARKETS DURING COVID-19: EVIDENCE USING THE CSAD APPROACH

## Abstract

Herding behavior often emerges in uncertain market conditions, when investors, confronted with limited or ambiguous information, tend to imitate their peers' actions instead of relying on their own analytical assessments. This follow-on herd mentality phenomenon engenders analogous trading behavior among market participants, potentially undermining market efficiency. During times of increased volatility, such behavioral patterns become more noticeable, which has a substantial impact on asset values and skews the efficiency of financial markets. This study explores herding in the UAE stock markets during the COVID-19 outbreak, focusing on the Dubai Financial Market (DFM) and the Abu Dhabi Securities Exchange (ADX). Using daily data from January 1, 2019 through December 31, 2021, the Cross-Sectional Absolute Deviation (CSAD) model is implemented in static and dynamic forms to explore nonlinear and evolving aspects of investor behavior. The analysis indicates that during the initial months of the pandemic, clear evidence of herding emerged in the Dubai Financial Market ( $\gamma_3 = -3.087$ ;  $p < 0.05$ ), whereas the Abu Dhabi Exchange did not display statistically meaningful signs of such behavior. This contrast highlights how herding behaviors are not uniform across markets; they are shaped by factors such as institutional structures, liquidity levels, and the overall composition of traders. The results offer valuable implications for regulators, policymakers, and large investors, providing insights into how behavioral patterns can affect market resilience in emerging markets. Moreover, the study's findings highlight the importance of timely disclosure and targeted investor awareness initiatives in reducing irrational reactions during periods of distress or crisis.

## Keywords

herding, investors, volatility, UAE, CSAD, COVID-19

## JEL Classification

G41, G14, G15

## INTRODUCTION

Financial markets are often portrayed as efficient arenas where prices incorporate all available information and investor choices are guided by rational analysis (Fama, 1970). Yet, in times of heightened uncertainty, this ideal breaks down. Investors may go their own judgments and imitate the behavior of others, a tendency widely recognized as herding (Banerjee, 1992; Bikhchandani & Sharma, 2000; Raafat et al., 2009). Such collective movements can push prices away from fundamentals, amplify volatility, and create vulnerabilities for overall market stability (Bouri et al., 2021; Yousaf et al., 2021; Bogdan et al., 2022).

The COVID-19 pandemic created conditions rarely seen in financial history, making it a powerful setting for exploring how investors behave under stress (Mishra & Mishra, 2023). Markets around the world moved sharply, economies were disrupted, and uncertainty rose to extraordinary levels. Investors often had to make choices with information that was both incomplete and contradictory, ranging from unstable oil prices to rapidly shifting Government measures. In such



This is an Open Access article, distributed under the terms of the [Creative Commons Attribution 4.0 International license](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

**Conflict of interest statement:**  
Author(s) reported no conflict of interest

circumstances, the temptation to follow the crowd rather than rely on individual judgment became stronger. Examining whether herding occurred in this environment provides insights not only for theory but also for understanding how well markets can withstand times of severe strain (Wen et al., 2022; Ampofo et al., 2023).

While herding has been extensively investigated in mature markets, there is still limited evidence from emerging economies. The United Arab Emirates (UAE) offers a distinctive case: its two principal exchanges, the Dubai Financial Market (DFM) and the Abu Dhabi Securities Exchange (ADX), share regional importance but differ in structural aspects such as liquidity, investor mix, and trading activity. Despite their rising prominence, little is known about the behavioral dynamics shaping these markets. This study seeks to fill the identified gap by analyzing how herding behavior manifested in the UAE's two principal stock exchanges the DFM and ADX, throughout the COVID-19 period. By assessing investor responses during a phase of exceptional uncertainty, the research enhances understanding of behavioral dynamics in emerging markets and provides fresh empirical insight into how such behavior influences market efficiency.

## 1. LITERATURE REVIEW AND HYPOTHESES

### 1.1. Theoretical perspectives on herding behavior

Over the past decade, herding behavior has gained more interest in behavioral finance, particularly in the wake of a financial crisis, since it amplifies volatility and destabilizes the financial markets (Filip et al., 2015). Behavioral finance has increasingly recognized herding behavior as a significant deviation from rational investor behavior, particularly in times of uncertainty. The notion of informational cascades explains why individuals imitate others when private information is limited (Banerjee, 1992). Froot et al. (1992) further contend that when the costs of acquiring information are high, investors are more likely to emulate the actions of others rather than rely on independent analysis. Herding has also been linked to risk-avoidance and reputational concerns, where aligning with the majority is seen as safer than acting independently (Devenow & Welch, 1996; Hasan, & Tunaru, 2023). In reality, markets frequently alternate between herding and anti-herding states, with market volatility acting as the primary force driving such transitions (Balciar et al., 2013; Balciar et al., 2014). Moreover, Teraji (2003) highlights the self-reinforcing nature of confidence in prevailing majority opinions as a key mechanism through which herding behavior is sustained among investors. This dynamic suggests that once collective beliefs take hold, they can am-

plify and perpetuate imitative trading, particularly under conditions of uncertainty. Similarly, argued that widespread conformity provides psychological reinforcement, making herding an adaptive strategy in uncertain environments. Research in behavioral biology suggests that moving as a group often serves as a protective response in risky environments. Seghers (1974) shows that schooling in guppies develops as an adaptive reaction to predation, helping individuals reduce vulnerability by staying within the group. In a similar way, investors facing heightened uncertainty may follow others not out of irrationality, but as a practical response to perceived risk. Such perspectives align with evolutionary psychology, which views herding as an adaptive strategy for survival under uncertain conditions.

Investor sentiment is widely recognized as a key factor behind herding behavior (Sibande et al., 2023). The shifts in mood, whether overly optimistic or deeply pessimistic, can have a strong impact on market fluctuations, as highlighted by Sun et al. (2021) in China and Xu and Zhou (2018) during the COVID-19 crisis. Retail investors rely heavily on informal and digital sources of information, including social media, which increases the emotional contagion (Da et al., 2015). Investor sentiment strongly influences asset valuations, as investors react emotionally to news and adjust trading positions (Antweiler & Frank, 2004). This sentiment-driven herding is reinforced by disparities in information access, with Yoon and Oh (2022) introducing the concept of Abnormal Information Creation Activity (AICA) to explain how such in-

formation structures intensify collective movements. The literature highlights that a shift in sentiment can create possible predictable patterns of demand that drive markets in waves rather than through rational price discovery (Barberis et al., 2005). Expanding further on this, sentiment indices have been shown to outperform traditional valuation measures in explaining behavioral influences on stock returns (Baker & Wurgler, 2007).

Detecting herding behavior has long been a methodological challenge, and researchers have developed many approaches to capture its presence in financial markets. Early studies relied heavily on the Cross-Sectional Standard Deviation (CSSD) measure, which estimates herding by examining the dispersion of stock returns around the market average. Although widely used, CSSD is highly sensitive to outliers, making it less reliable in periods of crisis or extreme volatility (Aharon, 2021). To overcome this limitation, the CSAD model was introduced as a more robust alternative. The CSAD method proposed by Chiang and Zheng (2010) is widely used for capturing non-linear relationships among stock returns. The CSAD approach accounts for non-linear links between market returns and their dispersion, making it more effective in times of instability and sudden shifts. Evidence from Chiang and Zheng (2010) shows that CSAD can capture herding patterns that the older CSSD method often misses. More recent studies confirm this advantage: Shahzad et al. (2023) applied CSAD to the S&P 500 and found that herding pressures were particularly visible in the first months of the COVID-19 crisis, while Bogdan et al. (2022) observed similar dynamics in emerging European markets, demonstrating that the framework works across diverse settings.

Other methods include CSSD, the Lakonishok, Shleifer, and Vishny (LSV) model. Such methods have also been applied in studies examining the behavior of institutional investors, where they offer useful perspectives on portfolio-level strategies and collective tendencies (Lakonishok et al., 1994). However, their scope is somewhat limited, as they do not adequately reflect the dynamic, market-wide forms of herding that become particularly evident during episodes of financial turmoil or systemic crises.

## 1.2. Global evidence on herding during COVID-19

The studies conducted during the COVID-19 period suggest that investors in emerging markets were especially prone to herding. Fragile market structures and higher exposure to uncertainty made participants more reliant on cues from external sources. During the pandemic, investors in many emerging markets often looked to collective cues rather than fundamentals, which left them more exposed to contagion effects (Bouri et al., 2021; Luu & Luong, 2020; Kumar & Kumar, 2022). Developed markets, on the other hand, presented a more complicated picture. Herding was observed, but it tended to fade quickly and showed little consistency, even when financial stocks were severe (Javaira et al., 2023; Espinosa-Méndez & Arias, 2021).

Regional evidence reinforces the idea that herding is not universal and uniform, but rather shaped by context. Asian markets with a strong retail presence and dependence on informal information channels saw a clear rise in imitation during COVID-19 (Luu & Luong, 2020; Kumar & Kumar, 2022; Vidya et al., 2023). Further, Fei and Zhang (2023) pronounced herding behavior in Chinese stock markets, with the intensity of imitation amplified during the pandemic period. In Europe, findings diverged: some scholars identified significant herding during periods of peak stress (Ferreruela & Mallor, 2021; Bogdan et al., 2022), while others emphasized country-level differences, linking outcomes to the strength of institutions and regulatory systems (Espinosa-Méndez & Arias, 2021). In American markets, no evidence of herding behavior was discerned using the static model of the CSAD approach, consistent with findings in developed markets (Alexakis et al., 2023). However, this contradicts the outcomes of a comparative study by Ampofo et al. (2023) between the USA and UK, where herding behavior was detected in the former but not the latter. Moreover, herding tendencies were observed during bullish market conditions in both countries and during bearish states in the US market. During COVID-19, the United States showed herding surfaced sharply in the first months of the crisis but receded once policy interventions helped calm markets (Shahzad et al., 2023).

Overall, the research points to the conclusion that the impact of COVID-19 on herding cannot be generalized across all markets. Instead, institutional quality, investor demographics, and access to reliable information shaped outcomes in different ways. Cross-country comparisons confirm that patterns from developed economies do not always extend to emerging markets, where weaker institutions and distinct investor profiles play a defining role (Zaremba et al., 2021). These findings collectively suggest that the prevalence of herding behavior is contingent on the developmental status of the studied country (Mishra & Mishra, 2023; Kizys et al., 2021). Within this landscape, the UAE stands out as an especially relevant case because its market behavior and structures diverge from both advanced and peer emerging economies.

### 1.3. Gaps in UAE market studies

The ongoing literature on herding behavior spans a wide range of asset classes, including stock markets, cryptocurrency markets, and energy stocks (Fang et al., 2021; Javaira et al., 2023; Brahmana et al., 2023; Yousaf et al., 2021). Despite growing interest in behavioral finance, studies focusing on herding in the UAE remain scarce. Abdeldayem and Al Dulaimi (2020) provided early insights using the CSSD method, but their limited dataset and method sensitivity to outliers present concerns. Yousaf and Alokla (2023) examined herding across Gulf Cooperation Council (GCC) countries, including the UAE, but focused only on a narrow sample of banking stocks. Earlier work on Gulf equity markets more broadly (Al-Khazali & Mirzaei, 2017).

Beyond these studies, only limited work has addressed herding in the wider Middle East and North Africa (MENA) and Gulf Cooperation Council (GCC) setting. Research on herding within the broader MENA and GCC region remains relatively scarce, and the limited studies available often lack a UAE-specific focus (Albaity et al., 2022). Some investigations have highlighted how external shocks intensify financial contagion and investor imbalances in Middle Eastern markets (Bouri & Roubaud, 2019). Others have documented cross-market herding patterns in emerging economies, in-

cluding MENA, though these analyses remain largely aggregated and provide little insight into the UAE's distinct exchanges (Kenourgios, 2020). Evidence from North African markets also points to herding behavior, but again, the focus has been outside the Gulf context (Naoui & Liouane, 2019). Taken together, the existing studies show clear signs of behavioral irregularities across regional markets. What they are unable to provide, however, is a thorough evaluation of how such dynamics play out within the UAE's distinct financial framework.

The lack of systematic inquiry is particularly striking given the importance of the Dubai Financial Market (DFM) and the Abu Dhabi Securities Exchange (ADX) in directing regional capital flows. Despite their shared prominence, the two exchanges differ markedly in liquidity, ownership concentration, and the composition of their investor base. These structural contrasts provide a useful context for assessing whether herding tendencies manifest in a uniform manner or adapt to the characteristics of each market. Yet, comprehensive applications of advanced approaches such as the CSAD model remain absent. This omission is especially relevant during the COVID-19 crisis, a period defined by heightened global uncertainty and pronounced local disruptions. Investigating herding within the UAE's leading exchanges under these conditions offers insights not only for regional financial scholarship but also for broader debates on the role of behavioral dynamics in shaping market efficiency across emerging economies. Evidence from developed economies generally points to weaker or short-lived manifestations of this behavior. In contrast, emerging markets often display stronger and more persistent forms of herding, a tendency linked to structural fragilities and uneven access to reliable information.

Despite the central role of DFM and the ADX in channeling regional capital, the UAE has attracted relatively little scholarly attention. The lack of in-depth analyses employing rigorous models such as the CSAD framework limits our understanding on how herding develops under conditions of heightened uncertainty, including the disruptions brought about by COVID-19.

Considering this gap, the present study investigates whether herding tendencies strengthened in the UAE's equity markets during the pandemic and considers how structural contrasts between DFM and ADX may have shaped these outcomes.

The purpose of this study is to investigate whether herding behavior in the UAE's equity markets intensified during the COVID-19 crisis, and to consider how the distinct structures of the DFM and the ADX may have shaped the way these behavioral patterns developed.

This study follows the CSAD approach for detecting herding. Thus, the null hypothesis can be stated as herding does not exist, as evidenced by the significant positive relationship between dispersion and squared market returns. This can be reformulated mathematically as presented in equation (1):

$$H_0: \gamma_3 \geq 0, \quad (1)$$

where  $H_0$  is the null hypothesis to be rejected to detect herding, and  $\gamma_3$  is the coefficient of squared market returns calculated using equation (1). Moreover, static analysis alone was found insufficient to identify herding behavior in stock markets. Therefore, a dynamic approach was employed through rolling window regressions. A review of earlier research reveals that herding behavior in emerging markets is shaped not only by shifts in investor sentiment but also by market characteristics, such as liquidity, investor composition, and the level of regulatory transparency. Building on these insights, the present study examines how these factors influenced investor behavior in the UAE's stock exchanges during the COVID-19 period, as reflected in the following hypotheses. Based on the gaps identified, the following hypotheses are formulated.

*H1: Investor behavior in the UAE equity markets exhibited signs of herding during the COVID-19 pandemic.*

*H2: The intensity of herding in the UAE equity markets increased significantly during periods of elevated market volatility.*

*H3: Variations in herding across the DFM and the ADX can be attributed to differences in their structural and institutional characteristics.*

## 2. METHODS

### 2.1. Model Framework

This study utilizes the CSAD methodology developed by Chang et al. (2000) and refined by Chiang and Zheng (2010) to empirically detect herding behavior in stock markets. The CSAD model addresses key limitations of earlier models, such as the CSSD introduced by Christie and Huang (1995), which assumes linearity and is sensitive to outliers during periods of market stress.

The CSAD at time  $t$  is computed using the following equation (2):

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{N-1}}, \quad (2)$$

where  $R_{i,t}$  is the return of the stock of company  $I$  at time  $t$ ,  $R_{m,t}$  is the return of the market index for the market  $m$ , and time  $t$ ,  $N$  is the total number of firms.

The CSSD model has been a popular tool for spotting herding behavior, but it is not perfect. One big issue is that it is easily thrown off by extreme values, which can mess up the results (Dhall & Singh, 2020). Also, the model assumes a straight-line relationship between the dispersion of the stock returns (CSSD) and the overall market's ups and downs during herding periods. The CSAD model was developed as an improvement over earlier approaches to better capture the non-linear and often irregular behavior of investors. It has since been refined to enhance its applicability in real-world financial markets, particularly under conditions of heightened uncertainty. The model is expressed in equation (3) as follows:

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

The regression analysis explores the presence of herding behavior, which is often characterized by a non-linear relationship. Specifically, it inves-

tigates whether there is a notable inverse association between return dispersions and the square of overall market returns. Chiang and Zheng (2010) proposed a model that can capture and effectively account for such non-linearity in testing for herding tendencies. The following equation (4) is used in the study:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_{i,t}. \quad (4)$$

In this context,  $R_{m,t}$  represents the average return across all stocks in the sample at time  $t$ , reflecting overall market sentiment during that period. This measure helps reveal how investors behave under different market conditions, especially when such behavior deviates from linear patterns typically assumed in traditional models. The term  $|R_{m,t}|$ , which captures the absolute value of market returns, indicates the strength of market movements regardless of whether they are positive or negative, and is crucial for examining how strongly investors react to changes in market direction.  $R_{m,t}^2$ , the squared market return, is included to identify non-linear patterns in return dispersion. A negative and statistically significant coefficient  $\gamma_3$  provides evidence of herding behavior, while a positive and significant  $\gamma_3$  suggests its absence.

## 2.2. Data

This study investigates the presence of herding behavior in the two primary stock exchanges of the UAEs, the DFM and the ADX, during periods of pronounced market turbulence, with specific reference to the COVID-19 pandemic as a recent case of systemic stress (Ullah, 2023). NASDAQ Dubai is another stock market that operates in the UAE, but it has not been included in this research for several reasons. The listed stocks in this market are primarily international in nature and are priced in US dollars, whereas all the stocks listed in the

DFM and ADX are priced in UAE dirhams and, hence, would not be comparable. Furthermore, the prominent stock market index used to measure the NASDAQ Dubai is the Financial Times Stock Exchange (FTSE) NASDAQ Dubai UAE 20, which includes stocks listed in the DFM and would cause data duplication.

This study employs the daily closing prices of individual stocks comprising the respective benchmark indices of the UAE stock exchanges. Table 1 provides a comprehensive overview of the sample selection, detailing the specific stock markets under investigation, the indices utilized, and the number of constituent firms included in the analysis. For the selected time frame, firm-level daily stock prices and corresponding market index values were obtained from the database.

The data spans from January 1, 2019 to December 31, 2021. For the static analysis, this period is further divided into three sub-periods. The first case of the COVID-19 virus was confirmed on January 29, 2020, in the UAE (Turak, 2020), so this date serves as the cut-off point for the period before and after the outbreak. The period before the outbreak in this research has been chosen as January 1, 2019 to January 28, 2020. Under typical conditions, individuals would have adequate time to gather information and make rational decisions. However, attributable to the accelerating diffusion of news, there has been a surge in the volume of information engulfing investors, resulting in heightened levels of attention. As evidenced by substantial literature, a negative relationship exists between investor attention and market returns (Baker et al., 2020; Blasco et al., 2012; Demirer et al., 2019; Bouri et al., 2021; Bogdan et al., 2022; Shear et al., 2021; Dash & Maitra, 2022; Smales, 2021). Numerous studies employing Google Search Volume (GSV) as a proxy have corroborated the notion that investor attention adversely affects global stock returns

**Table 1.** Stock markets of the United Arab Emirates

Source: Official stock exchange website for ADX and DFM.			
Stock Market	Stock Market Index	Number of Components in Index	Number of Companies Used in Research
Dubai Financial Market	DFM General (DFMGI)	35	28
Abu Dhabi Securities Exchange	FTSE ADX General (FTFADGI)	70	59

*Note:* 7 companies and 11 companies have been excluded from the research from DFM and ADX, respectively, as the companies were listed after the relevant time frame of 31 December 2021 and are thus outside the scope of this research.

during periods of crisis. The average period in the studies where GSV for “coronavirus” and related terms has peaked in the first 5 months of the outbreak (Bogdan et al., 2022; Shear et al., 2021; Dash & Maitra, 2022; Smales, 2021). Further, herding has been suggested to be a short-lived phenomenon in the stock markets induced by investors’ instantaneous and dynamic behavior (Kumar and Kumar, 2022). Thus, for this research, the outbreak period has been chosen from January 29, 2020, to June 29, 2020. The remaining June 30, 2020, to December 31, 2021, has been chosen as the post-outbreak period. The above has been summarized as follows:

1. Whole sample period: January 1, 2019, to December 31, 2021.
2. Pre-COVID-19 outbreak period: January 1, 2019, to January 28, 2020.
3. Outbreak period: January 29, 2020, to June 29, 2020.
4. Post-COVID-19 outbreak period: June 30, 2020, to December 31, 2021.

After the daily closing prices and market index were collated, the daily returns were calculated using the following formula, evident in equation (5).

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \cdot 100, \quad (5)$$

where  $R_t$  is the return at time  $t$ ,  $P_t$  is the closing price on day  $t$ , and  $P_{t-1}$  is the closing price on the day before  $t$ .

### 3. RESULTS

The analysis was carried out in three stages to capture both the overall and time-varying nature of herding behavior. The process began with a static regression, using ordinary least squares (OLS) with robust standard errors to provide an initial assessment of whether the relationship between market returns and dispersion aligns with herding tendencies. Since investor behavior is rarely constant over time, a dynamic approach was then applied. Rolling-window regressions were used

to re-estimate the model across overlapping intervals, allowing shifts in herding behavior to be observed as market conditions evolved. This approach is particularly relevant during COVID-19, when rapid changes in sentiment were expected.

Finally, the robustness of the findings was examined by splitting the sample into three distinct phases: pre-COVID, early COVID, and later COVID. Comparing results across these periods helps determine whether the detected herding patterns persist under different market conditions or are limited to specific episodes of heightened uncertainty. To ensure clarity, the estimation procedure can be summarized in three steps:

*Step 1. Static analysis: OLS with robust standard errors on the full sample.*

*Step 2. Dynamic analysis: Rolling-window regressions to capture time-varying herding.*

*Step 3. Robustness checks: Sub-period estimation (pre-COVID, early COVID, later COVID).*

#### 3.1. Descriptive statistics

Table 2 (Panel A and Panel B) presents the descriptive statistics for the CSAD values and corresponding market returns ( $R_{m,t}$ ) across the analyzed periods for the ADX and the DFM, respectively.

During the COVID-19 period, both the ADX and the DFM reported negative average market returns, indicative of prevailing bearish sentiment, plausibly driven by elevated levels of investor uncertainty and market-wide panic. During this period, the CSAD recorded its highest average and variability, indicating a notable increase in the dispersion of stock returns. Such patterns are often indicative of high uncertainty in the market and may point toward the presence of herding behavior among investors. An increase in the average CSAD usually reflects growing market-wide volatility, while a rise in its standard deviation suggests irregularities in return behavior potentially triggered by external shocks or structural disruptions. Additionally, the skewness analysis of the sample shows a rightward skew in CSAD values, suggesting that large positive deviations occur more frequently. In contrast, market returns exhibit a

**Table 2.** Descriptive statistics for Abu Dhabi Securities Exchange (ADX) and Dubai Financial Market (DFM)

Source: Authors' calculations based on data obtained from the Dubai Financial Market (DFM) and the Abu Dhabi Securities Exchange (ADX).

Panel A – ADX		Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis
CSAD	Full Sample	0.0139	0.0033	0.0841	0.0081	3.3757	17.2803
	Pre-COVID	0.0122	0.0033	0.0433	0.0054	2.0307	7.2237
	During COVID	0.0215	0.0055	0.0841	0.0153	1.7840	3.066
	Post COVID	0.0129	0.0039	0.0442	0.0051	1.5684	5.5261
$R_{m,t}$	Full Sample	0.0008	-0.0806	0.0841	0.0122	-0.1745	15.3358
	Pre-COVID	0.0003	-0.0332	0.0368	0.0079	0.3584	3.7873
	During COVID	-0.0014	-0.0806	0.0841	0.0265	0.0378	2.6041
	Post COVID	0.0018	-0.0232	0.0397	0.0070	0.8651	4.5180
Panel B – DFM		Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis
CSAD	Full Sample	0.0141	2.7406	0.0530	0.0070	2.2096	7.3132
	Pre-COVID	0.0124	2.7406	0.0428	0.0051	1.2838	4.9042
	During COVID	0.0203	0.0067	0.0530	0.0108	1.3058	1.1321
	Post COVID	0.0135	0.0038	0.0521	0.0058	2.1791	8.3197
$R_{m,t}$	Full Sample	0.0004	-0.083	0.0732	0.0127	-0.7476	10.8485
	Pre-COVID	0.0004	-0.0396	0.0476	0.0089	0.3412	4.7937
	During COVID	-0.0026	-0.0829	0.0732	0.0252	-0.3655	2.5245
	Post COVID	0.0012	-0.0516	0.0395	0.0092	-0.3392	5.0758

left-skewed distribution, indicating a tendency for losses to be more pronounced during the period under review. Furthermore, the kurtosis values for the entire sample for the CSAD measures and market returns are leptokurtic, indicating outliers in the data. This validates the use of CSAD as the method for detecting herding.

### 3.2. Static analysis

This section reports the empirical results of the static analysis, conducted using the CSAD methodology as refined by Chiang and Zheng (2010).

Table 3 summarizes the results obtained through equation (4) and the adjusted  $R^2$ . The explanatory power (goodness-for-fit) of the model as measured by adjusted  $R^2$  is also provided. Table 3 presents the baseline CSAD regression results. For DFM, the squared return term ( $\gamma_3$ ) is negative and statistically significant during the outbreak ( $-3.087, p < 0.05$ ), indicating herding behavior. No significant evidence of herding is detected in ADX during the same period. The relatively high-adjusted  $R^2$  indicates that the model largely explains the variations. As discussed in the Research Methodology section, a negative and statistically significant  $\gamma_3$  coefficient indicates the presence of herding behavior. A statistically positive  $\gamma_3$  coefficient indicates anti-herding behavior.

From the findings in Table 3, a negative and significant  $\gamma_3$  coefficient was observed in DFM during the COVID-19 pandemic, leading to the rejection of the null hypothesis and the assertion that herding behavior was present during this period. In ADX, however, herding behavior was not detected during the pandemic outbreak, as the  $\gamma_3$  coefficient did not exhibit negativity or significance, providing insufficient evidence to reject the null hypothesis. The contrast in the findings could be attributed to the fact that differences in the period and method used could yield different results. Prior to the pandemic, ADX displayed a significantly positive  $\gamma_3$  coefficient, indicative of anti-herding tendencies. Similarly, the post-outbreak period in DFM exhibited similar patterns.

When performing the static analysis using different dates, different results are obtained. In ADX, splitting the onset of the pandemic period provides exciting results. An analysis of 29 January 2020 to 11 March 2020, the date COVID-19 was declared a pandemic by the World Health Organization (n.d.), showed that herding behavior was detected at 10% significance in this period. If 11 March 2020 to 30 June 2020 is considered, herding behavior is undetected as the  $\gamma_3$  coefficient is negative but insignificant. However, the same conclusions are not evident in DFM, where herding was not detected in the former period but in the latter. This provides

**Table 3.** Estimates of herding behavior

Source: Authors' calculations based on data obtained from the Dubai Financial Market (DFM) and the Abu Dhabi Securities Exchange (ADX).

Market	Sample Period	$\gamma_0$	$\gamma_1$	$\gamma_2$	$\gamma_3$	Adjusted R <sup>2</sup>
ADX	Full Sample	0.009 *** (47.749)	0.054 *** (5.593)	0.748 *** (27.129)	0.005 (0.010)	0.8456
	Pre-COVID	0.008 *** (28.905)	0.015 (0.756)	0.683 *** (10.487)	6.324 *** (2.558)	0.7829
	During COVID	0.009 *** (18.901)	0.064 *** (6.001)	0.735 *** (16.669)	0.076 (0.126)	0.9641
	Post COVID	0.009 *** (27.609)	0.027 (0.920)	0.622 *** (7.950)	3.772 (1.296)	0.5229
DFM	Full Sample	0.009 *** (34.921)	0.025 (1.839)	0.599 *** (15.779)	-1.133 (-1.708)	0.5754
	Pre-COVID	0.009 *** (23.656)	0.053 ** (2.038)	0.444 *** (5.795)	3.211 (1.354)	0.4714
	During COVID	0.010 *** (9.425)	0.010 (0.394)	0.698 *** (7.182)	-3.087 ** (-2.276)	0.6944
	Post COVID	0.011 *** (25.3636)	0.048 (1.856)	0.296 *** (3.731)	8.477 *** (3.675)	0.4126

Note: The values in parentheses denote t-statistics. \*\*\*, \*\*, and \* represent the significance levels at 1%, 5%, and 10%, respectively.

evidence that herding is a short-lived occurrence. One plausible explanation for the non-detection of herding behavior in ADX during the pandemic could be its comparatively lower daily trading volume, resulting in reduced liquidity. Consequently, the limited trading activity in ADX may have hindered the formation and detection of herd behavior patterns during the pandemic.

### 3.3. Dynamic analysis

Herding behavior is widely acknowledged as a temporary and time-sensitive market phenomenon. The use of static models in its analysis has been critiqued for potentially producing biased or misleading results, given their underlying assumption of time-invariant parameters, which may fail to capture the dynamic nature of investor behavior. Given its inherently dynamic nature, a static analysis of herding behavior may prove to be insufficient in practice. Therefore, the subsequent step in the analysis involves conducting a rolling window regression (Stavroyiannis and Babalos, 2017). Rolling regressions estimate model parameters using a fixed time window applied across the entire dataset. There is no rule for determining the appropriate size of a rolling window, but a rolling window that is too short or too long may lead to incorrect conclusions. Based on previous studies, this study determined the rolling window of 150 observations (Bogdan et al., 2022; Stavroyiannis & Babalos, 2017; Cakan et al., 2019; Sibande et al., 2023). Following

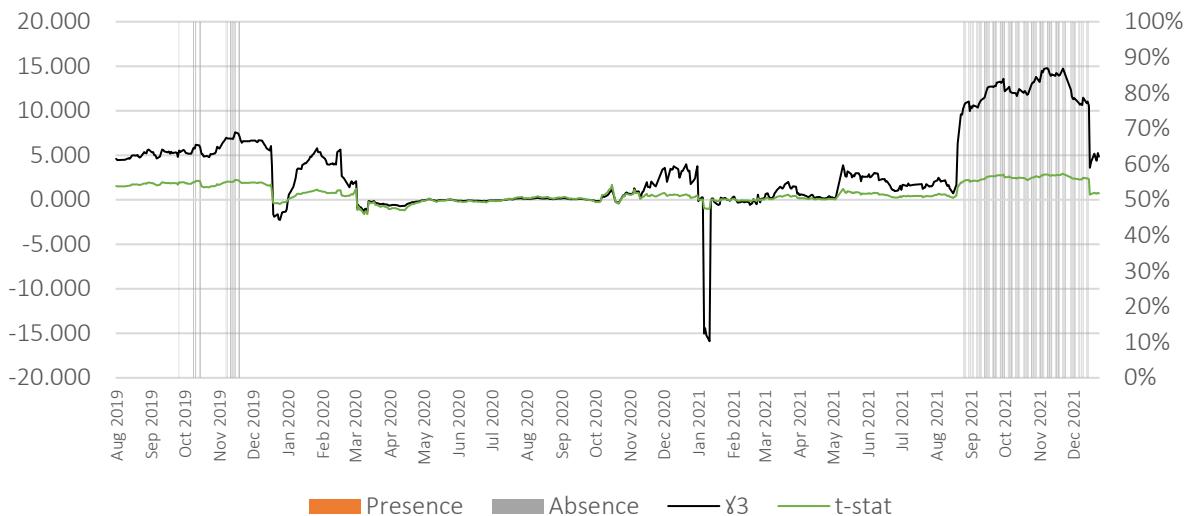
the specification of the window width, the estimation window was systematically shifted forward in one-time-step intervals to capture the evolving dynamics of the data over time. For example, the dataset from January, 2 2019 to August, 7 2019 will constitute the first regression window. Moving one step forward in time, the second regression window will contain the dataset from January 3, 2019 to August 8, 2019. This process is continued until the entire sample period is covered. While no strict rule exists for determining the optimal rolling window size, an excessively short or long window may result in misleading conclusions.

The rolling window regression analysis is depicted in Figures 1 and 2. According to the CSAD model, a negative and statistically significant  $\gamma_3$  coefficient indicates the presence of herding behavior. A statistically positive  $\gamma_3$  coefficient indicates no evidence of herding. As such, the  $\gamma_3$  coefficient and the t-stat are plotted in the line graphs. The periods in which herding behavior is detected and not detected are shaded.

In ADX, herding behavior was not detected at a significance level of 1% and 5%. However, the absence of herding was detected in parts of October, November, and December 2019. The absence of herding was detected at a significance level of 1% and 5% during September, October, November, and December of 2021. This is like the static analysis results, where the absence of herding behav-

Source: Graph generated based on data collection.

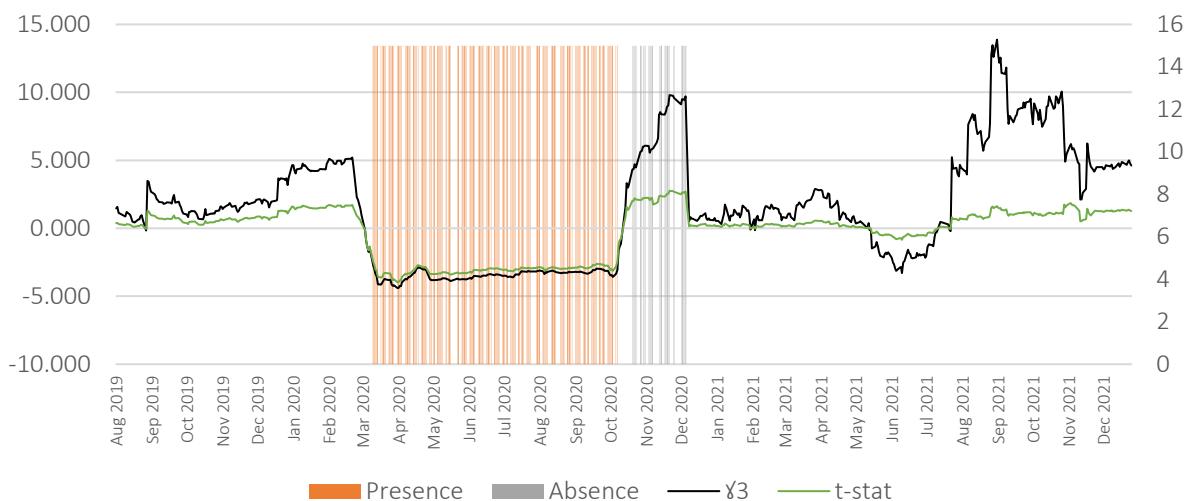
### Presence of Herding Behaviour in Abu Dhabi Securities Exchange (ADX) Using Rolling Window Regression



**Figure 1.** CSAD rolling window analysis of herd behavior in Abu Securities Exchange (ADX)

Source: Graph generated based on data collection.

### Presence of Herding Behaviour in Dubai Financial Market (DFM) Using Rolling Window Regression



**Figure 2.** CSAD rolling window analysis of herd behavior in the Dubai Financial Market (DFM)

ior was detected before the COVID-19 pandemic outbreak. In the Dubai Financial Market, the presence of herding behavior was detected in the months from March to October 2020 at a significance level of 1% and 5%, like the outbreak period in the static analysis. Further, the absence of herding was also detected in November and December

2020, as discovered in the static analysis. The results obtained through the dynamic analysis are similar to the static analysis results, which reinforces the findings.

As established, literature has presented diverse views on the formation of herd behavior from the

perspectives of biology, economics, and finance. The presence of herding behavior during market uncertainty highlights the fact that investors follow group trends rather than relying on individual analysis, which further suggests understanding through an evolutionary lens. In the UAE's equity markets, periods of stress often bring to the surface investors' instinctive inclination to move with the crowd. Such behavior can distort price discovery and fuel additional volatility when uncertainty is already high. Such observations reinforce the importance of behavioral finance in explaining market outcomes and hint that herding may stem from deeply ingrained human tendencies shaped by evolution.

This study offers insights that are highly relevant to both investors and regulators. One of the key takeaways is the clear link between herd behavior and the lack of accessible or reliable information, an issue that is particularly relevant in emerging markets like the UAE. In situations where investors feel uncertain or perceive an informational disadvantage, they mostly prefer to follow the herd. For this reason, policy responses should focus not only on improving transparency and access to credible data but also on addressing misinformation promptly, thereby strengthening trust and reducing unnecessary market turbulence.

For investors, an environment with greater informational clarity enables more effective decision-making, particularly in designing risk management approaches such as diversification and hedging. At the same time, the findings highlight the need for scholars and financial theorists to reconsider conventional models of asset valuation.

Analyzing investor behavior during periods of crisis provides critical evidence on the mechanisms through which price movements occur and volatility propagates. Sentiment tracking in such contexts allows researchers to identify movements from fundamental values and to evaluate the timeliness of corrective interventions. Accordingly, this study generates insights that are directly relevant for financial policymakers and regulators concerned with market stability.

Hypotheses were examined using the CSAD framework, where herding is identified when the coefficient on the squared market return term ( $\gamma_3$ )

is negative and statistically significant, leading to rejection of the null hypothesis. The findings indicate that H1 is partially supported, as DFM showed signs of herding behavior during the COVID-19 outbreak, while such behavior was not consistently observed in the ADX. H2 is supported, showing that herding intensified during periods of heightened market volatility. H3 is also supported, as differences in herding behavior between the two exchanges appear to reflect underlying structural and institutional variations. Overall, the results suggest that herding in the UAE equity markets was episodic and market-specific, rather than persistent or uniform across exchanges.

## 4. DISCUSSION

The results show a clear divergence between the UAE's two main exchanges. Herding was observed in DFM during the outbreak phase but not in ADX. This difference can be explained by market structures: DFM has higher retail investor participation and lower institutional dominance, making it more prone to sentiment-driven clustering. ADX's deeper capitalization and relatively higher institutional presence likely dampened collective swings, consistent with evidence that liquidity and investor mix shape the intensity of herding (Chiang & Zheng, 2010; Economou et al., 2011).

The finding that herding in DFM was short-lived aligns with global evidence showing that COVID-induced herding peaked early in 2020 but faded as stabilizing policies took effect (Bouri et al., 2021; Shahzad et al., 2023). Splitting the outbreak into pre- and post-WHO declaration phases highlights this transience, as herding is detected in one but not the other window. This episodic nature supports prior arguments that herding is context-dependent and crisis-specific rather than persistent (Kumar & Kumar, 2022).

The detection of anti-herding in ADX before COVID and contrarian behavior in DFM after COVID suggests that UAE investors adjust their trading styles once uncertainty eases. Similar post-crisis contrarian effects have been noted in other emerging markets, where investors exploit short-term mispricing after volatility spikes (Bogdan et al., 2022).

From a policy perspective, the evidence underscores the importance of timely and transparent information flows in curbing uncertainty driven clustering. In markets such as the DFM, where retail investors represent a significant share of activity, enhancing the dissemination of accurate and timely information is critical for mitigating herd tendencies. From an investment perspective, the findings stress the necessity of reinforcing risk management mechanisms, with particular em-

phasis on diversification and hedging strategies, to better navigate periods of heightened uncertainty when clustering behavior is most evident. At a theoretical level, the study contributes to ongoing debates on valuation by suggesting that models integrating behavioral dynamics alongside traditional fundamentals provide a more realistic account of market functioning, especially under extreme stress, where conventional frameworks often fail to capture the full extent of risk.

## CONCLUSION, LIMITATIONS, AND SCOPE FOR FUTURE RESEARCH

The study investigated whether herding behavior emerged in the UAE's equity markets during the COVID-19 pandemic, with emphasis on the DFM and the ADX. By applying the CSAD model in both static and rolling forms, the analysis captured how investor behavior shifted over the various stages of the crisis. The analysis shows that herding was statistically significant in DFM during the outbreak phase, while no such evidence was found in ADX. This contrast demonstrates that investor reactions to uncertainty are far from uniform, even within the same country. Instead, they appear to be shaped by the depth of the market, trading activity, and the mix between retail and institutional investors. The findings support the idea that herding in emerging economies tends to be temporary, flaring up in moments of stress and receding as stability returns.

Several key lessons emerge. Markets with higher participation from retail traders appear more vulnerable to collective swings driven by sentiment rather than fundamentals. In contrast, exchanges with stronger institutional participation and greater liquidity, such as ADX, may be more resilient to sudden waves of imitative trading. These insights suggest that robust regulatory practices, especially timely disclosure of reliable information and enhanced investor awareness, are crucial for reducing herd-driven volatility during times of crisis.

The study does have limitations. It concentrates on two exchanges within a fixed period, which may not fully capture longer-term dynamics or broader regional patterns. Future research could build on these findings by integrating measures of media sentiment, exploring demographic differences among investors, and considering the influence of digital trading platforms. Comparative studies across the GCC and other emerging markets would also help determine whether the UAE's experience is unique or part of a wider regional trend.

## AUTHOR CONTRIBUTIONS

Conceptualization: Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara, Ashish Dwivedi, Tripti Singh.

Data curation: Mariam Joseph Sebastian.

Investigation: Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara.

Methodology: Suchi Dubey, Anjleen Kaur Thiara.

Project administration: Suchi Dubey.

Resources: Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara, Ashish Dwivedi, Tripti Singh.

Supervision: Suchi Dubey, Mayank Joshipura, Anjleen Kaur Thiara, Ashish Dwivedi, Tripti Singh.

Validation: Suchi Dubey, Mariam Joseph Sebastian, Anjleen Kaur Thiara.

Visualization: Tripti Singh.

Writing – original draft: Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara, Ashish Dwivedi.

Writing – review & editing: Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara, Ashish Dwivedi.

Suchi Dubey, Mayank Joshipura, Mariam Joseph Sebastian, Anjleen Kaur Thiara, Ashish Dwivedi.

## ACKNOWLEDGMENT

We are grateful to our co-authors for their invaluable contributions and collaboration in this research. A special thanks to the young independent researchers who are also the co-authors for their dedication and efforts in data collection and analysis, which have significantly enriched this study. We also appreciate the support provided by our institutions and the insightful feedback from our peers and reviewers.

## DISCLAIMER

- The authors have no conflict of interest to declare.
- Data is available from the corresponding author on request.

## REFERENCES

---

1. Abdeldayem, M. M., & Al Dulaimi, S. H. (2020). Investors' herd behavior related to the pandemic-risk reflected on the GCC stock markets. *Zbornik Radova Ekonom-skog Fakulteta u Rijeci / Proceedings of Rijeka Faculty of Economics*, 38(2), 563-584. <https://doi.org/10.18045/zbefri.2020.2.563>
2. Aharon, D. Y. (2021). Uncertainty, fear and herding behavior: Evidence from size-ranked portfolios. *Journal of Behavioral Finance*, 22(3), 320-337. <https://doi.org/10.1080/15427560.2020.1774887>
3. Albaity, M., Mallek, R. S., & Mustafa, H. (2022). Bank Stock Return Reactions to the COVID-19 Pandemic: The Role of Investor Sentiment in MENA Countries. *Risks*, 10(2), 0-15. <https://doi.org/10.3390/risks10020043>
4. Alexakis, C., Chantziras, A., Economou, F., Eleftheriou, K., & Grose, C. (2023). Animal Behavior in Capital markets: Herding formation dynamics, trading volume, and the role of COVID-19 pandemic. *North American Journal of Economics and Finance*, 67(September 2022), 101946. <https://doi.org/10.1016/j.najef.2023.101946>
5. Al-Khazali, O., & Mirzaei, A. (2017). Stock market anomalies, market efficiency and the adaptive market hypothesis: Evidence from Gulf Cooperation Council (GCC) stock markets. *Applied Economics*, 49(18), 1794-1807. Retrieved from <https://ideas.repec.org/a/eee/infin/v51y2017icp190-208.html>
6. Ampofo, R. T., Aidoo, E. N., Ntiamoah, B. O., Frimpong, O., & Sasu, D. (2023). An empirical investigation of COVID-19 effects on herding behaviour in USA and UK stock markets using a quantile regression approach. *Journal of Economics and Finance*, 47(2), 517-540. <https://doi.org/10.1007/s12197-022-09613-8>
7. Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, 59(3), 1259-1294. <https://doi.org/10.1111/j.1540-6261.2004.00662.x>
8. Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129-152. <https://doi.org/10.1257/jep.21.2.129>
9. Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyo-sin, T. (2020). The unprecedented stock market reaction to COVID-19. *Review of Asset Pricing Studies*, 10(4), 742-758. <https://doi.org/10.1093/rapstu/raaa008>
10. Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. *Journal of International Financial Markets, Institutions and Money*, 23(1), 295-321. <https://doi.org/10.1016/j.intfin.2012.09.007>
11. Balcilar, M., Demirer, R., & Hammoudeh, S. (2014). What drives herding in oil-rich, developing stock markets? Relative roles of own volatility and global factors. *North American Journal of Economics and Finance*, 29, 418-440. <https://doi.org/10.1016/j.najef.2014.06.009>
12. Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, 107(3), 797-817. <https://doi.org/10.2307/2118364>
13. Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, 75(2), 283-317. <https://doi.org/10.1016/j.jfineco.2004.04.003>

14. Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets: A review. *IMF Staff Papers*, 47(3), 279-310. <https://doi.org/10.2307/3867650>
15. Blasco, N., Corredor, P., & Ferreruela, S. (2012). Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, 12(2), 311-327. <https://doi.org/10.1080/14697688.2010.516766>
16. Bogdan, S., Suštar, N., & Draženović, B. O. (2022). Herding Behavior in Developed, Emerging, and Frontier European Stock Markets during COVID-19 Pandemic. *Journal of Risk and Financial Management*, 15(9). <https://doi.org/10.3390/jrfm15090400>
17. Bouri, E., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters*, 29, 216-221. <https://doi.org/10.1016/j.frl.2018.07.008>
18. Bouri, E., Demirer, R., Gupta, R., & Nel, J. (2021). Covid-19 pandemic and investor herding in international stock markets. *Risks*, 9(9). <https://doi.org/10.3390/risks9090168>
19. Brahmana, R. K., Hashmi, M. A., Abdullah, & Yau, J. T. H. (2023). Herding Behavior in Volatile Market Regimes: an in-Depth Analysis of Coins, Tokens, Pandemic, Penny, and Pricey Cryptocurrencies. *International Journal of Business and Society*, 24(2), 746-760. <https://doi.org/10.33736/ijbs.5960.2023>
20. Cakan, E., Demirer, R., Gupta, R., & Marfatia, H. A. (2019). Oil speculation and herding behavior in emerging stock markets. *Journal of Economics and Finance*, 43(1), 44-56. <https://doi.org/10.1007/s12197-018-9427-0>
21. Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679. [https://doi.org/10.1016/S0378-4266\(99\)00096-5](https://doi.org/10.1016/S0378-4266(99)00096-5)
22. Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance*, 34(8), 1911-1921. Retrieved from <https://ideas.repec.org/a/eee/jbfina/v34y2010i8p1911-1921.html>
23. Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal*, 51(4), 31-37. <https://doi.org/10.2469/faj.v51.n4.1918>
24. Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies*, 28(1), 1-32. Retrieved from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1509162](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1509162)
25. Dash, S. R., & Maitra, D. (2022). The COVID-19 pandemic uncertainty, investor sentiment, and global equity markets: Evidence from the time-frequency co-movements. *North American Journal of Economics and Finance*, 62(May), 101712. <https://doi.org/10.1016/j.najef.2022.101712>
26. Demirer, R., Leggio, K. B., & Lien, D. (2019). Herding and flash events: Evidence from the 2010 Flash Crash. *Finance Research Letters*, 31, 476-479. <https://doi.org/10.1016/j.frl.2018.12.018>
27. Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3-5), 603-615. [https://doi.org/10.1016/0014-2921\(95\)00073-9](https://doi.org/10.1016/0014-2921(95)00073-9)
28. Dhall, R., & Singh, B. (2020). The COVID-19 Pandemic and Herding Behaviour: Evidence from India's Stock Market. *Millennial Asia*, 11(3), 366-390. <https://doi.org/10.1177/0976399620964635>
29. Economou, F., Kostakis, A., & Philippas, N. (2011). Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, 21(3), 443-460. <https://doi.org/10.1016/j.intfin.2011.01.005>
30. Espinosa-Méndez, C., & Arias, J. (2021). COVID-19 effect on herding behaviour in European capital markets. *Finance Research Letters*, 38(June 2020), 1-6. <https://doi.org/10.1016/j.frl.2020.101787>
31. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2), 383-417. <https://doi.org/10.1111/j.1540-6261.1970.tb00518.x>
32. Fang, H., Chung, C. P., Lee, Y. H., & Yang, X. (2021). The Effect of COVID-19 on Herding Behavior in Eastern European Stock Markets. *Frontiers in Public Health*, 9(July), 1-9. <https://doi.org/10.3389/fpubh.2021.695931>
33. Fei, F., & Zhang, J. (2023). Chinese stock market volatility and herding behavior asymmetry during the COVID-19 pandemic. *Cogent Economics and Finance*, 11(1). <https://doi.org/10.1080/23322039.2023.2203436>
34. Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. *North American Journal of Economics and Finance*, 58(August), 101531. <https://doi.org/10.1016/j.najef.2021.101531>
35. Filip, A., Pochea, M., & Pece, A. (2015). The Herding Behaviour of Investors in the CEE Stocks Markets. *Procedia Economics and Finance*, 32(15), 307-315. [https://doi.org/10.1016/s2212-5671\(15\)01397-0](https://doi.org/10.1016/s2212-5671(15)01397-0)
36. Froot, K. A., Scharstein, D. S., & Stein, J. C. (1992). Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation. *The Journal of Finance*, 47(4), 1461-1484. <https://doi.org/10.1111/j.1540-6261.1992.tb04665.x>
37. Hasan, I., & Tunaru, R. D. V. (2023). Herding behavior and systemic risk in global stock markets. *Journal of Empirical Finance*, 73(September 2023), 107-133. <https://doi.org/10.1016/j.jempfin.2023.05.004>
38. Javaira, Z., Sahar, N. U., Hashmi, S. D., & Naz, I. (2023). Volatility and Dynamic Herding in Energy Sector of Developed Markets During COVID-19: A Markov Regime-Switching Approach. *Fudan Journal of the Humanities and Social Sciences*, 17(1), 115-138. <https://doi.org/10.1007/s40647-023-00395-9>
39. Kenourgios, D., Umar, Z., & Lemonidi, P. (2020). On the effect of credit rating announcements on sovereign bonds: International evidence. *International Economics*, 163, 58-71. <https://doi.org/10.1016/j.inteco.2020.04.006>

40. Kizys, R., Tzouvanas, P., & Donadelli, M. (2021). From COVID-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions. *International Review of Financial Analysis*, 74(December 2020), 101663. <https://doi.org/10.1016/j.irfa.2021.101663>

41. Kumar, B., & Kumar, A. (2022). Exploring Herding Behaviour in Indian Equity Market during COVID-19 Pandemic: Impact of Volatility and Government Response. *Millennial Asia*, 13(3), 513-531. <https://doi.org/10.1177/09763996211020687>

42. Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49(5), 1541-1578. <https://doi.org/10.1111/j.1540-6261.1994.tb04772.x>

43. Luu, Q. T., & Luong, H. T. T. (2020). Herding behavior in emerging and frontier stock markets during pandemic influenza panics. *Journal of Asian Finance, Economics and Business*, 7(9), 147-158. <https://doi.org/10.13106/JAFEB.2020.VOL7.NO9.147>

44. Mishra, P. K., & Mishra, S. K. (2023). Do Banking and Financial Services Sectors Show Herding Behaviour in Indian Stock Market Amid COVID-19 Pandemic? Insights from Quantile Regression Approach. *Millennial Asia*, 14(1), 54-84. <https://doi.org/10.1177/09763996211032356>

45. Organization, W. H. (n.d.). *Coronavirus disease (COVID-19) pandemic*. Retrieved from <https://www.who.int/europe/emergencies/situations/covid-19>

46. Raafat, R. M., Chater, N., & Frith, C. (2009). Herding in humans. *Trends in Cognitive Sciences*, 13(10), 420-428. <https://doi.org/10.1016/j.tics.2009.08.002>

47. Seghers, B. H. (1974). Schooling behavior in the guppy (*Poecilia reticulata*): An evolutionary response to predation. *Evolution*, 28(3), 486-489. <https://doi.org/10.2307/2407174>.

48. Shahzad, M. F., Xu, S., Rehman, O. ul, & Javed, I. (2023). Impact of gamification on green consumption behavior integrating technological awareness, motivation, enjoyment and virtual CSR. *Scientific Reports*, 13(1), 1-18. <https://doi.org/10.1038/s41598-023-48835-6>

49. Shear, F., Ashraf, B. N., & Sadaqat, M. (2021). Are investors' attention and uncertainty aversion the risk factors for stock markets? International evidence from the COVID-19 crisis. *Risks*, 9(1), 1-15. <https://doi.org/10.3390/risks9010002>

50. Sibande, X., Gupta, R., Demirer, R., & Bouri, E. (2023). Investor Sentiment and (Anti) Herding in the Currency Market: Evidence from Twitter Feed Data. *Journal of Behavioral Finance*, 24(1), 56-72. <https://doi.org/10.1080/15427560.2021.1917579>

51. Smales, L. A. (2021). Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis*, 73(June 2020), 101616. <https://doi.org/10.1016/j.irfa.2020.101616>

52. Stavroyiannis, S., & Babalos, V. (2017). Herding, Faith-Based Investments and the Global Financial Crisis: Empirical Evidence from Static and Dynamic Models. *Journal of Behavioral Finance*, 18(4), 478-489. <https://doi.org/10.1080/15427560.2017.1365366>

53. Sun, Y., Wu, M., Zeng, X., & Peng, Z. (2021). The impact of COVID-19 on the Chinese stock market: Sentimental or substantial? *Finance Research Letters*, 38(October 2020), 101838. <https://doi.org/10.1016/j.frl.2020.101838>

54. Teraji, S. (2003). Herd behavior and the quality of opinions. *Journal of Socio-Economics*, 32(6), 661-673. <https://doi.org/10.1016/j.soc.2003.10.004>

55. Turak, N. (2020). *First Middle East cases of coronavirus confirmed in the UAE*. CNBC. Retrieved from <https://www.cnbc.com/2020/01/29/first-middle-east-cases-of-coronavirus-confirmed-in-the-uae.html>

56. Ullah, S. (2023). Impact of COVID-19 Pandemic on Financial Markets: a Global Perspective. *Journal of the Knowledge Economy*, 14(2), 982-1003. <https://doi.org/10.1007/s13132-022-00970-7>

57. Vidya, C. T., Ravichandran, R., & Deorukhkar, A. (2023). Exploring the effect of Covid-19 on herding in Asian financial markets. *MethodsX*, 10(December 2022), 101961. <https://doi.org/10.1016/j.mex.2022.101961>

58. Wen, C., Yang, Z., & Jiang, R. (2022). Herding behavior in Hong Kong stock market during the COVID-19 period: a systematic detection approach. *Journal of Chinese Economic and Business Studies*, 20(2), 159-170. <https://doi.org/10.1080/14765284.2021.1948320>

59. Xu, H. C., & Zhou, W. X. (2018). A weekly sentiment index and the cross-section of stock returns. *Finance Research Letters*, 27, 135-139. <https://doi.org/10.1016/j.frl.2018.02.009>

60. Yoon, J., & Oh, G. (2022). Investor herding behavior in social media sentiment. *Frontiers in Physics*, 10(October), 1-16. <https://doi.org/10.3389/fphy.2022.1023071>

61. Yousaf, I., & Alokla, J. (2023). Herding behaviour in the Islamic bank market: evidence from the Gulf region. *Review of Behavioral Finance*, 15(5), 617-633. <https://doi.org/10.1108/RBF-02-2021-0018>

62. Yousaf, I., Ali, S., Bouri, E., & Dutta, A. (2021). Herding on Fundamental/Nonfundamental Information During the COVID-19 Outbreak and Cyber-Attacks: Evidence from the Cryptocurrency Market. *SAGE Open*, 11(3). <https://doi.org/10.1177/21582440211029911>

63. Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2021). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. *Finance Research Letters*, 35, 101597. <https://doi.org/10.1016/j.frl.2020.101597>