Zhongguo Kuangye Daxue Xuebao

2026 | Vol 31 | Issue 1 | Page 28-35
Journal Homepage: https://zkdx.ch/
DOI: 10.1654/zkdx.2026.31.1-03

Herding Behavior and Crypto Currency Market in the Context of Health and Geopolitical Crises

COVID-19 Pandemic, Russo-Ukrainian War and Palestine–Israel Conflict

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Abstract
This study analyses the impact of the COVID-19 pandemic, the Russian-Ukrainian war and and the Palestine–Israel conflict on the presence of herding in the USD crypto currency market for two distinct sub-periods (bearish regime and bullish regime). To do this, we will examine the daily closing prices of the 7 main largest cryptocurrencies, including Bitcoin, Ethereum, Binance coin, Cardano, XRP, Tether USD, and Dogecoin. These crypto currencies are selected based on rank and market capitalization from January 1, 2018 to December 31, 2023. This research uses the CUSUM test proposed by Ploberger and Kramer (1992) to detect structural breaks and to divide the sample into sub-periods. Then, we test for herding behavior using a cross-sectional absolute deviation (CSAD) model. Our results show that COVID-19 and geopolitical events do not increase herding behavior in cryptocurrency markets during the study period.

Keywords
Herding behavior, Cryptocurrency market, COVID-19 pandemic, Russia-Ukraine war, the Palestine-Israel conflict, Market regimes

1. Introduction
Over the past four years, the world has experienced one of the most unsettled and alarming periods of the 21st century, shaping a tense global economic and geopolitical environment. The spread of Covid-19 in early 2020 triggered the deepest global recession since the Second World War. This instability was further exacerbated by the outbreak of the Russo-Ukrainian war on February 24, 2022, which led to major political tensions and market disruptions worldwide. More recently, the escalation of the Palestine-Israel conflict on October 7, 2023 has intensified geopolitical uncertainty, adding additional pressure to global markets and deepening concerns regarding regional and international security. Some researchers ((Gyamerah, 2021), (Yarovaya and al., 2022), (Liu and Zhang, 2024), (Aljifri, 2024), (Sharma and al., 2024)) have compared the COVID-19 health crisis, the Russian-Ukrainian war and the Palestine-Israel conflict as black swan events for stock markets, because these three large-scale disasters caused excess mortality and were difficult to predict as they took most people by surprise, had a huge economic impact, and affected the world order (Aljifri, 2024).

In this context, geopolitical and health risks have a substantial impact on financial market stability and economic growth, making them a key factor in investment decisions (Elsayed and Helmi, 2021). Researchers and policymakers increasingly focus on these risks (Ren and al., 2023), as the unpredictability of extreme events such as wars, conflicts, and global crises can significantly disrupt economic activity and shape investor sentiment. Existing studies mostly focus on single crises or limited time periods, leaving a gap in understanding how investors react across multiple consecutive shocks. This research aims to address this gap by examining herding behavior in major cryptocurrencies during several global crises, providing new insights into market efficiency, investor psychology, and the role of digital assets in times of turmoil.

Investor sentiment plays an essential role in financial market dynamics because it influences price movements and increases uncertainty about future returns (Gunay and al., 2024). From the perspective of Black Swan theory, this sentiment is largely driven by fear and anxiety associated with rare but highly disruptive events, including pandemics, wars, and financial crises. In response to such shocks, investors often seek to reduce exposure by shifting toward safer assets, which may lead to episodes of panic trading and heightened market volatility.

Crypto currency markets are often criticized as risky, inefficient, and immature and heavily subject to psychological and sociological factors (Bouri and al., 2019). In fact, an important fraction of the early academic research on herding in cryptocurrency markets shows that strong behavioral phenomena exist. The first attempt to detect herding was made by (Bouri and al., 2019) on 12 major crypto currencies in the crypto currency market over the period from April 28, 2013 to May 2, 2018. They apply both the static model developed by (Chang and al., 2000) and the dynamic model proposed by (Stavroyiannis and Babalos, 2017). The authors argue that herding exists in crypto currency markets but its intensity is not stable over time. The static model finds no sign of herding while the results support that higher uncertainty strengthens herding phenomena. (Stavroyiannis and Babalos, 2019), on the other hand, show that herding is more intense during bull markets compared to bear markets using ordinary least squares (OLS), time-varying parameter (TVP) and regression methodologies. This is in accordance with the findings of (Vidal-Tomás and al., 2019). The use of time variation model shows the absence of herding phenomena in cryptocurrency markets. However, (Youssef, 2022) confirm the presence of anti-herding behavior. (Ballis and Drakos, 2020) used daily data of six major cryptocurrencies (Bitcoin, Ethereum, Litecoin, Monero, Dash, and Ripple) for the period from August 2015 to December 2018 to test the hypothesis that different behavior exists in either upward or downward movements. They adopt cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) as methodologies. The empirical results reveal that market dispersion movements, in market returns, are less than proportional to fluctuations. Moreover, they find that market dispersion during bullish events is faster than bearish events. As a result, an asymmetrical herd behavior exists. Furthermore, (Kaiser and Stockl, 2020) test herding behavior in the cryptocurrency market, based on daily cryptocurrency data from January 1, 2015 to March 25, 2019, using the static model of (Chang and al., 2000) and the beta-herding state-space model of Hwang and Salmon (2004). They document strong support for herding behavior in the cryptocurrency market and support that this market is characterised by a high level of irrationality regarding investor decisions.

There are nevertheless limited bibliographic studies exploring herd behavior in the cryptocurrency market during periods of health and geopolitical crisis. (Yarovaya et al., 2022) investigated the herding behavior in the crypto currency market for the period from January 1, 2019 to March 13, 2020 using the hourly prices of the four most crypto currency markets traded in USD (United States Dollar), EUR (European Union Euro), JPY (Japanese yen), and KRW (South Korean Won). These cryptocurrencies are BTC, LTC, ETH, BCH, MONA, XEM, ZAIF, BTG, XMR and XRP. They indicated the presence of herding for all markets except KRW. Nevertheless, the authors stated that COVID-19 does not increase herding behavior in crypto currency markets for the period studied. (Liu and Zhang, 2024) selected the top 21 leading crypto currencies, from 2016 to May 2023, to study their trading behavior. The study outcomes showed that from 2016 to March 12, 2020, the crypto currency market exhibited strong and significant herding behavior. However, after March 12, 2020 significant herding activity could not be detected. The implication of this study is that March 12, 2020 appeared to be a turning point where significant market conditions could have changed, such that the leading force in crypto currency trading shifted from individuals to institutional investors. (Rubbaniy et al., 2022) confirm the existence of herd behavior in the crypto currency market and show that herding asymmetry is present during bull and bear periods. (Gyamerah, 2021) verified the occurrence of herding in the crypto currency market for four sub-periods (pre and during COVID-19, bull and bear markets) and proved the existence of herd behavior during the COVID-19 period and in the bull market. This indicates that investors in the crypto currency market during the COVID-19 pandemic period make similar trading decisions for positive market returns. (Bougatef and Nejah, 2022) proved that the war between Russia and Ukraine caused the appearance of herd behavior between Moscow Exchange investors.

(Aljifri, 2024) used the cross-sectional dispersion of daily stock return for the full period and four sub-periods to estimate

The degree of herding in the Saudi stock market. The results showed that herding behavior did not take place before COVID-19. However, it occurred during COVID-19 and disappeared after COVID-19, and did not happen during the Russo-Ukrainian conflict. Moreover, no difference exists between bearish and bullish days. (Le and al., 2024) examined the herd behavior at the period of conflict between Russia and Ukraine in the cryptocurrency market. Empirical results indicated anti-herding behavior throughout the conflict period. (Chen & Nguyen, 2024) find persistent anti-herding in the cryptocurrency market during the Russia–Ukraine conflict. Investors acted independently rather than following the crowd, reflecting the market's growing maturity and rapid information integration.

Sharma et al. (2024) analyze herding behavior in cryptocurrency markets during major global crises, including the COVID-19 pandemic, the Russo-Ukrainian War, and the Israeli-Palestinian conflict. Using daily prices from December 31, 2019 to May 20, 2024 for five major cryptocurrencies (Bitcoin, Ethereum, Tether, BNB, and Solana) and the CRYPTO20 index, they apply CSAD and CSSD methods, with a GARCH model for robustness. The results consistently show anti-herding behavior, indicating that investors act independently rather than follow the crowd during periods of high uncertainty. This study highlights the distinctive dynamics of crypto markets under stress and the influence of geopolitical and health crises on investor behavior.

It appears from the above that the results are controversial. Understanding investor behavior in the cryptocurrency market before and during crises is therefore essential for researchers.

Therefore, the interest of this study is to understand the psychology of investors involved in making financial decisions in times of crisis. Based on recent work, we test the existence of herd behavior in the cryptocurrency market during sub-periods, according to bullish and bearish period, and according to market stability. This article is divided into two parts. The first part presents the data and the methodology that we followed in this work. The second part presents the empirical results and the interpretations of these results.

2. Data and Methodology

2.1. Data

The target population is composed of the ten largest crypto-currencies (BTC ; ETH ; BNB ; ADA ; USDT ; XRP ; SOL ; DOT ; DOGE ; USDC) in the most active USD cryptocurrency market, as reported in Table 1. observed over the period from January 2018 to December 2023. However, cryptocurrencies with missing data over the entire study period are eliminated. We have selected as a sample for our research only seven crypto-currencies that are selected on market capitalization criteria with a size of 2577 daily observations for each cryptocurrency. The daily data used for this research, coming from the publicly available cryptocurrency database of the investing.com website, consists of daily closing prices and market capitalization from the coingecko.com website.

Table 1 Top 10 Cryptocurrencies by Market Capitalization

Rank	Cryptocurrency	Symbol	Market cap (USD)	Percentage (%)
1	Bitcoin	BTC	1.074.290.409.108	56%
2	Ethereum	ETH	414.767.519.987	22%
3	Binance Coin	BNB	77.346.857.989	4%
4	Cardano	ADA	70.859.089.045	4%
5	Tether	USDT	68.772.354.331	4%
6	XRP	XRP	51.982.408.604	3%
7	Solana	SOL	43.474.730.362	2%
8	Polkadot	DOT	41.015.132.316	2%
9	USD Coin	USDC	32.846.717.473	2%
10	Dogecoin	DOGE	30.161.912.703	2%

Source: Authors' compilation based on data from CoinMarketCap, retrieved January 12, 2021

2.2. Methodology

2.2.1. Cryptocurrency returns over the study period

Using the market capitalization of the selected crypto-currencies, we can calculate the market portfolio, which is the weighted market return depending on the capitalization, rm, given in the following equation:

$$r_{m,t} = n_{1,t} * r_{1,t} + n_{2,t} * r_{2,t} + \cdots + n_{i,t} * r_{i,t} = \sum_{i=0}^{N} n_{i,t} * r_{i,t}$$

With $r_{m,t}$: The weighted average return during day t, $r_{i,t}$: The return of cryptocurrency i at time t, and as proposed by Chiang and Zheng (2010), the daily stock return is calculated by the natural logarithm difference of daily prices: $R_{i,t} = \log(P_{i,t}/P_{i,t-1})$, $n_{i,t}$: The weight of cryptocurrency i at time t calculated from the market capitalization $n_{i,t} = \frac{CB_{i,t}}{CB_{m,t}}$, $CB_{i,t}$: The market capitalization of cryptocurrency i during period t, $CB_{m,t}$: The total market capitalization of the market during period t $CB_{m,t} = \sum_{i=1}^{7} CB_{i,t}$

2.2.2. Herding indicator for the entire sample

(Chang et al., 2000a) explained a linear association between the dispersion of an asset's returns and the absolute value of market returns from asset pricing models; therefore, they constructed the cross-sectional absolute deviation (CSAD) model. In this study, the CSAD model is used to analyse and interpret the concept of herding behavior in the cryptocurrency market. It is given as follows:

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

with $R_{m,t}$: The weighted average return during day t, $R_{i,t}$: The return on security i during day t.

2.2.3. Testing the stability of the CSAD series using the CUSUM test

In this study, it is possible to observe a structural change in the relationship between CSAD and Rm when using a regression model on time series. By structural change we mean that the unstable model has its coefficients that vary during the period considered. It only applies to a long-term model. In order to test the stability of the model, the CUSUM test which is based on the cumulative sum of the recursive residuals is the most relevant with a null hypothesis of stability of the relationship, between two lines representing the limits of the interval.

2.2.4. Estimate the models according to the decomposition provided by the CUSUM test

We have a benchmark model based on the following quadratic model of return dispersion and squared market return:

$$CSAD_t = \beta_0 + \beta_1 * |r_{m,t}| + \beta_2 * r_{m,t}^2 + \varepsilon_t \qquad (1)$$

with β_0, β_1 et β_2 : The regression coefficients, $|r_{m,t}|$: The absolute value of the average market return of all studied crypto-currencies in the USD market at time t and ε_t : The error term.

This equation is used to explore the existence of herd behavior in the cryptocurrency market. To prove the existence of nonlinearity in herd behavior, β_2 must be negative and significant. The presence of herding is tested through the following hypotheses:

H0 : In the absence of herding behavior, we expect that in the equation that $\beta_1 > 0$ et $\beta_2 = 0$.
H1 : If herding behavior exists, we expect $\beta_2 < 0$.
H2 : If anti-herding behavior exists, we expect $\beta_2 > 0$

Chiang and Zheng (2010) use a dummy variable to detect market movements in a single model to study the herding asymmetry in investor behavior during bull and bear regimes. Following Chiang and Zheng (2010), we study the herding asymmetry in the cryptocurrency market using the model in the following equations:

$$CSAD_t = \beta_0 + \beta_1 * D^{UP} * |r_{m,t}| + \beta_2 * D^{UP} * (r_{m,t}^2) + \varepsilon_t \ (2)$$
$$CSAD_t = \beta_0 + \beta_1 * D^{DOWN} * |r_{m,t}| + \beta_2 * D^{DOWN} * (r_{m,t}^2) + \varepsilon_t \ (3)$$

where the dummy variable D^{UP} takes the value 1 if $r_{m,t} > 0$ and the value 0 otherwise; and the dummy variable D^{DOWN} takes the value 1 if $r_{m,t} < 0$ and value 0 otherwise.
Moreover, the bull market is the situation where $r_{m,t} > 0$, otherwise we would have a bear market situation.
A significantly negative value of β_2 signals the presence of a herd effect in the cryptocurrency market during a bull market situation.

3. Empirical results and interpretations

3.1. Descriptive statistics

The following Table presents descriptive statistics calculated using Eviews13 for the average daily returns $r_{m,t}$ and the daily absolute cross-sectional deviations $CSAD_t$:

Table 2 Descriptive statistics for market return and CSAD series (USD)

	CSAD	Rm
Mean	0.008871	0.000137
Median	0.006770	0.000459
Maximum	0.262625	0.066968
Minimum	0.000789	-0.218302
Std. Dev.	0.010530	0.016600
Skewness	13.79254	-1.410048
Kurtosis	309.5195	19.25839
Jarque-Bera	8642755.	24846.30
Probability	0.000000	0.000000
Sum	19.42748	0.301010
Sum Sq. Dev.	0.242704	0.603193
Observations	2577	2577

Source*: prepared by the authors*

The results in the table indicate that the cryptocurrency market has positive average returns (0.000137) and fluctuates during the sample period between 0.066968 and -0.218302. Looking at the $\mathbf{CSAD_t}$, we observe a mean value of 0.008871, indicating a large deviation of crypto-currencies from the market consensus. The higher values associated with the Jarque Bera test highlight abnormal distributions in both data sets, CSAD and Rm clearly indicate that these distributions are abnormal. Moreover, the distribution of CSAD is peaked, with high positive skewness and very high kurtosis, while the distribution of Rm is negatively skewed.

3.2. CUSUM Stability Test

Applying the CUSUM test on Eviews13, it gave us the following graph:

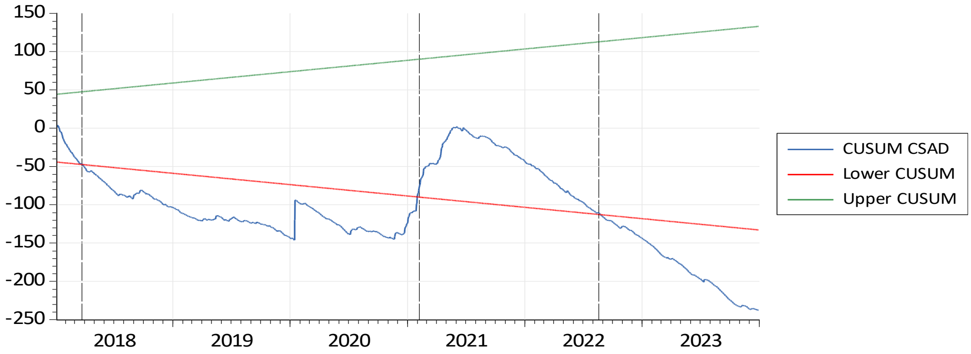

Figure 1 CUSUM stability test for CSAD series

***Source**: prepared by the authors*

Based on the above graph, the results indicate that the cumulative sum of recursive residuals exceeds the 5% significance bounds several times over the period 2018–2023. Therefore, the null hypothesis of parameter stability is rejected. These crossings highlight the presence of structural breaks in the CSAD model, suggesting that the relationship between market returns and cross-sectional dispersion varies significantly over time. These breaks coincide with major shocks such as the COVID-19 pandemic (2020), the Russia–Ukraine war (from February 2022), and the escalation of the Israel–Palestine conflict (October 2023). Such events generated substantial economic and geopolitical uncertainty, altering investor sentiment and market dynamics. Consequently, estimating the model over distinct sub-periods is necessary to better capture the heterogeneity of the cryptocurrency market under different conditions of health and geopolitical stress.

Following the CUSUM test, the sample is divided into four sub-periods to account for the structural breaks associated with these major shocks. The first period (01/01/2018–22/03/2018) corresponds to a stable market phase. The second period (23/03/2018–04/02/2021) covers the phase before and during the COVID-19 pandemic. The third sub-period (05/02/2021–17/08/2022) reflects the post-COVID dynamics as well as the outbreak of the Russia–Ukraine war in February 2022. The fourth period (18/08/2022–31/12/2023) incorporates the escalation of the Israel–Palestine conflict, which introduced an additional layer of geopolitical uncertainty likely to influence investor behavior.

3.3. Detection of herd behavior during the four sub-periods

We tested the existence of herding while taking into account the structural breaks detected in the CSAD series.
Table 3 presents the regression results for selected cryptocurrencies in the USD market after decomposing the sample provided by the CUSUM test (see Table 3).

3.4. Results' interpretation

Before starting the interpretation, it should first be recalled that in this model, a β_2 that is positive and statistically significant would imply that there is no evidence of herding. It indicates that dispersion is growing at an increasing rate, which is expected under normal market conditions, while a β_2 equal to zero would indicate a linear relationship, in parity with the capital asset pricing model.

In this sense, the regression results of the Table 3 show that for the USD cryptocurrency market the coefficient β_2 is positive and significant for the linear model of absolute cross-sectional deviation (CSAD) and for the bearish regime respectively at the threshold of 10% and 1% in the first sub-period (01/01/2018 – 22/03/2018). This result is consistent with the study of (Stavroyiannis & Babalos, 2019), (Bouri et al., 2019) and (Youssef, 2022) among others, who reported the absence of herd behavior in the cryptocurrency market based on the static approach. This result can be explained by the fact that the first sub-period corresponds to a relatively stable market phase, during which investors reacted in a more rational and less synchronized manner, in sharp contrast with the subsequent sub-periods characterized by the COVID-19 pandemic and major geopolitical tensions.

For the second sub-period (23/03/2018 – 04/02/2021) the coefficient β_2 is positive and significant at the 5% threshold only during the bearish regime. In contrast, the results obtained for the static model and for the bullish regime show coefficients that are negative and positive, respectively, but both are statistically insignificant, indicating that no clear herding or anti-herding behavior can be inferred from these two specifications. These results highlight the asymmetric impact of extreme market conditions, particularly during periods of heightened uncertainty such as the COVID-19 crisis.

Regarding the third sub-period (05/02/2021 – 17/08/2022) the coefficient β_2 is positive and significant for the three models estimated at the 1% threshold. This indicates a strong presence of herding behavior across different market regimes during this period, reflecting heightened investor uncertainty and pronounced market reactions to both geopolitical tensions and ongoing pandemic-related disruptions.

And for the last sub-period (18/08/2022 – 31/12/2023), still affected by the ongoing Russia–Ukraine conflict and heightened geopolitical tensions, including the escalation of the Israel–Palestine conflict, the coefficient β_2 e is positive and statistically significant during the bullish regime and the bearish regime respectively at the 1% and 10% threshold. While for the linear cross-sectional absolute deviation (CSAD) model the coefficient β_2 has a negative value with a significance level of 5%, which means the existence of herd behavior only during this period.

Table 3 Summary table of regression results in four sub-periods

Sub-periods (Test CUSUM)	$CSAD_t = \beta_0 + \beta_1 * \lvert r_{m,t} \rvert + \beta_2 * r_{m,t}^2 + \varepsilon_t$			$CSAD_t = \beta_0 + \beta_1 * D^{UP} * \lvert r_{m,t} \rvert + \beta_2 * D^{UP} * (r_{m,t}^2) + \varepsilon_t$			$CSAD_t = \beta_0 + \beta_1 * D^{DOWN} * \lvert r_{m,t} \rvert + \beta_2 * D^{DOWN} * (r_{m,t}^2) + \varepsilon_t$		
	β_0	β_1	β_2	β_0	β_1	β_2	β_0	β_1	β_2
01/01/2018 – 22/03/2018	0.014034	-0.076457	4.462198	0.014322	0.144697	0.093307	0.016228	-0.353670	7.709922
	(0.0000***)	(0.6346)	(0.0519*)	(0.0000***)	0.6146	0.9904	(0.0000***)	(0.015**)	(0.0006***)
	R-squared : 0.157079 Adjusted R-squared : 0.135185 Prob(F-statistic) : 0.001389			R-squared : 0.033343 Adjusted R-squared : 0.008235 Prob(F-statistic) : 0.271009			R-squared : 0.170554 Adjusted R-squared : 0.149010 Prob(F-statistic) : 0.000747		
23/03/2018 – 04/02/2021	0.005858	0.322188	-0.349337	0.007813	0.233052	1.561643	0.00878	0.087322	0.771806
	(0.0000***)	(0.0000***)	0.3466	(0.0000***)	(0.011**)	0.492	(0.0000***)	(0.0849*)	(0.0496**)
	R-squared : 0.083534 Adjusted R-squared : 0.081784 Prob(F-statistic) : 0.00000			R-squared : 0.045459 Adjusted R-squared : 0.043636 Prob(F-statistic) :0.0000			R-squared : 0.024208 Adjusted R-squared : 0.022344 Prob(F-statistic) :0.0000		
05/02/2021- 17/08/2022	0.007448	0.107589	3.678117	0.009056	0.026558	5.430412	0.009695	-0.128795	6.417128
	(0.0000***)	(0.0306**)	(0.0000***)	(0.0000***)	0.69	(0.0014***)	(0.000***)	(0.01***)	(0.000***)
	R-squared : 0.249617 Adjusted R-squared : 0.246918 Prob(F-statistic) : 0.00000			R-squared : 0.095744 Adjusted R-squared : 0.092491 Prob(F-statistic) : 0.0000			R-squared : 0.141775 Adjusted R-squared : 0.138688 Prob(F-statistic) : 0.0000		
18/08/2022- 31/12/2023	0.002869	0.386958	-1.616755	0.004668	0.14102	4.96509	0.004932	0.127689	1.966724
	(0.0000***)	(0.0000***)	(0.0426**)	(0.0000***)	(0.0051***)	(0.0028***)	(0.0000***)	(0.0055***)	(0.0635*)
	R-squared : 0.435403 Adjusted R-squared : 0.433135 Prob(F-statistic) : 0.00000			R-squared : 0.2129 Adjusted R-squared : 0.2097 Prob(F-statistic) : 0.000			R-squared : 0.1249 Adjusted R-squared : 0.1214 Prob(F-statistic) : 0.0000		

Source: Prepared by the authors on Eviews10

Our results suggest that investors in the USD cryptocurrency market tended to act independently rather than following other investors, regardless of the time period considered.

The results of our study are consistent with previous studies conducted by (Yarovaya et al., 2022), (Youssef, 2022), (Liu & Zhang, 2024), (Aljifri, 2024), (Sharma et al., 2024) and (Chen & Nguyen, 2024) all of which present evidence of anti-herding in the cryptocurrency market. Furthermore, our study differs from the results of Chiang and Zheng (2010) who found that crises could lead to herd behavior in the stock market. In the context of the health and geopolitical crisis, our study does not discover the same evidence of herding within the USD cryptocurrency market.

4. Conclusion

The main objective of our study is to analyse the existence of herd behavior in the USD cryptocurrency market across different sub-periods. The total period is divided into four distinct sub-periods, identified using the CUSUM test, and classified according to market trends (bullish and bearish regimes).

For this we tested our research hypotheses by analysing daily data of seven main cryptocurrencies including Bitcoin, Ethereum, Binance coin, Cardano, XRP, Tether USD and Dogecoin, selected based on market capitalization, while using both the herding measure of (Chang et al., 2000) and an ordinary least squares model for each sub-period.

Our results show that COVID-19 and geopolitical events do not increase herding behavior in cryptocurrency markets during the study period.

The observed anti-herding behavior in the cryptocurrency market can be explained by the increase in market efficiency. These results support the idea that the increasing efficiency of the cryptocurrency market may contribute to the observed anti-herding behavior.

Our analysis contributes to the literature on investor behavior in the cryptocurrency market by highlighting anti-herding behavior across market trends and crisis periods. We are the first to employ the CUSUM test to segment sub-periods, providing more precise results. These findings offer valuable insights for investors, regulators, and policymakers facing uncertainty, such as during the COVID-19 pandemic, the Russia–Ukraine war, and the Israel–Palestine conflict.

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