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Herding behavior in the cryptocurrency market: the case of the Russia–Ukraine conflict

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Abstract
This study investigates the herding behavior in the cryptocurrency market during the period of the Russia and Ukraine conflict using intraday cryptocurrency price data of the five largest cryptocurrencies in terms of market capitalization. The empirical results indicate an anti-herding behavior during the whole period of the conflict, especially after the conflict officially happens. The research contributes to the growing literature on herding behavior in the cryptocurrency market by using intraday data and examining the Russia–Ukraine conflict period.

Keywords Herding · Cryptocurrency · Geopolitical conflict

JEL Classification G41

1 Introduction and context

Cryptocurrency has become a focal point of interest for both investors and policy makers, prompting the emergence of an extensive body of literature on the subject in recent years. The academic literature on cryptocurrencies tackles various facets of this burgeoning field. A strand of literature discusses the returns and risks of cryptocurrencies (e.g., Adhami & Guegan, 2020; Goodell et al, 2022; Liu & Tsyvinski, 2021; Nguyen et al., 2019; Ma et al., 2022) while numerous articles analyse USD-pegged stablecoins (e.g., Grobys et al., 2021; Thanh et al.,

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2022) and Central Bank Digital Currencies (e.g., Corbet et al., 2022). Moreover, other branches of literature illuminate the process of price discovery in cryptocurrencies (Moosa, 2020; Doan et al., 2022) and delve into the question of market efficiency within the realm of cryptocurrency market (e.g. Köchling et al., 2019; Tiwari et al., 2018).

Given the absence of robust regulations and market infrastructure, which could potentially foster irregular trading behavior, an expanding sector of cryptocurrency literature is devoted to examining investor behavior in the cryptocurrency market. Investors in cryptocurrencies are very active on social media platforms such as Twitter, Reddit, Facebook, etc., enabling them to read and spread the news more quickly. Operating on a global scale and conducted digitally 24/7, the cryptocurrency market offers investors a unique setting. With the added advantage of immediate access to popular social media platforms like Twitter and Facebook, investors are equipped to rapidly assimilate and utilize timely information in their trading decisions. This context has resulted in a surge in studies determining the prevalence of herding behavior within the cryptocurrency market. Moreover, the notorious volatility of the cryptocurrency market, along with its substantial impact on other financial markets, as explicated by Liu (2019) cannot be overlooked. As traditional valuation frameworks do not adequately account for cryptocurrencies, it becomes essential to analyze herding behavior in this market to decipher the dynamics driving the determination of cryptocurrency prices.

Herding behavior refers to a phenomenon where investors, bypassing their own rational judgment, behave irrationally (Bikhchandani & Sharma, 2000; Christie & Huang, 1995; Yousaf & Ali, 2020). Moreover, when people engage in communication, they tend to adopt similar thought patterns and actions, a behavior indicative of a certain degree of irrationality (Liu 2019). This propensity to mirror others' irrational thought processes and actions can lead to violations of the Efficient Market Hypothesis (EMH). EMH posits that assets, including equities and commodities, generally trade at their fair price. A violation of EMH could result in assets being mispriced, as investors fail to consider all available information in the market due to their own irrational behavior. However, recent literature suggests that the cryptocurrency market is garnering increased attention from serious investors and is thought to be moving toward greater efficiency (Noda, 2021; Fernandes et al., 2022). This development could lead to a reduction or even reversal of herding behavior in the cryptocurrency market.

A multitude of studies have delved into the potential existence of herd behavior in the cryptocurrency market, yielding contradictory evidence. For instance, Bouri et al. (2019) conducted a study on 14 leading cryptocurrencies from 2013 to 2018, with their findings suggesting a propensity towards herding behavior in times of heightened uncertainty. Likewise, Amirat and Alwafi (2020) analyzed 20 of the largest cryptocurrencies from January 2015 to January 2019, identifying a significant fluctuating herding behavior throughout this period. Ballis and Drakos (2020) echoed this sentiment, affirming the existence of herding behavior within the cryptocurrency market based on daily data sampled from 2015 to 2018. Vidal-Tomas et al. (2019) also noted herding behavior during market downturns in their analysis of cryptocurrency data from 2015 to 2017.

However, contrasting evidence can be seen in Coskun et al. (2020) study. Upon investigating 14 leading cryptocurrencies during 2017–2018, Esra identified a trend of anti-herding behavior within the cryptocurrency market. Youssef (2022) supported this stance when examining herding behavior using data from 2013 to November 2019, finding signs of anti-herding behaviors. In sum, the literature presents conflicting findings concerning the presence or absence of herding behavior in the cryptocurrency market.

Given the mixed findings of the literature on herding behavior in the cryptocurrency market, the current study contributes to the ongoing discussion by testing whether herding behavior exists during the Ukraine-Russia crisis. While the literature on the stock market has analyzed herding behavior during crisis periods and finds evidence that crises could trigger herding behavior, e.g., Chiang and Zheng (2010), there are surprisingly few discussions on the presence of herding behavior during crisis periods in the cryptocurrency market. The absence of regulatory supervision in the cryptocurrency market can expose investors to considerable psychological strain during periods of crisis, such as wars triggered by events causing geopolitical risk. In such situations, investors may be more inclined to liquidate volatile investments in favor of retaining safer assets like cash or gold (Al Mamun et al., 2020). This is highlighted by Colon et al. (2021), who tested the top 25 cryptocurrencies with monthly observations and discovered that the cryptocurrency market is notably responsive to economic policy uncertainty and geopolitical risk.

Significant political events, such as the Ukraine-Russia crisis, have the capacity to shape herding behavior within this market. The crisis was characterized by a heightened level of uncertainty within financial markets and a frequent emergence of new information. The volume of cryptocurrency-related information also saw a significant surge during this period as major nation-states made substantial decisions impacting the cryptocurrency market. For example, the Ukrainian government sought funding from the international public via cryptocurrencies. Therefore, the Ukraine-Russia conflict presents a fascinating backdrop to explore the occurrence of herding behavior in the cryptocurrency market.

Our research findings point to significant anti-herding behavior within the cryptocurrency market during the Russia-Ukraine crisis. This outcome is in line with recent studies indicating an increasing level of efficiency in the cryptocurrency market. The remaining sections of this paper are structured as follows: Sect. 2 presents the data and methodology used in our study. The findings are discussed in detail in Sect. 3. Finally, Sect. 4 concludes the paper.

2 Data and methodology

2.1 Data

While most previous studies investigating herding behavior in the cryptocurrency market have relied on daily price data, the 24/7 nature of cryptocurrency trading and the instantaneous dissemination of information through social media imply that daily price data may not encapsulate the full scope of information influencing investor behavior. To more thoroughly examine the price dynamics in the cryptocurrency market, our study employs data at a 30 min frequency. This high-resolution data allows us to capture a wider range of information and provides a more intricate understanding of herding behavior in the cryptocurrency market.

Our data has been sourced from the Thompson Reuters Database. Our focus was specifically directed toward the top five cryptocurrencies by market capitalization, excluding stablecoins, which include BTC (Bitcoin), XRP (Ripple), ETH (Ethereum), SOL (Solana), and BNB (Binance coin). The data collection period stretches from December 10, 2021, to January 10, 2023, with a 30 min frequency. We have amassed a total of 18,484 observations, which comprise 3,603 trading prices pre-event and 14,881 prices post-event. The event date we have considered is February 24, 2022, which marks the invasion of Ukraine by Russian forces. Prices observed before this date are classified as “Before the event,” while those documented after are categorized as “After the event.”

We have excluded stablecoins and asset-backed coins from our analysis due to the influence of third parties in regulating their values and volatility, as per the findings of Colon’s research (2021). After this exclusion, the selected five currencies collectively represent nearly 80% of the total market capitalization of the cryptocurrency market. Consequently, we argue that these five coins provide a suitable representation of the market. Table 1 offers a descriptive statistic of the calculated market return.

2.2 Methodology

To detect herding behavior, we implement two widely recognized methodologies: (i) Cross-sectional standard deviation of returns (CSSD) (Eqs. 1,2) follows Christie and Huang (1995) and (ii) Cross-sectional absolute deviation of returns (CSAD) (Eqs. 3,4) follows Chang et al. (2000), as a means to measure return dispersion.

The CSSD method, as outlined by Christie and Huang (1995), quantifies the variability of returns across different assets in a given period by calculating the standard deviation of returns of each cryptocurrency and capturing the dispersion of returns within the cross-sectional dataset. On the other hand, the CSAD method, as introduced by Chang et al. (2000), focuses on the absolute deviation of returns across assets rather than their standard deviation. CASD captures the extent of deviation from the mean return within the cross-sectional dataset. Moreover, following Caparrelli et al. (2004), we use an additional regression function with a dummy variable representing the before and after-event (Eq. 5).

$$CSSD_{m,t} = CSSD_{m,t} = \sqrt{\frac{\sum_{i=1}^{n} \left(r_{i,t} - r_{m,t}\right)^2}{N-1}} \tag{1}$$

$$CSSD_{m,t} = \alpha + \beta^U D_t^U + \beta^L D_t^L + u_t \tag{2}$$

Table 1 Descriptive statistics of the market for the whole sample, pre-, and post-period samples

	R_m	CSSD	CSAD	rBTC	rXRP	rSOL	rETH	rBNB
Whole sample								
Mean	– 0.008	0.286	0.212	– 0.006	– 0.005	– 0.016	– 0.007	– 0.005
SD	0.592	0.264	0.192	0.506	0.675	0.948	0.654	0.565
Median	0.008	0.220	0.164	0.001	0.014	0	0.003	0
Variance	0.350	0.070	0.037	0.256	0.455	0.899	0.428	0.319
Max	7.208	6.592	5.267	13.342	8.969	12.461	8.058	13.517
Min	– 14.268	0.007	0.005	– 13.898	– 17.513	– 24.191	– 10.833	– 11.082
Count	18,484	18,484	18,484	18,484	18,484	18,484	18,484	18,484
Pre-period sample								
Mean	– 0.011	0.299	0.220	– 0.006	– 0.004	– 0.019	– 0.012	– 0.012
SD	0.564	0.222	0.159	0.486	0.692	0.854	0.629	0.551
Median	0.010	0.237	0.176	0.001	0.005	– 0.007	0.006	0.006
Variance	0.318	0.049	0.025	0.236	0.479	0.730	0.395	0.304
Max	3.279	2.273	1.625	4.060	5.342	4.796	3.972	4.588
Min	– 4.094	0.015	0.013	– 3.535	– 7.052	– 6.482	– 4.030	– 4.333
Count	3603	3603	3603	3603	3603	3603	3603	3603
Post-period sample								
Mean	– 0.007	0.283	0.210	– 0.006	– 0.005	– 0.015	– 0.005	– 0.003
SD	0.598	0.273	0.199	0.511	0.670	0.969	0.660	0.568
Median	0.007	0.215	0.161	0.001	0.015	0	0.002	0
Variance	0.358	0.074	0.039	0.261	0.449	0.940	0.436	0.323
Max	7.208	6.592	5.267	13.342	8.969	12.461	8.058	13.517
Min	– 14.268	0.007	0.005	– 13.898	– 17.513	– 24.191	– 10.833	– 11.082
Count	14,881	14,881	14,881	14,881	14,881	14,881	14,881	14,881

$$CSAD_{m,t} = \sqrt{\frac{\sum_{i=1}^{n} \left| r_{i,t} - r_{m,t} \right|}{N}} \tag{3}$$

$$CSAD_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 \left| r_{m,t} \right| + \beta_3 r_{m,t}^2 + u_t \tag{4}$$

$$\begin{aligned} CSAD_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 \left| r_{m,t} \right| + \beta_3 r_{m,t}^2 \\ + \alpha Dummy + \beta_1 Dummy r_{m,t} + \beta_2 Dummy \left| r_{m,t} \right| \\ + \beta_3 Dummy r_{m,t}^2 + u_t \end{aligned} \tag{5}$$

Whee: $r_{m,t}$ demotes the market return, $r_{i,t}$ denotes each cryptocurrency 30 min return, N is the number of cryptocurrencies, D_t^U and D_t^L are respectively dummies equal to 1 if market return lies in the extreme upper tail and extreme lower tail, α, $\beta_{U;L,1,2,3}$ are the regression coefficients. *Dummy* represents a dummy variable with a value of 1 assigned to the period after the event.

The herding behavior is detected if:

(1) Negative coefficients for $\beta^U and \beta^L$ when implementing the CSSD model.
(2) Negative coefficient for Squared market return (β_3) when implementing CSAD model

3 Empirical results

3.1 Descriptive statistics

Table 1 presents the descriptive statistics of key variables, including the average market return, the cross-sectional absolute standard deviation (CSAD) and Cross-sectional standard deviation of returns (CSSD), during the period spanning from December 2021 to December 2022. The data is collected at 30 min trading intervals.

The average market return exhibits a range of − 14.268% to a maximum of 7.208%. Comparing the pre-period and post-period samples, it is evident that the post-period exhibits higher volatility compared to the pre-period. Specifically, the pre-period returns for each coin vary from − 7.052% (rXRP) to 5.342% (rXRP). In contrast, the post-period returns range from − 24.191% (rSOL) to 13.517% (rBNB).

In the pre-period sample, the market return stands at − 0.011%, with a standard deviation of 0.564%, indicating slightly lower volatility when compared to the entire sample. Furthermore, the coefficient of CSAD and CSSD for the pre-period sample are determined to be 0.220% and 0.299% respectively. These values suggest a slightly higher degree of return dispersion and variation in comparison to the post-period sample, where the CSAD and CSSD are calculated to be 0.210% and 0.283% respectively.

3.2 Results

Tables 2 and 3 report the results obtained from our regression analyses. In line with recommendations by Chang et al. (2000) and Mobarek et al. (2014), regarding autocorrelation and heteroscedasticity, we employed Newey and West (1987) estimator in our analytical framework to mitigate the potential impact of these issues and enhance the reliability of our analysis. Specifically, Table 2 displays the estimated coefficients for the CSAD of returns, while Table 3 displays the coefficients for the CSSD returns. These coefficients were derived from Eqs. (2) and (4), respectively with the aim of detecting the existence of herding behavior in the cryptocurrency market. The results for CSAD and CSSD of returns have been categorized into four distinct sets of samples. In column (1), we consider the whole sample, including all observations. Column (2) focuses solely on observations before 24/02/2022, the designated event date. Column (3) includes only observations after 24/02/2022. Finally, column (4) represents the regression model with a dummy variable that equals one for the post-war period and zero for the prior-war period following Caparrelli et al. (2004).

Table 2 Regression result using CASD model

	(1) CSAD	(2) CSAD	(3) CSAD	(4) CSAD
r_m	0.017***	0.021***	0.016**	0.021**
	(0.005)	(0.006)	(0.006)	(0.006)
r_m^2	0.011***	– 0.010	0.010***	– 0.029**
	(0.007)	(0.012)	(0.002)	(0.010)
$\|r_m\|$	0.235***	0.220***	0.249***	0.273***
	(0.002)	(0.019)	(0.009)	(0.013)
$D \times r_m$				– 0.005
				(0.009)
$D \times \|r_m\|$				– 0.030*
				(0.012)
$D \times r_m^2$				0.039***
				(0.010)
Constant	0.119***	0.138***	0.112***	0.116***
	(0.002)	(0.004)	(0.002)	(0.002)
t test				12.29***
				(0.0005)
N	18,484	3603	14,881	18,484

The standard errors are reported in parentheses

*$p < 0.1$

**$p < 0.05$

***$p < 0.01$. (1), (2), (3) is the regression using respectively full sample, only observations before 24/02/2022, and only observations after 24/02/2022. r_m, r_m^2, $|r_m|$ are respectively the market return, squared market return and absolute market return. (4) is the regression using dummy variables. D represents a dummy variable with a value of 1 assigned to the period after the event

Our findings provide strong evidence of statistically significant anti-herding behavior throughout the studied period, as indicated by the CSAD and CSSD models. This suggests that investors within the cryptocurrency market displayed a tendency to act independently rather than following the herd, irrespective of the time frame under consideration.

The first regression analysis is presented in (Table 2) using the CSAD model. The findings reveal significantly positive coefficients at the 1% level for the entire sample throughout the research period (0.011**) as well as after the event (0.010*). Additionally, the coefficients associated with the squared market return variable are positive in both cases. This indicates a significant presence of anti-herding behavior in the cryptocurrency market. However, upon examining the sample prior to February 24, 2022, the results indicate the existence of herd behavior. This is evidenced by a negative coefficient (– 0.010 *), implying that there was a tendency for market participants to follow the herd during this period.

Table 3 Regression result using CSSD model

	(1) CSSD	(2) CSSD	(3) CSSD	(4) CSSD
Right	0.409***	0.328***	0.429***	0.349***
	(0.019)	(0.027)	(0.022)	(0.027)
Left	0.380***	0.276***	0.405***	0.298***
	(0.018)	(0.023)	(0.021)	(0.023)
$D \times Right$				0.075*
				(0.035)
$D \times Left$				0.102**
				(0.031)
Constant	0.247***	0.269***	0.242***	0.247***
	(0.002)	(0.004)	(0.002)	(0.002)
N	18,484	3603	14,881	18,484

The standard errors are reported in parentheses

*p < 0.1

**p < 0.05

***p < 0.01. (1), (2), (3) is the regression using, respectively full sample, only observations before 24/02/2022, and only observations after 24/02/2022. Right and Left are dummy variables that take value of 1 when the $r_m \geq$ or $\leq$ its 95 or 5 percentile value. D represents a dummy variable with a value of 1 assigned to the period after the event

Following Eq. (5) and employing the method elucidated by Caparrelli (2004), we integrate dummy variables to denote the periods before and after the event. The outcomes, as presented in column (4), unveil a presence of anti-herding behavior across the observation span. Additionally, herding tendencies are identified during the pre-event period, akin to what Eq. (2) suggests. Nevertheless, when considering the entire dataset, the findings indicate a prevalence of anti-herding behavior during both the entire post-event period and the overall timeframe.

The obtained results are also substantiated by the CSSD regression model, which reveals positive and statistically significant coefficients at the 1% for the entire sample throughout the research period, as well as for both the pre-and post-event periods (Table 3). These findings provide further support for the presence of anti-herding behavior within the cryptocurrency market during the Ukraine-Russia crisis.

The findings of our study align with prior research conducted by Coskun et al. (2020) and Youssef (2022), both of which provided evidence of anti-herding behavior in the cryptocurrency market. These findings stand in contrast to earlier studies by Bouri et al. (2019), Amirat and Alwafi (2020) that yielded contradictory results. Furthermore, our study diverges from the findings of Chiang and Zheng (2010), who found that crises can induce herding behavior in the stock market. In the context of the Ukraine- Russia crisis, our study does not uncover similar evidence of herding behavior within the cryptocurrency market.

One potential explanation for the observed anti-herding behavior in the cryptocurrency market is its reported increase in efficiency. Recent studies, such as Fernandes et al. (2022), have indicated that the cryptocurrency market has become more efficient over time. This implies that investors in the "top" currencies are more likely to respond logically to market conditions rather than blindly imitate the actions of other investors. These findings lend support to the notion that the growing efficiency of the cryptocurrency market may contribute to the observed anti-herding behavior.

4 Robustness tests

We implemented (i) the ARMA-ARCH/GARCH model following the methodology employed by Yousaf and Ali (2020) and Barde (2016) model to test the robustness of our herding behavior detection. Herding behavior, by definition, refers to a scenario where investors deviate from their individual investment strategies and instead choose to follow the crowd, leading to a reduction in volatility, which is commonly captured through the concept of conditional variance and represents the variation in market returns based on historical market information. Specifically, our assumption is that if market participants collectively adjust their decision in response to the actions of others, it would result in a decrease in variance. This interpretation aligns conveniently with the GARCH framework, which allows us to examine the conditional variance and its relationship with potential herding behavior. The result presented in Table 4, featuring notabaly positive coefficients (0.057***, 0.088***, 0.053***), indicate a pronounced pattern of anti-herding behavior among investors for the entire sample, as well as during the pre- and post- periods. This outcome aligns with our principal findings.

Table 4 The estimate coefficients of the GARCH (1,1) model

	(1) r_m	(2) r_m	(3) r_m
Constant mean Eq	0.004	0.006	0.004
	(0.003)	(0.007)	(0.003)
ARCH	**0.057*****	**0.088*****	**0.053*****
	(0.003)	(0.010)	(0.003)
GARCH	0.939***	0.891***	0.943***
	(0.003)	(0.012)	(0.003)
Constant	0.001***	0.006***	0.001***
	(0.000)	(0.001)	(0.000)
N	18,484	3603	14,881

The ARCH(1) and GARCH (1) with t-distribution are assumed. Again, the standard errors are reported in parentheses

$^{*}p<0.1$

$^{**}p<0.05$

$^{***}p<0.01$. (1), (2), (3) is the regression using respectively full sample, only observations before 24/02/2022, only observations after 24/02/2022

5 Conclusion

In this study, we aim to examine the herding behavior in the cryptocurrency market under the Russia- Ukraine conflict. We use 30 min price data from a sample of the top 5 major cryptocurrencies, including BTC (Bitcoin), XRP (Ripple), ETH (Ethereum), SOL (Solana), and BNB (Binance coin) represent almost 80% of total market capitalization over the research period. We employ CSSD and CSAD to test the herding behavior.

Our findings suggest a significantly anti-herding behavior in the cryptocurrency market during the Russia-Ukraine conflict period. We are one of the first to examine herding effects using intraday data, which is more appropriate for the cryptocurrency market. Our results are consistent with some recent studies that found no herding behavior in the cryptocurrency market. We also provide robust evidence that is consistent with our primary results.

The findings also support the results of more recent studies, which show that the cryptocurrency market is getting more efficient (e.g., Fernandes et al., 2022), with investors reacting more rationally to new information. Besides interestingly, the findings of Chiang and Zheng (2010), who found that a crisis could trigger herding behavior in the stock market, did not carry over to the cryptocurrency market during the Russia-Ukraine crisis. A possible explanation is that the cryptocurrency market operates around-the-clock, and information is quickly shared nowadays across social media platforms and can therefore be incorporated quickly and rationally by investors.

In the realm of studying herding behavior in cryptocurrency markets, the recent research conducted by Tabak et al. (2023) has provided another perspective. In their study, Tabak et al. (2023) explored herding behavior using daily closing price data for a broad range of cryptocurrencies. However, we sought to complement their findings by investigating herding behavior in a distinct manner with a different approach. Specifically, we utilized intra-day data, collected at 30 min intervals, to analyze the herding behavior of five major cryptocurrencies. This choice of data frequency and the focus on a subset of prominent cryptocurrencies aimed to provide a more detailed and precise representation of market dynamics. Further research that encompasses a wide range of cryptocurrencies and utilizes varying data frequencies could enhance the robustness of our findings and aid in forming more comprehensive insights into the intricate nature of herding behavior in the ever-changing landscape of cryptocurrency markets.

A caveat of our study is that our sample data capture mainly the period of the market downturn in the cryptocurrency market that started end of 2021. Kyriazis (2020) finds significant herding behavior only during bull market situations while our findings suggest anti-herding behavior in the cryptocurrency market during the period of market downturn. In light of those results, future studies could investigate the herding behavior further and control for the bull and bear market periods while utilizing intraday data.

Author contributions HHL is the lead author and has developed the idea of the study as well as has drafted the work. BNT is the co-author and has substantively revised the paper. NNT is a co-author and handles the technical aspects as well as gathering data.

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Data availability Data is collected from the Thompson Reuters Database and can be provided upon request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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