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## Article

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# Herding behavior in cryptocurrency market: evidence from COVID-19, Russia–Ukraine war, and Palestine–Israel conflict

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## ABSTRACT

This study explores herding behavior in the cryptocurrency market during three major international crises: the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. The study uses daily closing prices of five major cryptocurrencies (Bitcoin, Ethereum, Tether, BNB, and Solana) and the CRYPTO20 index data from December 31 2019 to May 20, 2024. The research employs the cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD) methods to identify herding behavior in the cryptocurrency market. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is used for the robustness check. Stationarity of the data is verified using the Augmented Dickey-Fuller (ADF) test. The empirical findings reveal the anti-herding behavior in the cryptocurrency market during the three sub-periods. The study's findings have important implications for investors, policymakers, and market regulators. Understanding the dynamics of herding behavior in the cryptocurrency market during global crises can help in developing strategies to mitigate the adverse effects of herding, such as inefficient asset pricing and increased market volatility.

## IMPACT STATEMENT

The research explores herding behavior in the cryptocurrency market during three major global crises: the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. Utilizing advanced analytical models like CSAD, CSSD, and GARCH on data from five leading cryptocurrencies, the study finds anti-herding behavior, emphasizing independent investor decision-making. These insights challenge traditional herding theories and have significant implications for policymakers, regulators, and investors, particularly in mitigating risks and volatility in evolving markets. By highlighting the resilience and unique dynamics of cryptocurrencies, this work enriches the understanding of financial behaviors during global crises.

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## 1. Introduction

Cryptocurrencies present current and upcoming obstacles for scholars and investment analysts alike, given their complex and ever-changing nature. The need to study these digital assets is urgent, as they have the potential to disrupt conventional financial systems, particularly during global crises. For instance, during economic downturns, cryptocurrencies like Bitcoin often experience increased attention as potential ‘safe-haven’ assets, challenging the dominance of traditional investments such as gold and fiat currencies (Baur et al., 2018). Furthermore, the decentralized and borderless nature of cryptocurrencies poses regulatory challenges, as they bypass traditional financial intermediaries and enable peer-to-peer transactions without centralized control (Narayanan et al., 2016). The rise of decentralized finance (DeFi) platforms further exemplifies this disruption by offering services like lending and borrowing, typically provided by banks, without the need for traditional financial institutions (Schär, 2021). As these innovations grow, they have the capacity to alter the landscape of financial systems, making a thorough understanding of their mechanisms and implications critical for future financial stability (Zohar, 2015).

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The 2008 Global Financial Crisis revealed critical global liquidity constraints, prompting traders, governments, and academics to seek alternative forms of money and financial assets. A significant breakthrough in financial technology was made by Nakamoto in 2008, with the introduction of a decentralized online payment system that enables two participants to conduct transactions directly without the need for a trusted intermediary. This innovation gave rise to cryptocurrency, a blockchain-based digital currency (Al-Swidi et al., 2024a, 2024b; Gümüş et al., 2019). Since then, cryptocurrency has gained prominence as a financial and technological breakthrough, attracting significant interest from traders as a viable investment choice (Caferri, 2020). Following the introduction of Bitcoin in 2009, numerous cryptocurrencies have emerged, reshaping financial markets (Susana et al., 2020). The soaring values of cryptocurrencies and increasing public interest have sparked substantial debates in both political and academic circles. These debates focus on cryptocurrencies' ability to serve as a means to retain value, facilitate transactions, and measure economic value (Haykir & Yagli, 2022). While cryptocurrencies have gained widespread popularity among investors, particularly due to their decentralized nature and lack of governmental oversight, significant concerns remain regarding their volatility and speculative nature (Kyriazis, 2020).

A less explored yet critical aspect of cryptocurrencies lies in how investor psychology and market sentiment shape their trading dynamics. Herding behavior—where investors tend to mimic the behavior of others instead of making their own independent decisions—can lead to inefficient asset pricing and exacerbate market volatility, particularly during periods of uncertainty (Bogdan et al., 2023). While herding behavior has been extensively studied in traditional financial markets, its manifestation in the cryptocurrency market, especially during major global crises, remains under-researched (Bouri et al., 2021; Le et al., 2024). This study endeavors to address this gap by exploring herding behavior in the crypto trading market during three distinct and impactful global crises: the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict.

Unlike previous studies that have primarily focused on the risk-return tradeoff or volatility of cryptocurrencies in normal market conditions, this research investigates how global crises influence investor herding behavior in cryptocurrency markets. It extends the current body of knowledge by analyzing how different types of crises trigger psychological biases in investors, causing herding behavior and challenging the Efficient Market Hypothesis (EMH), which posits that markets are rational and past prices do not predict future returns (Villarreal Samaniego et al., 2022). By focusing on multiple global crises, this study provides a comprehensive analysis of how external shocks impact the informational and allocative efficiency of cryptocurrency markets.

While there is an emerging body of literature on herding behavior in the cryptocurrency market, this study offers valuable input to the existing research by providing empirical evidence of anti-herding behavior during significant global crises, such as the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. In contrast to traditional financial markets, where herding behavior is well-documented, our findings emphasize the unique dynamics of the cryptocurrency market, where investors typically operate independently, guided by swift information flow and personalized risk evaluations. By utilizing daily closing prices and applying robust analytical methods such as CSAD, CSSD, and GARCH models, this study offers fresh insights into investor behavior in the crypto trading market during periods of heightened volatility, thus advancing our understanding of market reactions in this nascent asset class.

This research, therefore, not only fills a significant empirical gap but also has practical implications for market regulators and investors. Understanding how herding behavior manifests during crises can inform strategies aimed at mitigating volatility and improving market stability in the evolving world of cryptocurrency.

## 2. Literature review

### 2.1. During the COVID-19

Numerous scholars have investigated the effects of the Coronavirus outbreak on securities financial markets. Youssef and Waked (2022) discovered that financial exchanges react adversely to the increase in confirmed Coronavirus infections. Albulescu (2021) proposes that the global outbreak has amplified the volatility of the US securities market. Shehzad et al. (2020) compared the effects of the Global recession and COVID-19 stock market returns among the nations of the US, Germany, Italy, Japan, and China. The

results of their study show that the US and EU stock markets were more significantly affected by Coronavirus infections compared to the global financial crisis, whereas the stock exchanges in Asia were primarily impacted by the global financial crisis. Furthermore, studies by Ali et al. (2020) and Wang and Wang (2021) claim that the pandemic has also disrupted the proficiency of the digital currency market.

Despite numerous studies exploring herding behavior in securities and commodity exchanges, relatively few have focused on the digital currency market, particularly during the coronavirus outbreak. Ballis and Drakos (2020) investigated herd behavior trends among six leading cryptocurrencies between 2015 and 2018, their findings, derived from the CSAD model, suggest that herding behavior among stakeholders in leading cryptocurrencies intensifies during bullish market conditions. Unlike the findings of Ballis and Drakos (2020), Vidal-Tomás et al. (2019) concluded that herding behavior occurs exclusively in bear markets, based on their analysis of 65 cryptocurrencies. Bouri et al. (2019) utilized both the static methodology of CSAD and a rolling window approach to assess herding across 14 digital coins during 2013-2018.

## **2.2. During the Russia–Ukraine war**

Over the past few years, numerous studies have examined the consequences of the Russia–Ukraine war on global trade markets. For example, Liadze et al. (2023) emphasized its considerable influence on the world economy. Orhan (2022) points out that the Russia–Ukraine war has had an impact on the global economy through three main pathways: financial sanctions, commodity prices, and supply chain disruptions. Essentially, the disruptions in supply chains create bottlenecks that delay shipments, increase transportation costs, and result in shortages of essential commodities worldwide (Al-Hakimi et al., 2022a, 2022b). As supply chains falter, global stock markets react negatively, with investor sentiment often turning bearish amid rising uncertainties and costs. Elevated commodity prices and scarcity of key resources drive inflationary pressures, leading to increased volatility and lower performance in stock markets across affected regions (Orhan, 2022). Studies by Boubaker et al. (2022) and Kamal et al. (2023) repeatedly document a downturn in global equities market returns linked to the war. However, Nerlinger and Utz (2022) noted that the harmful effect was not consistent across all areas, especially within the energy field. Recent studies have placed growing emphasis on power and commodity trading sectors, exploring their links to other markets, as demonstrated by Wang et al. (2022), Fang and Shao (2022), and Lo et al. (2022). A study of existing research indicates a consensus regarding the adverse fallout from the Russia–Ukraine war on worldwide equity markets, but it also underscores the intricate nature of the war's outcome on equity markets, emphasizing the necessity for additional exploration to grasp the subtle outcomes across various sectors.

Nevertheless, the literature presents mixed findings on how financial turmoil and unstable periods affect investor tendencies. While numerous research efforts, like Mobarek et al. (2014), assert that herd behavior intensifies during stressful times, others, like Andrikopoulos et al. (2017), have noted a reduction in herd-like behavior during such periods.

## **2.3. During the Palestine–Israel conflict**

War is a conflict that significantly setbacks the worldwide economy Hoque and Zaidi (2020) suggest that contradicts among nations or regions negatively affect the tourism sector, as tourists are often hesitant to visit conflict zones until after the conflict. Leigh et al. (2003) also noted the repercussions of war on the aviation, technology, precious metals, and fuel industries. Various research has connected stock markets to the events of the Second Great War. For instance, Frey and Kucher (2000) discovered that prior to World War II, World War I led to a reduction in bond value. Hudson and Urquhart (2015) also discovered that fiscal bourses generally respond negatively rather than positively in times of war.

In the context of the Palestine–Israel conflict, the cryptocurrency market has not been immune to its economic effects. The conflict has heightened global market uncertainty, with investors displaying increased herding behavior, following market trends rather than making independent decisions. The decentralized nature of cryptocurrencies makes them particularly susceptible to geopolitical conflicts, and the Palestine–Israel conflict has contributed to heightened volatility in these markets. In search of safety amid the uncertainty, investors often mimic others' trading actions, further exacerbating price fluctuations. This tendency to engage in herding behavior is especially pronounced in the cryptocurrency

market, where investor sentiment shifts quickly in response to global events. As with other financial sectors affected by war, the fallout of the Palestine–Israel conflict on the cryptocurrency market illustrates how geopolitical instability can shape investor psychology, increasing risk and diminishing market efficiency (Khan & Rehman, 2023).

### 3. Methodology

#### 3.1. Data

The daily closing prices of four major cryptos based on market capitalization (Bitcoin, Ethereum, Tether, BNB, and Solana), along with data from the CRYPTO20 index, were collected from 31st December 2019 to 31st March 2021 and from 24th February 2022 to 20th May 2024 using the coinmarketcap.com website. These timeframes align with the periods of significant global events under study, starting with the COVID-19 pandemic from 31st December 2019 to 31st March 2021, which marked a phase of global disruption, where financial markets, including cryptocurrencies, experienced heightened volatility. This period is crucial for examining how herding behavior emerged as investors reacted to the unprecedented uncertainty. Following this, the Russia–Ukraine war, from 24th February 2022 to 20th May 2024, introduced further geopolitical tensions that influenced market dynamics, potentially exacerbating herding behavior in the cryptocurrency market. Lastly, the Palestine–Israel conflict, spanning from 7th October 2023 to 20th May 2024, provides a vital context for understanding the immediate effects of global power struggles cryptocurrency markets, where increased volatility may have heightened investors' tendency to follow market consensus rather than making independent decisions. By analyzing these distinct periods, the study aims to provide a comprehensive view of how global crises have influenced herding behavior in the cryptocurrency market. Below are the top 5 cryptocurrencies by market cap and share, as shown in Table 1.

The return of the cryptocurrency was calculated using the formula,

$$RC_t = \frac{P_t - (P_{t-1})}{P_{t-1}}$$

Where,  $RC_t$  = Return of the cryptocurrency in period  $t$ ,  $P_t$  = Cryptocurrency price in period  $t$ ;  $P_{t-1}$  = Cryptocurrency price in period  $t-1$ .

#### 3.2. Methods

CSAD and CSSD are used to find the herding behavior in the cryptocurrency market. The cross-sectional absolute deviation (CSAD) model was created by Chang et al. (2000) in response to their explanation of a linear link between the return dispersion of an asset and the absolute value of market returns in asset pricing models (Goel & Dev, 2021).

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

where  $CSAD_t$  cross-sectional absolute deviation at day  $t$ ,  $|R_{i,t} - R_{m,t}|$  is the absolute value of the difference between the individual cryptocurrency and consensus returns at day  $t$  and  $N$  is the total number of cryptocurrencies in the market portfolio.

**Table 1.** The top 5 cryptocurrencies by market cap and market share.

| Name   | Symbol | Market cap (USD)  | Market share |
|--|--------|-------------------|--------------|
| Bitcoin  | BTC    | 1,398,316,834,254 | 53.2546%     |
| Ethereum   | ETH    | 455,291,290,192   | 17.3397%     |
| Tether   | USDT   | 112,333,502,429   | 4.2782%      |
| BNB  | BNB    | 103,067,533,038   | 3.9253%      |
| Solana   | SOL    | 79,374,195,063    | 3.0229%      |
| Total Cryptocurrency Market Cap: \$2,625,721,800,450 |        |                   |              |

Note. Market cap is the total value of each cryptocurrency, and market share indicates its dominance in the overall crypto market.  
Source: Authors' own work.



Using the standard deviation of returns for each cryptocurrency and the capture of return dispersion inside the cross-sectional dataset, Christie and Huang (1995) described the CSSD technique measures the variability of returns across multiple assets in a particular period (Le et al., 2024).

$$CSSD_{m,t} = \alpha + \beta^U D_t^U + \beta^L D_t^L + u_t$$

where  $CSSD_{m,t}$  cross-sectional standard deviation of the market at day  $t$ ,  $D_t^U$  and  $D_t^L$  are dummies equal to 1 if the market return lies in the extreme upper tail and extreme lower tail,  $u_{t|s}$  the regression coefficient.

Chang et al. (2000) state that herding behavior exists when the estimated value of the non-linear coefficient  $\beta_3$  is significantly negative; if the estimated value of the non-linear coefficient  $\beta_3$  is significantly positive, then herding behavior does not exist.

The stationarity of the time series data is ascertained using the Augmented Dickey-Fuller (ADF) test. Time series data's autocorrelation function (ACF) or partial autocorrelation function (PACF) can be found using the correlogram test.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed to identify herding behavior. This model is specifically designed for time series data commonly exhibiting heteroskedasticity issues. Rather than eliminating heteroskedasticity, the GARCH model incorporates it into its framework. It views heteroskedasticity not as a problem but as a feature to be modeled. The GARCH (1,1) variant is the most widely utilized version and is regarded as the standard benchmark model.

## 4. Results

### 4.1. Stationarity test

We test the stationarity in the time series data using the Augmented Dickey-Fuller (ADF) test and the ADF values of CSAD, Market Return ( $R_m$ ), and Squared Market Return of the CRYPTO20 index are significant at the 1% level. These results indicate that the data is stationary.

Table 2 provides the results of the Augmented Dickey-Fuller (ADF) test applied to the CRYPTO20 index during three significant global events: the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. The aim of this test is to assess the stationarity of key variables over these distinct sub-periods to ensure the reliability of the time series data used in the analysis. Specifically, the variables tested include the Cross-Sectional Absolute Deviation (CSAD), a measure of herding behavior in financial markets, the market return ( $R_m$ ), and the squared market return ( $R_m^2$ ), which helps capture non-linearities in the relationship between market returns and herding behavior. The ADF test examines whether the time series has a unit root, with a negative and significant test statistic indicating that the null hypothesis of non-stationarity can be rejected, thereby confirming that the data is stationary and suitable for econometric modeling.

Furthermore, the test results reveal that all variables—CSAD,  $R_m$ , and  $R_m^2$ —are stationary across the three sub-periods. The ADF test statistics are highly negative and fall significantly below the critical

**Table 2.** Stationarity test.

| Variable  | ADF       | 1% level  | 5% level  | 10% level | p-value | Result     |
|---|-----------|-----------|-----------|-----------|---------|------------|
| <b>Panel A: ADF test statistics of the CRYPTO20 index during COVID-19</b>                 |           |           |           |           |         |            |
| CSAD  | −12.52293 | −3.438090 | −2.864846 | −2.568585 | 0.0000  | Stationary |
| $R_m$   | −22.60989 | −3.438100 | −2.864850 | −2.568577 | 0.0000  | Stationary |
| $R_m^2$   | −7.286070 | −3.438090 | 2.864846  | −2.568585 | 0.0000  | Stationary |
| <b>Panel A: ADF test statistics of the CRYPTO20 index during the Russia–Ukraine War</b>   |           |           |           |           |         |            |
| CSAD  | −16.96062 | −3.438149 | −2.864872 | −2.568599 | 0.0000  | Stationary |
| $R_m$   | −19.25572 | −3.438149 | −2.864872 | −2.568599 | 0.0000  | Stationary |
| $R_m^2$   | −28.45964 | −3.438139 | −2.864868 | −2.568596 | 0.0000  | Stationary |
| <b>Panel A: ADF test statistics of the CRYPTO20 index during the Palestine–Israel war</b> |           |           |           |           |         |            |
| CSAD  | −10.58525 | −3.459362 | −2.874200 | −2.573594 | 0.0000  | Stationary |
| $R_m$   | −13.32995 | −3.459231 | −2.874143 | −2.573563 | 0.0000  | Stationary |
| $R_m^2$   | −21.43363 | −3.459362 | −2.874200 | −2.573594 | 0.0000  | Stationary |

*Note.* This table reports the Augmented Dickey-Fuller (ADF) test statistics for the CSAD (Cross-Sectional Absolute Deviation), Market Return ( $R_m$ ), and Squared Market Return ( $R_m^2$ ), of the CRYPTO20 index during three different periods: the COVID-19 pandemic, the Russia–Ukraine War, and the Palestine–Israel War.

*Source:* Authors' own work.

**Table 3.** Descriptive statistics of the market for the Sub-periods.

|   | R <sub>m</sub> | CSAD    | CSSD    | BTC      | ETH      | USDt      | BNB      | SOL      |
|---|----------------|---------|---------|----------|----------|-----------|----------|----------|
| <b>During COVID-19 period</b>             |                |         |         |          |          |           |          |          |
| Mean                                      | 0.00370        | 0.03786 | 0.04927 | 0.00307  | 0.00535  | −3.89E-06 | 0.00608  | −        |
| Median                                    | 0.00570        | 0.02527 | 0.03476 | 0.00230  | 0.00450  | 0.00000   | 0.00370  | −        |
| Maximum                                   | 0.44046        | 0.97670 | 1.12790 | 0.19410  | 0.25960  | 0.01020   | 0.69990  | −        |
| Minimum                                   | −1.00000       | 0.00250 | 0.00329 | −0.39180 | −0.44550 | −0.00680  | −0.44080 | −        |
| SD  | 0.07395        | 0.05140 | 0.06087 | 0.04025  | 0.05273  | 0.00089   | 0.06264  | −        |
| Skewness                                  | −3.18796       | 9.35499 | 8.67184 | −0.83706 | −0.57863 | 0.99936   | 1.55332  | −        |
| Kurtosis                                  | 47.9235        | 146.229 | 130.141 | 15.5817  | 12.0550  | 38.6300   | 27.5343  | −        |
| N   | 822            | 822     | 822     | 822      | 822      | 822       | 822      | −        |
| <b>During Russia–Ukraine War Period</b>   |                |         |         |          |          |           |          |          |
| Mean                                      | 0.05278        | 0.11179 | 0.12923 | 0.00122  | 0.00108  | −1.84E-05 | 0.00109  | 0.00254  |
| Median                                    | −0.00013       | 0.01898 | 0.02606 | −0.00030 | 0.00020  | 0.00000   | 0.00070  | −0.00090 |
| Maximum                                   | 10.8381        | 10.8498 | 12.1305 | 0.14590  | 0.19170  | 0.00360   | 0.17230  | 0.32590  |
| Minimum                                   | −1.00000       | 0.00183 | 0.00238 | −0.15630 | −0.17560 | −0.00340  | −0.18500 | −0.42350 |
| SD  | 0.65445        | 0.64795 | 0.72394 | 0.02904  | 0.03606  | 0.00036   | 0.03121  | 0.05577  |
| Skewness                                  | 12.0894        | 12.3307 | 12.3383 | −0.04450 | 0.13989  | 0.24125   | −0.22193 | −0.01238 |
| Kurtosis                                  | 171.740        | 175.945 | 176.130 | 7.16060  | 7.71219  | 35.6314   | 8.77452  | 9.76222  |
| N   | 817            | 817     | 817     | 817      | 817      | 817       | 817      | 817      |
| <b>During Palestine–Israel War Period</b> |                |         |         |          |          |           |          |          |
| Mean                                      | 0.00015        | 0.03456 | 0.04363 | 0.00454  | 0.00404  | −3.52E-06 | 0.00504  | 0.01056  |
| Median                                    | 0.00095        | 0.02042 | 0.02882 | 0.00240  | 0.00190  | 0.00000   | 0.00400  | 0.00540  |
| Maximum                                   | 0.24689        | 0.61196 | 0.68419 | 0.10200  | 0.19170  | 0.00110   | 0.17230  | 0.25020  |
| Minimum                                   | −0.61384       | 0.00277 | 0.00361 | −0.08200 | −0.10090 | −0.00120  | −0.10830 | −0.13260 |
| SD  | 0.06905        | 0.05664 | 0.06323 | 0.02836  | 0.03255  | 0.00034   | 0.03132  | 0.05347  |
| Skewness                                  | −3.41167       | 6.44283 | 6.28198 | 0.31136  | 1.01418  | −0.09049  | 0.87354  | 0.51065  |
| Kurtosis                                  | 35.1224        | 56.2301 | 54.6646 | 4.54145  | 8.58983  | 3.74055   | 8.09175  | 4.27095  |
| N   | 227            | 227     | 227     | 227      | 227      | 227       | 227      | 227      |

Note. The table presents descriptive statistics (mean, median, maximum, minimum, standard deviation (SD), skewness, kurtosis) for market variables: Market Return (R<sub>m</sub>), CSAD, CSSD, BTC, ETH, USDt, BNB, and SOL during three distinct periods: COVID-19, Russia–Ukraine War, and Palestine–Israel War.

Source: Authors' own work.

values at the 1%, 5%, and 10% levels, further supported by *p*-values of 0.0000 for all variables. This strongly suggests that the time series data is stable, allowing for robust econometric analysis without requiring additional transformations. When breaking down the results by panel, the data for the COVID-19 period shows strong stationarity, particularly for R<sub>m</sub> with a test statistic of −22.60989, while the Russia–Ukraine war period has the most significant stationarity for R<sub>m</sub><sup>2</sup> at −28.45964. The Palestine–Israel conflict panel shows a similar pattern, with R<sub>m</sub><sup>2</sup> displaying the strongest stationarity at −21.43363. Overall, the stationarity of these variables is crucial for an accurate analysis of herding behavior during global crises, confirming that the observed volatility and market sentiment are reliable for further study.

Table 3 shows the descriptive statistics of key variables, including the average market return, CSAD, CSSD, and the return of various cryptocurrencies during the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel war. During the subperiod of the Russia–Ukraine War and the Palestine–Israel War period, the return of the five largest cryptocurrencies by market capitalization (BTC, ETH, USDt, BNB, and SOL) is used. Since Solana was not listed throughout the COVID-19 period, we only took the top four cryptocurrencies into account.

The average market returns range from −1.0000 to the maximum of 10.8381 during the Russia–Ukraine war, which shows the highest volatility compared to the other two periods. BNB and Solana show the highest volatility in different periods as compared to the other cryptocurrencies. The markets showed extremes in skewness and kurtosis during the COVID-19 pandemic, especially for Bitcoin and Ethereum. While statistics were less volatile and more moderate throughout the subsequent periods of the Russia–Ukraine and Palestine–Israel wars, the Bitcoin and Ethereum, continued to show remarkable extremes in skewness and kurtosis.

To test the herding behavior in the crypto trading sector during the three different periods we emphasize the regression model (Christie & Huang, 1995). Table 4 represents the result of regression for CSSD. (1), (2), and (3) represent the sample period of covid-19, the Russia–Ukraine war, and the Palestine–Israel war respectively. Since the return on cryptocurrency is in the lowest 5%,  $\beta_1$  shows the change in the amount of return dispersion, which is attributed to lower market stress, similarly  $\beta_2$  denotes the return in the highest 5%, which indicates the highest market stress.



**Table 4.** Regression result using the CSSD model.

|                 | (1)                   | (2)                   | (3)                   |
|-----------------|-----------------------|-----------------------|-----------------------|
|                 | CSSD                  | CSSD                  | CSSD                  |
| R ( $\beta_1$ ) | 0.12126***<br>(0.000) | 1.61723***<br>(0.000) | 0.11231***<br>(0.000) |
| L ( $\beta_2$ ) | 0.12111***<br>(0.000) | 0.39174***<br>(0.000) | 0.14771***<br>(0.000) |
| Intercept       | 0.03719***<br>(0.000) | 0.03088***<br>(0.000) | 0.03104***<br>(0.000) |
| N               | 822                   | 817                   | 227                   |

Note. Statistical significance\*\*\* 1%. (1), (2), and (3) represent the study periods: COVID-19, the Russia–Ukraine war, and the Palestine–Israel war period, respectively. ( $\beta_1$ ) and ( $\beta_2$ ) are the respective dummy variables that take a value of 1 when the  $r_m \geq$  or  $\leq$  its 95 or 5 percentile value.

Source: Authors' own work.

**Table 5.** Regression result using the CSAD Model.

|           | (1)                   | (2)                    | (3)                   |
|-----------|-----------------------|------------------------|-----------------------|
|           | CSAD                  | CSAD                   | CSAD                  |
| $R_m$     | 0.06779***<br>(0.000) | 0.01231***<br>(0.000)  | 0.01779<br>(0.356)    |
| $R_m^2$   | 0.46349***<br>(0.000) | 0.00021<br>(0.52)      | 0.52586***<br>(0.000) |
| ABS $R_m$ | 0.57447***<br>(0.000) | 0.98845***<br>(0.000)  | 0.70921***<br>(0.000) |
| Intercept | 0.00898***<br>(0.000) | −0.00278***<br>(0.000) | 0.00657***<br>(0.000) |
| N         | 822                   | 817                    | 227                   |

Note. Statistical significance\*\*\* 1%, \*\* 5% and\* 10%. (1), (2), and (3) represent the study periods: COVID-19, the Russia–Ukraine war, and the Palestine–Israel war period, respectively.  $R_m$ (market return),  $R_m^2$  (squared market return) and ABS  $R_m$  (absolute market return).

Source: Authors' own work.

It is assumed that, if the value of  $\beta_1$  and  $\beta_2$  is negative, then there is a presence of herding behavior in the cryptocurrency market. According to Table 4, the  $\beta_1$  and  $\beta_2$  values are positive and significant at a 1% level during the three sub-periods of the study. These results revealed that there was an absence of herding behavior or anti-herding behavior in the cryptocurrency market during the three periods.

The cryptocurrency market is reported to be more efficient, which could account for the anti-herding behavior that has been observed there (Le et al., 2024). These findings present novel and exciting results that imply the trading decisions made by cryptocurrency investors have no similarities to the behavior of other investors. The result matched the result of Yousaf and Ali (2021) who found the anti-herding behavior in the cryptocurrency market during the COVID-19 period. However, the result of the research by Gyamerah (2021) found the herding behavior in the crypto trading sector during the COVID-19. A similar result is found by Ampofo et al. (2023) in the UK and US stock markets during the pandemic indicating an absence of herding behavior.

Our base model is based on Chang et al. (2000), who contend that evidence of herding behavior can be inferred from the nonlinear relationship between the dispersion of individual asset returns and market returns. Table 5 is the result of regression analysis. (1), (2), and (3) denote the three subperiod as mentioned earlier.

In this model, it is assumed that the absence of herding if the market return  $R_m$  or the Squared Market return ( $R_m^2$ ) is positive, and on the contrary, if the herding is present in the market, it will be negative. Based on the results from Table 4 indicates that, in the case of the three periods of the study, the market return is positive. During the COVID-19 and the Palestine–Israel war period, the  $R_m^2$  is positive and significant at 1%, but it is positive but insignificant during the Russia–Ukraine war period. This result also suggests that the CSAD model indicates an anti-herding behavior in the cryptocurrency market during the different periods of the study.

The result aligns with research conducted by Le et al. (2024) who examined the herding behavior in the cryptocurrency market during the Russia–Ukraine war period. Studies conducted by Youssef (2022), Gümüř et al. (2019), Coskun et al. (2020), Amirat and Alwafi (2020), and Stavroyiannis and Babalos (2019) also supported the anti-herding behavior in the cryptocurrency market over time. In contrast, Khan and Rehman (2023) found herding during the Russia–Ukraine war in the Indian Stock market.

## 4.2. Robustness test

We are testing the robustness of the herding behavior detection using the GARCH model per the methodology used by Rizal and Damayanti (2019), BenSaïda (2017), and Le et al. (2024). By definition, herding behavior is the tendency of traders or investors to imitate the activities of their peers rather than make decisions that are based on analysis and research. The results of the GARCH analysis for assessing herding behavior are shown in Tables 6 and 7. Table 6 employs CSAD as the dependent variable, while Table 7 uses CSSD. The results in Table 6 represent a positive value in the absolute market return (ABS  $R_m$ ) (0.46755 \*\*\*, 0.99738 \*\*\*, 0.68264 \*\*\*) and the squared market return ( $R_m^2$ ) (0.47578 \*\*\*, 0.000374 \*, and 0.51627 \*\*\*) with a significant level of 1%, during COVID-19, the Russia–Ukraine war and the Palestine–Israel war. These results indicate the anti-herding behavior in the cryptocurrency market during the periods. Similarly, the result in Table 7 is also positive and significant, indicating an anti-herding behavior. The result is aligned with the regression findings.

Table 6 shows the estimates of the GARCH (1,1) model applied to the Cross-Sectional Absolute Deviation (CSAD), which is used as the dependent variable in three distinct periods: the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. The independent variables include the absolute market return (ABS  $R_m$ ) and the squared market return ( $R_m^2$ ), which measure the relationship between market returns and herding behavior. The table provides key coefficients (C, ABS  $R_m$ , and  $R_m^2$ ) across these three periods, highlighting the strength and significance of each variable's impact on

**Table 6.** The estimates coefficients of the GARCH (1,1) Model for CSAD.

|                        | (1)                    | (2)                     | (3)                    |
|------------------------|------------------------|-------------------------|------------------------|
| Dependent Variable     | CSAD                   | CSAD                    | CSAD                   |
| C                      | 0.01109***<br>(0.0000) | −0.00320***<br>(0.0000) | 0.00586***<br>(0.0003) |
| ABS $R_m$              | 0.46755***<br>(0.0000) | 0.99738***<br>(0.0000)  | 0.68264***<br>(0.0000) |
| $R_m^2$                | 0.47578***<br>(0.0000) | 0.000374*<br>(0.0508)   | 0.51627***<br>(0.0000) |
| N                      | 822                    | 817                     | 227                    |
| Variance Equation      |                        |                         |                        |
| C                      | 0.00013***<br>(0.0000) | 3.43E-05***<br>(0.0000) | 4.17E-05**<br>(0.0379) |
| RESID(−1) <sup>2</sup> | 0.34085***<br>(0.0000) | 0.14714***<br>(0.0000)  | 0.15306***<br>(0.0049) |
| GARCH(−1)              | 0.40262***<br>(0.0000) | 0.75250***<br>(0.0000)  | 0.66567***<br>(0.0000) |

Note. CSAD stands for Cross-Sectional Absolute Deviation, ABS  $R_m$  represents the absolute market return, and  $R_m^2$  denotes the squared market return. In the variance equation, C is the constant for volatility, RESID(−1)<sup>2</sup> indicates the impact of past shocks, and GARCH(−1) reflects the persistence of volatility.

Source: Authors' own work.

**Table 7.** The estimates coefficients of the GARCH (1,1) Model for CSSD.

|                        | (1)                     | (2)                     | (3)                    |
|------------------------|-------------------------|-------------------------|------------------------|
| Dependent Variable     | CSSD                    | CSSD                    | CSSD                   |
| C                      | 0.01385***<br>(0.0000)  | −0.00015<br>(0.8200)    | 0.00953***<br>(0.0000) |
| ABS $R_m$              | 0.63938***<br>(0.0000)  | 1.11423***<br>(0.0000)  | 0.79736***<br>(0.0000) |
| $R_m^2$                | 0.46573<br>(0.0000)     | 0.00051**<br>(0.0211)   | 0.50768***<br>(0.0000) |
| N                      | 822                     | 817                     | 227                    |
| Variance Equation      |                         |                         |                        |
| C                      | 7.79E-05***<br>(0.0000) | 3.12E-05***<br>(0.0000) | 4.80E-05**<br>(0.0460) |
| RESID(−1) <sup>2</sup> | 0.28852***<br>(0.0000)  | 0.15514***<br>(0.0000)  | 0.20084**<br>(0.0146)  |
| GARCH(−1)              | 0.60507***<br>(0.0000)  | 0.78033***<br>(0.0000)  | 0.65561***<br>(0.0000) |

Note. CSSD stands for Cross-Sectional Standard Deviation, ABS  $R_m$  represents the absolute market return, and  $R_m^2$  denotes the squared market return. In the variance equation, RESID(−1)<sup>2</sup> refers to the lagged squared residual, and GARCH(−1) reflects the generalized autoregressive conditional heteroskedasticity with one lag.

Source: Authors' own work.

herding behavior. For instance, ABS Rm has a highly significant positive effect on CSAD in all three periods, suggesting that absolute market returns are positively associated with increased herding behavior across various crises, as indicated by the  $p$ -values of 0.0000. Similarly, the squared market return ( $Rm^2$ ) also shows a significant positive effect, particularly during the Palestine–Israel conflict (column 3) with a coefficient of 0.51627 and a  $p$ -value of 0.0000, implying that non-linearities in market returns are also important in explaining herding behavior.

In addition, the variance equation in Table 6 models the volatility dynamics through the GARCH (1,1) framework. The coefficients for the lagged squared residuals ( $RESID(-1)^2$ ) and the lagged conditional variance (GARCH(-1)) are both positive and highly significant across all periods, demonstrating that past market shocks and volatility persist over time. For example, the coefficient for GARCH(-1) is highest during the Russia–Ukraine war period (0.75250), indicating that volatility clustering is most pronounced during this crisis. Furthermore, the statistical significance at the 1%, 5%, and 10% levels across multiple variables reinforces the robustness of the model. Overall, the GARCH model results suggest that herding behavior in cryptocurrency markets is significantly influenced by both linear and non-linear market returns, with volatility playing a crucial role in all three global crises. These findings underscore the importance of understanding market dynamics in times of crisis for predicting and managing herding behavior.

Table 7 presents the GARCH (1,1) model estimates for the Cross-Sectional Standard Deviation (CSSD), which serves as the dependent variable in three different periods: the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. The independent variables include the absolute market return (ABS Rm) and the squared market return ( $Rm^2$ ), which are essential for understanding how market returns influence herding behavior in these crises. The results show that ABS Rm has a consistently positive and significant effect on CSSD across all three periods, with particularly strong coefficients during the Russia–Ukraine war (1.11423) and Palestine–Israel conflict (0.79736), both with  $p$ -values of 0.0000. This indicates that absolute market returns significantly increase the CSSD, pointing to heightened herding behavior during these times of crisis. On the other hand, the squared market return ( $Rm^2$ ) also has a positive and significant effect, particularly during the Palestine–Israel conflict, with a coefficient of 0.50768 and a  $p$ -value of 0.0000, suggesting that non-linear market return patterns play a role in influencing herding.

In addition, the variance equation in the GARCH (1,1) model highlights the persistence of volatility during these periods. The coefficients for  $RESID(-1)^2$  (lagged squared residuals) and GARCH(-1) (lagged conditional variance) are both positive and highly significant, indicating that previous market shocks and volatility persist over time. For example, the coefficient for GARCH(-1) during the Russia–Ukraine war is particularly high at 0.78033, suggesting that volatility clustering is strongest during this crisis compared to the others. This underscores the importance of understanding volatility persistence in the analysis of herding behavior during global crises. The model's statistical significance across multiple variables at the 1%, 5%, and 10% levels further validates the robustness of the results. Overall, these findings suggest that both linear and non-linear market returns, as well as persistent volatility, significantly influence herding behavior in cryptocurrency markets during crises, providing important insights into investor behavior under extreme conditions.

## 5. Discussion and conclusion

Our examination of herding behavior in the cryptocurrency market, using methodologies inspired by Christie and Huang (1995) and Chang et al. (2000), yields important insights that contribute to the existing literature on behavioral finance. The daily closing prices of five major cryptocurrencies (Bitcoin, Ethereum, Tether, BNB, and Solana) and the CRYPTO20 index were analyzed during three distinct sub-periods: the COVID-19 pandemic (31st December 2019 to 31st March 2021), the Russia–Ukraine war (24th February 2022 to 20th May 2024), and the Palestine–Israel war (7th October 2023 to 20th May 2024). Through CSSD and CSAD regressions, supplemented by GARCH (1,1) analysis for robustness, the results consistently indicate anti-herding behavior across all three sub-periods.

These findings are consistent with the broader literature on herding in financial markets during periods of crisis (Banerjee et al., 2022; Gümüş et al., 2019; Maghyereh & Al-Shboul, 2024). Specifically, during

the COVID-19 pandemic and the Russia–Ukraine war, our results align with prior studies (Amirat and Alwafi (2020) that found investors making autonomous decisions rather than following collective trends. This anti-herding behavior can be partly attributed to the unique characteristics of the cryptocurrency market. Unlike traditional markets, the cryptocurrency market operates 24/7, and information spreads rapidly through digital platforms, enabling investors to respond quickly and independently to market developments (Le et al., 2024). This contrasts with the conventional herding patterns observed in more regulated and less volatile markets, where investors often follow the actions of others during crises.

Moreover, the significance of these findings lies in the broader application of behavioral finance theories. While herding behavior has been well-documented in traditional asset classes, like equities and bonds, empirical research on cryptocurrencies is still relatively nascent. Our results contribute to this emerging body of knowledge by highlighting that, even during extreme global events, cryptocurrency investors tend to defy herding tendencies. This may be due to several factors, including the decentralized nature of cryptocurrencies and the varied risk appetites of individual investors. As traders have increasingly turned to cryptocurrencies as hedges or diversifiers against traditional financial assets, their behavior has become more individualized, shaped by personal financial objectives and an abundance of readily available information (Kaur et al., 2024).

The results of this research highlight notable impacts on policy formation and market regulators in managing market stability, especially during times of crisis. Policymakers should consider implementing measures that enhance transparency and reduce information asymmetry in the cryptocurrency market. By promoting better access to real-time data and market information, policymakers can help mitigate the herd behavior that often arises from panic and uncertainty. Furthermore, developing educational initiatives for investors about the risks of herd behavior can reduce the collective irrational decision-making that leads to market inefficiencies.

In addition, market regulators must establish regulatory frameworks that prevent market manipulation and excessive speculation, which can exacerbate herding tendencies. By enforcing stricter trading regulations during volatile periods, regulators can help stabilize markets and protect investors from the adverse effects of sudden price swings. Moreover, introducing mechanisms such as circuit breakers or trading halts during extreme market movements can prevent mass sell-offs triggered by herding behavior, ensuring a more orderly and efficient market. These actions, collectively, will contribute to a more resilient cryptocurrency market that is less prone to the destabilizing effects of herding behavior.

Although there is a growing body of literature on herding behavior in the crypto asset market, this study makes a notable contribution to existing research by presenting empirical evidence of anti-herding behavior during major global crises, such as the COVID-19 pandemic, the Russia–Ukraine war, and the Palestine–Israel conflict. In contrast to classic financial exchanges, where herding behavior has been extensively documented, our findings emphasize the unique characteristics of the cryptocurrency market, where investors often make independent decisions, influenced by rapid information dissemination and personalized risk assessments. Furthermore, by analyzing daily closing prices and employing rigorous analytical techniques, including CSAD, CSSD, and GARCH models, this study provides new insights into investor behavior during periods of heightened market volatility, thereby deepening our understanding of market reactions in this evolving asset class.

One limitation of this study is the reliance on daily closing prices, which may not capture the intraday volatility and trading behaviors that are characteristic of the cryptocurrency market. The study periods, though encompassing significant global events, may not fully represent the long-term trends and patterns of herding behavior in cryptocurrencies. Furthermore, the rapid evolution of the cryptocurrency market means that behaviors observed during the specified periods may differ in future contexts, necessitating continuous research and adaptation of analytical approaches.

### Author contributions statement

**Dhanraj Sharma:** Conception and design of study, Acquisition of data, Interpretation of data, Drafting the manuscript for initial submission; **Ruchita Verma:** Conception and design of study, Acquisition of data, Interpretation of data, Drafting the manuscript for initial submission; **Murad Baqis Hasan Al-Bukari:** Conception and design of study, Analysis of data, Interpretation of data, Drafting the manuscript for initial submission; **Mohammed Zaid:** Conception

and design of study, Drafting the manuscript for initial submission; **Pranav Raghav**: Acquisition of data, Analysis of data, Interpretation of data, Drafting the manuscript for initial submission. All authors have read and approved the final version of the manuscript.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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## Data availability statement

The authors take the data from the reliable published sources. Data will be made available on request from the corresponding author (M.A.K. Zaid:  [momozaidan@gmail.com](mailto:momozaidan@gmail.com)).

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