Clean and Dirty Cryptocurrencies: Herding Behavior During Recent Geopolitical Crises

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Abstract
This study aims to investigate the presence of herding behavior in the cryptocurrency market during major geopolitical crises, including the COVID-19 pandemic, the Russo-Ukrainian conflict, and the Israeli-Palestinian conflict. Relying on the CSSD and CSAD approaches, we analyze daily returns for a panel of 17 cryptocurrencies, classified as either "clean" or "dirty" based on their consensus mechanisms and associated energy consumption levels, over the period from December 30, 2019, to December 31, 2024. The results reveal that herding is not a persistent phenomenon across all market phases or crises. However, signs of convergence in investor behavior are detected during the COVID-19 period, particularly among clean cryptocurrencies. The inclusion of a sentiment index indicates that economic uncertainty has a negative and significant impact on returns, suggesting heightened risk aversion during turbulent periods. Moreover, structural break analysis confirms that clean cryptocurrencies are more sensitive to stress events, exhibiting greater behavioral shifts. These findings underscore the heterogeneous nature of investor behavior in the cryptocurrency market and the influence of crisis-induced sentiment over traditional price dynamics. This highlights the need for closer monitoring of environmentally labeled crypto assets under extreme market conditions.

Keywords: Investor sentiment, Cryptocurrencies, herding, clean, dirty, market return, geopolitical crises

1. Introduction and Literature Review

Since their inception, cryptocurrencies have attracted growing interest due to their decentralized nature, enhanced security, and potential to transform traditional financial mechanisms. They stand out for their ability to facilitate fast, global transactions, reducing reliance on traditional institutions. Driven by the technological innovation of blockchain, they offer unprecedented opportunities in economic models. In recent years, they have gained a certain legitimacy as a store of value and a distinct asset class, notably attracting institutional investors for their diversification and return potential. However, recent crises such as the COVID-19 pandemic, the Russo-Ukrainian conflict, and the Israeli-Palestinian conflict have renewed questions regarding their behavior during times of turbulence, particularly concerning collective investor reactions and the possibility of intensified herding behavior. Understanding the effect of geopolitical and health crises on investors' herding behavior thus becomes essential to assess systemic risks, market volatility, and implications for overall financial stability. Recent literature on herding behavior in the cryptocurrency market highlights complex dynamics sensitive to the macroeconomic context, investor sentiment, and the specific characteristics of the assets. Several studies show that this behavior varies depending on the nature of the cryptocurrencies, notably between so-called "dirty" and "clean" assets, as well as according to market phases (bearish/bullish). In this context, Chen and Nguyen (2024) demonstrate that positive sentiment intensifies herding in clean cryptocurrencies during bearish periods, while it promotes anti-herding in dirty cryptocurrencies. Furthermore, Ren and Lucey (2022) identify asymmetric herding in dirty assets, more pronounced in bearish markets, with these assets exerting a dominant influence on clean assets during bullish phases. The work of Rubbaniy et al. (2021) confirms the effect of exogenous shocks, showing increased herding during COVID-19 in periods of extreme bullish markets but an absence of such behavior during strict lockdowns. Youssef and Waked (2022) also emphasize the amplification of herding during high volatility phases, combined with an inhibitory effect of media coverage, especially among less experienced investors. On an intraday basis, Scharnowski and Shi (2024) identify intensified herding during overlapping hours of the U.S. and European markets, often driven by a FOMO (Fear of Missing Out) effect, moderated by attention dispersion measured via online searches and forums. Moreover, Le, Nguyen, and Thien (2024) observe anti-herding behavior during the Russia–Ukraine conflict, suggesting a certain investor independence from geopolitical tensions, which contrasts with Tabak et al. (2023), who reveal increased herding in clean cryptocurrencies during the same event in a context of asymmetric contagion driven by dirty assets. Beyond these empirical contributions, the conceptual foundations of herding behavior in financial markets were established as early as the 1990s, notably with the works of Donaldson and Kim (1993), Ley and Varian (1994), and Cyree et al. (1999) on psychological barriers and price clustering. In the cryptocurrency market, Urquhart (2017) and Hu et al. (2019) confirm the existence of such effects. The model of Chang et al. (2000), based on return dispersion (CSAD), is one of the most widely used tools to identify herding, particularly in high-volatility contexts. Ballis and Drakos (2020) highlight asymmetric herding behavior depending on market direction. Other research, such as Polyzos et al. (2021), utilizes social media data (Twitter, Reddit) to capture investor sentiment influence, especially during the COVID-19 pandemic. Hachicha et al. (2023), using a hidden Markov model, explicitly link herding behavior to economic uncertainty. Their results show that herding is less marked during periods of uncertainty but becomes significant after the easing of lockdown measures, suggesting a restoration of investor confidence. Gemayel and Preda (2024) show that traders tend to imitate their own past decisions, a phenomenon amplified by adverse market conditions or low liquidity. Recent studies, including those of Abakah et al. (2023), Xiaoyang et al. (2024), and Hall and Jasiak (2024), corroborate the significant influence of emotions, cognitive biases, and media events on the emergence of herding in these emerging markets. The results of Abakah et al. (2023) also confirm that negative sentiment, measured by their RUWESsent index, influences trader behavior by exacerbating herding and loss aversion during periods of uncertainty, thus offering critical insights for investors and policymakers in times of geopolitical crises. These works converge on the idea that herding behavior in crypto markets strongly depends on asset nature, market conditions, and exogenous and informational shocks, highlighting the need to segment these markets according to their environmental and temporal characteristics to better anticipate their behavioral dynamics. Our research contributes to this field of study by offering a joint analysis of three major global crises: the COVID-19 pandemic, the Russia-Ukraine conflict, and the Israel-Palestine conflict, comparatively assess their respective impacts on herding behavior in cryptocurrency markets. It focuses on the comparative study of two distinct groups of digital assets: so-called "dirty" and "clean" cryptocurrencies. More precisely, we hypothesize that these exogenous events do not have a homogeneous effect on herding dynamics, and that their impacts vary according to the market phase (bullish or bearish), the energy nature of the cryptocurrencies (dirty or clean), and the level of uncertainty perceived by investors. By employing an empirical approach based on dispersion models such as CSSD and CSAD, incorporating sentiment variables as well as temporal indicators related to the three crises studied, our objective is to test for the existence of asymmetric herding conditioned by the context. This positioning thus allows us to shed light on investment behaviors during geopolitical or health crises, with both theoretical implications for understanding cognitive biases and practical implications for investors, analysts, and financial decision-makers.

The remainder of this paper is structured as follows. The data and methodology are presented in Section 2. The empirical results are covered in Section 3. Section 4 concludes the study.

2. Data and Methodology

The Christie and Huang (1995) model analyzes herding behavior in financial markets, where investors copy the decisions of their peers without considering their own assessment of asset values. This behavior can lead to overrepresentation or underrepresentation of assets, thereby affecting price formation and market volatility. Based on this model, we can assess the presence of herding in the cryptocurrency market. The risk of returns is defined by the cross-sectional standard deviation (CSSD), expressed as follows:

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

Herding behavior in the market is observed when the dispersion of returns is low during extreme movements. Christie and Huang (1995) analyze this phenomenon by focusing on the lower and upper tails of the market return distribution, as follows:

$$CSSD_t = \gamma_0 + \gamma_1 D_t^{UP} + \gamma_2 D_t^{Down} + \varepsilon_t \quad (2)$$

To establish the nonlinear relationship between the cross-sectional absolute dispersion of ten cryptocurrencies and the market return, we adopt the approach developed by Chang et al. (2000), formulated as follows:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (3)$$

where $R_{m,t}$ represents the return of the equally weighted cryptocurrency market portfolio, and $CSAD_t$ denotes the cross-sectional absolute dispersion of the portfolio on day t.

$$CSAD_t = \frac{\sum_{i=t}^{n}|R_{i,t}-R_{m,t}|}{n} \quad (4)$$

Where

$R_{i,t} = 100 * \ln(P_{i,t}/P_{i,t-1})$

$R_{i,t}$ is the return of cryptocurrency *i* on day *t*, with $P_{i,t}$ and $P_{i,t-1}$ representing the closing prices of cryptocurrency *i* on days *t* and *t−1*, respectively. $R_{m,t}$ denotes the average realized return of *n* cryptocurrencies on day *t*.

Building on the studies of Vidal-Tomás et al. (2019) and Kumar (2020), we consider the returns of the equally weighted cryptocurrency portfolio as those of the market. Chang et al. (2000) suggest that trader behavior can be influenced by herding, with a tendency to collectively follow market movements. Under normal conditions, a positive linear relationship between market returns and the cross-sectional dispersion of returns can be expected. However, in cases of collective investment during market stress, this relationship may become nonlinearly decreasing or even negative. In other words, if the estimate of γ_2 in equation 3 is significantly negative, it indicates that cryptocurrency traders tend to exhibit herding behavior in their investment decisions. Chiang and Zheng (2010) use a dummy variable to capture these movements, and Economou et al. (2011) suggest that their approach is more robust than that of Chang et al. (2000), providing a better understanding of trader behavior in response to market fluctuations and the impact of herding. Based on the study by Chiang and Zheng (2010), we analyze herding behavior in the cryptocurrency market using the following model:

$$CSAD_t = \gamma_0 + \gamma_1 D^{UP}|R_{m,t}| + \gamma_2 D^{UP} R_{m,t}^2 + \gamma_3 D^{DOWN}|R_{m,t}| + \gamma_4 D^{DOWN} R_{m,t}^2 + \varepsilon_t \qquad (5)$$

Where $D^{UP}$is a dummy variable that takes the value 1 if $R_{m,t}$ >0, and 0 otherwise, andD^{DOWN} is a dummy variable that takes the value 1 if $R_{m,t}$ <0, and 0 otherwise.

Recall that a bullish market is characterized by a general increase in financial asset prices. A significantly negative value of γ_2 indicates herding behavior in the cryptocurrency market during bullish periods, meaning that investors follow the actions of others instead of basing their decisions on their own asset evaluation. Similarly, a negative value of γ_4, which measures the influence of the asset during bearish periods, also indicates herding behavior, where investors continue to sell or avoid the asset, influenced by others' behavior despite falling prices. In summary, significantly negative values of γ_2 or γ_4 reveal the presence of herding behavior in the market, both in upward and downward trends.

Demirer and Kutan (2006) emphasize that collective investment strengthens during periods of extreme stress, mainly due to psychological factors, which intensifies herding behavior. Several studies have also explored herding behavior during periods of risk aversion. Gurdgiev and O'Loughlin (2020) used the VIX risk aversion indicator to analyze aggregation biases in the cryptocurrency market. Economou et al. (2018) demonstrated that market aggregation is exacerbated by high risk aversion, particularly during crises. However, while the VIX is a relevant indicator for measuring risk aversion in traditional financial markets, it does not directly capture overall economic sentiment or investors' perceptions of macroeconomic information. In this context and following the approach of Chen and Nguyen (2024), we opted to use the daily economic sentiment index developed by the Federal Reserve Bank of San Francisco, based on the methodology of Shapiro et al. (2020). Unlike the VIX, which is derived from S&P 500 option markets, the SENT index is not tied to a specific asset market and reflects a broader climate of optimism or concern, making it particularly relevant in a context of herding behavior. Moreover, the SENT index has the advantage of covering the entire sampling period of our study (December 30, 2019 – December 31, 2024), thereby ensuring both temporal consistency and data completeness. We define the following equation:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 Sent_t + \varepsilon_t \tag{6}$$

The investor sentiment index $Sent_t$ is an indicator of economic sentiment at time *t*. The coefficient γ_3 of economic sentiment is statistically significant and indicates that market participants cluster around a risk aversion index during periods of heightened uncertainty, suggesting that cryptocurrency investors adopt herding behavior in times of anxiety. The coefficient γ_2 is also statistically significant and negative, implying that economic sentiment has a substantial influence on herding behavior. To examine the degree of this influence on cryptocurrency investors' behavior under extreme conditions, we define the following model:

$$CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{UP} Sent_t + \gamma_4 D^{DOWN} Sent_t + \varepsilon_t \tag{7}$$

where the dummy variable D^{UP} (D^{DOWN}) takes the value 1 if $R_{m,t}$ lies in the extreme upper (lower) tail of the $Sent_t$ return distribution, and 0 otherwise. A negative and significant value of Υ_3 (Υ_4) indicates that crypto traders follow the general market trend during periods of high-risk aversion, as measured by the *Sent* index. Thus, when the cryptocurrency market is rising (falling) with extreme levels of risk aversion, traders exhibit herding behavior. Several studies have examined herding behavior during crises in the stock market (Chang et al., 2000; Chiang and Zheng, 2010; Economou et al., 2018; Indārs et al., 2019).

To analyze this phenomenon during the crisis period, we adopt the approach of Indārs et al. (2019) with the following equation:

$$CSAD^{Crisis}{}_t = \gamma_0 + \gamma_1 D^{Crisis} |R_{m,t}| + \gamma_2 D^{Crisis} R_{m,t}^2 + \varepsilon_t \tag{8}$$

The dummy variable D^{Crisis} takes the value 1 if day *t* falls within the period of the COVID-19 pandemic, the Russia-Ukraine conflict, or the Israel-Palestine conflict, and 0 otherwise. A significant negative value of Υ_2 indicates herding behavior during this period.

We analyze the impact of the pandemic on the cryptocurrency market using data from CoinMarketCap covering the period from December 30, 2019, to December 31, 2024. Our sample includes 17 cryptocurrencies (classified as clean and dirty cryptocurrencies), among the largest by market capitalization. Based on research by Ren and Lucey (2022), this classification distinguishes cryptocurrencies based on their energy consumption profiles, such as Proof-of-Work (high energy usage) versus more energy-efficient mechanisms like Proof-of-Stake. We used equally weighted portfolio returns, totaling 1,829 observations. To study the effect of recent crises on cryptocurrency returns and the role of risk aversion, we added three distinct dummy variables, each taking the value 1 if day *t* belongs to a crisis period (COVID-19, Russia-Ukraine conflict, and Israel-Palestine conflict) and 0 otherwise. Additionally, we collected data on the

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economic sentiment index Sent, a high-frequency measure based on lexical analysis of economic news articles from 24 major U.S. newspapers, provided by the Federal Reserve Bank of San Francisco.

Table 1 Concept and definition

Concept	Definition
Green cryptocurrencies	Green cryptocurrencies are built on more energy-efficient consensus algorithms, such as Proof-of-Stake (PoS), Proof-of-Authority (PoA), the Ripple Protocol, and other alternatives aimed at reducing the environmental footprint of transactions. Cardano, Algorand, EOS, Hedera, Tron, VeChain, Stellar, Ripple (XRP), Tezoss, Cosmos, IOTA
Dirty cryptocurrencies	Dirty cryptocurrencies rely on energy-intensive consensus algorithms, such as Proof-of-Work (PoW), which require substantial computational power and, consequently, consume a significant amount of energy. Bitcoin, Ethereum, Bitcoin Cash, Litecoin, Ethereum classic , Monero
Covid-19 period	COVID-19 pandemic (March 11, 2020 – December 31, 2021)
Russia-Ukraine Conflict	The outbreak of the Russia–Ukraine conflict occurred on February 24, 2022.
Israeli-Palestinian Conflict	The outbreak of the Israel–Palestine conflict occurred on October 7, 2023.

3. Results and Discussion

The descriptive statistics for the equal-weighted dirty and clean portfolios are shown in Appendix1. The variables for both portfolios show moderate sample variability and comparatively low mean values. High levels of skewness and excess kurtosis indicate that the distributions are significantly non-normal, especially for variables like CSSD, D^{Up} and D^{Down}. The presence of abrupt market movements and sentiment shocks is confirmed by the notable leptokurtic behavior and strong asymmetry displayed by the CSAD and Sent variables for both groups. For all variables, the Jarque-Bera statistics strongly reject normality at the 1% level, supporting the use of strong statistical techniques in further analysis.

The results of the CSSD regressions, based on the work of Christie and Huang (1995), presented in Table 2, indicate that the models are overall significant, with explanatory variables having a clear effect on the dispersion of returns. The coefficients of the dummy variables D^{UP} and D^{Down} are positive and significant, showing that both bullish and bearish periods increase the dispersion of returns, with a more pronounced effect during downturns for both dirty and clean cryptocurrencies.

Table 2 Estimation of Herding Behavior

	Clean	Dirty
γ_0	0.071511	0.044085
	0.0000***	0.0000***
γ_1	0.262406	0.158782
	0.0000***	0.0000***
γ_2	0.263320	0.168673
	0.0000***	0.0000***
Observations	1829	1829
Adj. R²	0.575734	0.556311

Eq (2) : $CSSD_t = \gamma_0 + \gamma_1 D_t^{UP} + \gamma_2 D_t^{Down} + \varepsilon_t$

**Denote the rejections of the null hypothesis at the 10% significance level.*

** Denote the rejections of the null hypothesis at the 5% significance level.

****Denote the rejections of the null hypothesis at the 1% significance level.*

Indeed, these results suggest an increase in the cross-sectional dispersion of returns (CSSD) during market stress periods, which refutes the hypothesis of herding behavior for the 17 cryptocurrencies studied: investors appear to react heterogeneously to shocks. In contrast, the results from the Chang et al. (2000) and Chiang & Zheng (2010) models (table 3) confirm the existence of herding behavior in both market segments. Specifically, the coefficient γ_2, significantly negative in both cases (-0.336 for "clean" assets and -0.251 for "dirty" assets), indicates that the dispersion of returns (CSAD) decreases when market movements are extreme, reflecting investors' tendency to imitate the market in these situations. Moreover, the intensity of herding behavior appears stronger in the clean cryptocurrency segment, as evidenced by the higher absolute value of the γ_2 coefficient. This difference could be attributed to a different investor composition or a more homogeneous perception of market signals within this sub-segment.

Table 3 Estimation of Herding Behavior

	Clean	Dirty
γ_0	0.012273	0.008582
	0.0000***	0.0000***
γ_1	0.278222	0.262121
	0.0000***	0.0000***
γ_2	-0.336123	-0.251436
	0.0003***	0.0018***
Observations	1829	1829
Adj. R²	0.213557	0.260881

Eq (3) $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

**Denote the rejections of the null hypothesis at the 10% significance level.*

** Denote the rejections of the null hypothesis at the 5% significance level.

****Denote the rejections of the null hypothesis at the 1% significance level.*

However, the results from including the dummy variables D^{UP} and D^{Down} in the CSAD regression (Table 4) show that the coefficients γ_1 and γ_2, associated with the bullish phase, are positive and statistically significant for both asset categories. This result indicates that during strong market upturns, the dispersion of individual returns increases nonlinearly, which contradicts the existence of herding behavior. For the bearish phase, the coefficient γ_3 is significant for both asset types. However, the coefficient γ_4, intended to detect herding behavior under negative stress, is not significant (p = 0.798 for clean cryptocurrencies and p = 0.881 for dirty cryptocurrencies). These observations suggest that the model does not evidence herding behavior during bearish market periods. In fact, this indicates that cryptocurrency returns tend to diverge more as the market evolves. This conclusion aligns with Bouri (2019) but contradicts the findings of Kaiser and Stöckl (2020) and Polyzos et al. (2021). A significant and positive difference between the coefficients of $D^{UP}R^2_{m,t}$and $D^{Down}R^2_{m,t}$ in Table 4 further supports the absence of herding behavior, both in bullish and bearish periods. Our results are consistent with those of Coskun et al. (2020) but diverge from Ballis and Drakos (2020) and Polyzos et al. (2021). Furthermore, the rolling regression analysis (fig. 1 and fig. 2) reveals contrasting herding dynamics between clean and dirty cryptocurrencies during the COVID-19 pandemic, the Russo-Ukrainian war, and the Israeli-Palestinian conflict. Clean cryptos exhibit significant herding behavior in periods of uncertainty, reflecting their perceived role as safe-haven assets. In contrast, dirty cryptos display anti-herding behavior, which intensifies during periods of geopolitical tension. These results confirm an asymmetric investor reaction based on the energy profile of the assets. They align with the findings of Ren and Lucey (2022) regarding the differentiated behavioral sensitivity between sustainable and energy-intensive cryptocurrencies. Moreover, our results corroborate those of Nguyen and Thien (2024), who revealed significant anti-herding behavior, particularly after the onset of the Russo-Ukrainian conflict.

Table 4 Estimation of Herding Behavior

	Clean	Dirty
γ_0	0.018250	0.013490
	0.0000***	0.0000***
γ_1	0.211536	0.228610
	0.0000***	0.0000***
γ_2	0.896705	0.722803
	0.0019***	0.0004***
γ_3	0.045786	0.085044
	0.0454**	0.0000***
γ_4	0.026831	-0.013992
	0.7978	0.8809
Observations	1829	1829
Adj. R²	0.266135	0.296346

Eq (5) : $CSAD_t = \gamma_0 + \gamma_1 D^{UP}|R_{m,t}| + \gamma_2 D^{UP} R^2_{m,t} + \gamma_3 D^{DOWN}|R_{m,t}| + \gamma_4 D^{DOWN} R^2_{m,t} + \varepsilon_t$

**Denote the rejections of the null hypothesis at the 10% significance level.*

** Denote the rejections of the null hypothesis at the 5% significance level.

****Denote the rejections of the null hypothesis at the 1% significance level.*

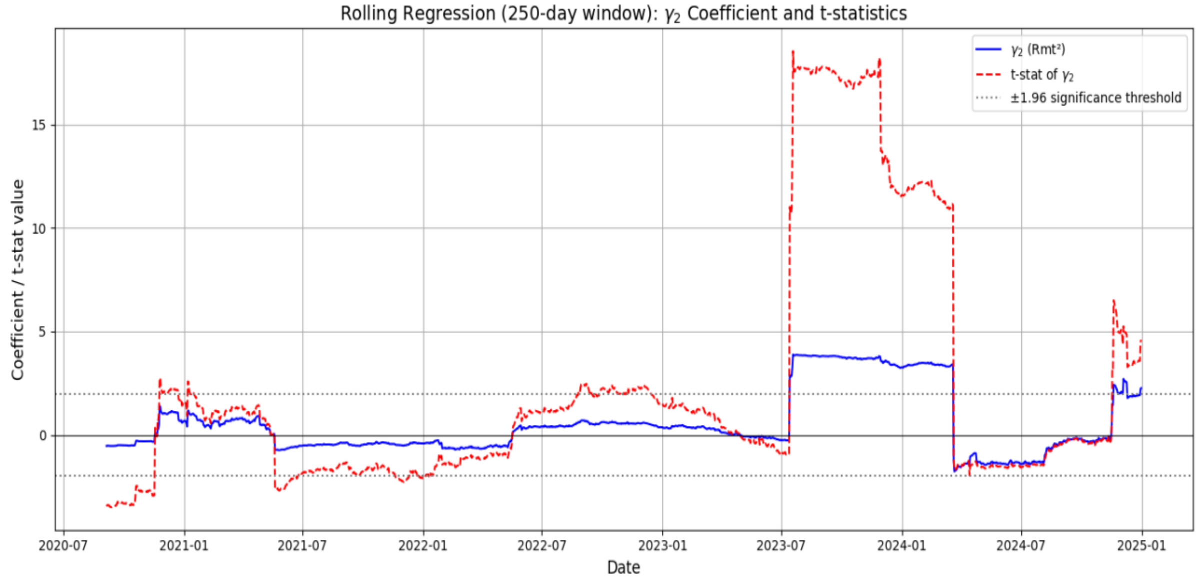

Fig. 1. Rolling regression results in the clean cryptocurrencies with a 250-day window

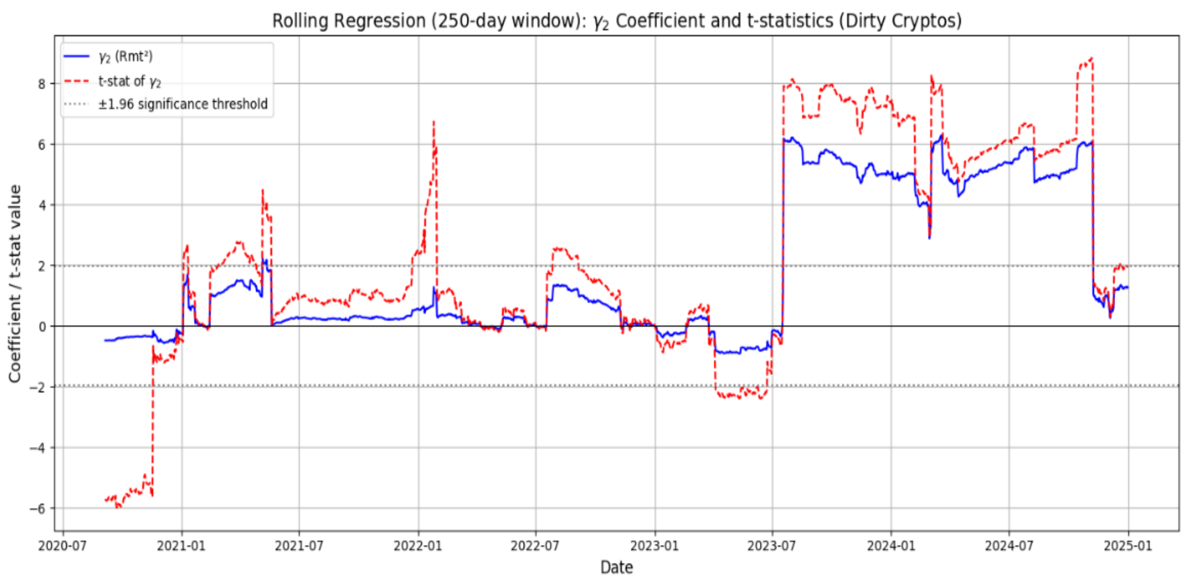

Fig. 2. Rolling regression results in the dirty cryptocurrencies with a 250-day window

Table 5 and Table 6 present the estimations of herding behavior incorporating the effect of investor risk aversion, measured through the sentiment variable $Sent_t$, designed to capture the aggregate risk aversion specific to the cryptocurrency market. The results show that the coefficient γ_2 is negative and significant for both segments (-0.325 for Clean and -0.231 for Dirty), providing robust evidence of herding behavior: when market returns are extreme, the dispersion among individual returns decreases, indicating investors' tendency to mimic market movements. Furthermore, the sentiment variable coefficient γ_3 is positive and significant, implying that risk aversion plays an amplifying role in dispersion: the higher the level of fear or uncertainty, the more divergent investment behaviors become.

Table 5 Estimation of Herding Behavior Based on Cryptocurrency Market-Specific Risk Aversion

	Clean	Dirty
γ_0	0.012708	0.009375
	0.0000***	0.0000***
γ_1	0.274270	0.256258
	0.0000***	0.0000***
γ_2	-0.325497	-0.231024
	0.0005***	0.0037***
γ_3	0.004555	0.009107
	0.0067***	0.0000***
Observations	1829	1829
Adj. R²	0.216287	0.279955

Eq (6) : $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 Sent_t + \varepsilon_t$
*Denote the rejections of the null hypothesis at the 10% significance level.
** Denote the rejections of the null hypothesis at the 5% significance level.
***Denote the rejections of the null hypothesis at the 1% significance level.

Table 6 Estimation of Herding Behavior on Cryptocurrency Market-Specific Risk Aversion

	Clean	Dirty
γ_0	0.012215	0.008424
	0.0000***	0.0000***
γ_1	0.283331	0.272124
	0.0000***	0.0000***
γ_2	-0.343068	-0.243771
	0.0002***	0.0023***
γ_3	0.037281	0.023419
	0.0000***	0.0001***
γ_4	0.016160	0.031030
	0.0408**	0.0000***
Observations	1829	1829
Adj. R²	0.225708	0.275560

Eq (7) : $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{UP} Sent_t + \gamma_4 D^{DOWN} Sent_t + \varepsilon_t$
**Denote the rejections of the null hypothesis at the 10% significance level.*
** Denote the rejections of the null hypothesis at the 5% significance level.
****Denote the rejections of the null hypothesis at the 1% significance level.*

The coefficients reported in Table 6 indicate that the effect of sentiment is more pronounced during downturns, especially for energy-intensive ("Dirty") assets, where γ_4=0.0310 compared to γ_4=0.01620 for "Clean" assets. This suggests that investors behave in a more emotional and less rational manner during periods of negative stress, which dampens the expected herding behavior. The results of Economou et al. (2018) show that herding behavior in the cryptocurrency market is indeed present but conditioned by the psychological climate of investors. Our findings corroborate the conclusions of Economou et al. (2018) and Polyzos et al. (2021), confirming that risk aversion, as measured by sentiment, plays a differentiated role depending on the market phase, reinforcing the idea that collective decisions are influenced not only by extreme returns but also by the perception of risk and prevailing market emotions.

Moreover, these conclusions align with the results of Chen and Nguyen (2024), who demonstrated that the asymmetric effect is more pronounced for "clean" assets, suggesting heightened sensitivity to external factors. Tables 7, 8, and 9 present the estimation results of equation 8, concerning the impact of recent financial crises such as COVID-19 and the Russia–Ukraine war on investor behavior in cryptocurrencies. Polyzos et al. (2021) identified herding behavior in the cryptocurrency market between January 2015 and June 2020, including during the COVID-19 lockdown. The authors highlight variations in herding behavior between bullish and bearish phases. These observations corroborate the findings of Stavroyiannis and Babalos (2019) and Ballis and Drakos (2020) but diverge from those of Coskun et al. (2020). Moreover, Polyzos et al. (2021) show that risk aversion in the cryptocurrency market does not deter investors from rational asset pricing theory in their decisions. In fact, these results contrast with those of Economou et al. (2018) in the stock market but align with the conclusions of Gurdgiev and O'Loughlin (2020). During periods of uncertainty, cryptocurrency investors appear to avoid correlated strategies, favoring a rational approach. However, our study reveals interesting dynamics in the cryptocurrency market, contrasting with Polyzos et al. (2021). The results shown in **T**able 7 indicate that for clean cryptocurrencies, the coefficient γ_2 is negative and highly significant, indicating strong herding behavior during the COVID-19 period. For dirty cryptocurrencies, γ_2 is positive and not significant (p = 0.6429), thus rejecting the herding behavior hypothesis.

Table 7 Herding Behavior During the COVID-19 Period

	Clean	Dirty
γ_0	0.016981	0.013337
	0.0000***	0.0000***
γ_1	0.275666	0.156371
	0.0000***	0.0000***
γ_2	-0.577270	0.041068
	0.0000***	0.6429
Observations	1829	1829
Adj. R^2	0.141113	0.115487

Eq (8) : $CSAD^{Crisis}{}_t = \gamma_0 + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2 D^{Crisis} R^2_{m,t} + \varepsilon_t$

**Denote the rejections of the null hypothesis at the 10% significance level.*

** Denote the rejections of the null hypothesis at the 5% significance level.

****Denote the rejections of the null hypothesis at the 1% significance level.*

Table 8 Herding Behavior During the Russo-Ukrainian Conflict Period

	Clean	Dirty
γ_0	0.021994	0.014522
	0.0000***	0.0000***
γ_1	-0.344498	-0.051965
	0.0000***	0.0825*
γ_2	4.228239	2.386538
	0.0000***	0.0000***
Observations	1829	1829
Adj. R^2	0.147552	0.082992

Eq (8) : $CSAD^{Crisis}{}_t = \gamma_0 + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2 D^{Crisis} R^2_{m,t} + \varepsilon_t$

**Denote the rejections of the null hypothesis at the 10% significance level.*

** Denote the rejections of the null hypothesis at the 5% significance level.

****Denote the rejections of the null hypothesis at the 1% significance level.*

Regarding the Israeli-Palestinian and Russo-Ukrainian conflict periods (Table 8 and 9), γ_2 is positive and significant for both categories of cryptocurrencies, indicating an absence of herding behavior, or even a dispersed or idiosyncratic behavior. The increase in dispersion with market returns suggests that investors reacted divergently to geopolitical uncertainty rather than converging around a common behavior. Thus, despite a major shock, the market did not exhibit a classic herd movement, especially for dirty assets.

Table 9 H*erding Behavior During the Israeli-Palestinian Conflict Period*

	Clean	Dirty
γ_0	0.020278	0.015049
	0.0000***	0.0000***
γ_1	-0.232149	-0.162452
	0.0000***	0.0003***
γ_2	4.112402	5.095129
	0.0000***	0.0000***
Observations	1829	1829
Adj. R^2	0.093808	0.065312

Eq (8) : $CSAD^{Crisis}{}_t = \gamma_0 + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2 D^{Crisis} R^2_{m,t} + \varepsilon_t$

**Denote the rejections of the null hypothesis at the 10% significance level.*

** Denote the rejections of the null hypothesis at the 5% significance level.

****Denote the rejections of the null hypothesis at the 1% significance level.*

Table 10 Chow Test for Structural Breaks (Clean vs. Dirty Equal Weights)

Geopolitical crisis	Clean F-statistic	p-value	Dirty F-statistic	p-value
COVID-19 (start of the period) 11/03/2020	16.37	0.0000	1.29	0.2775
COVID-19 (full period) 11/03/2020 – 31/12/2021	54.56	0.0000	1.74	0.1073
Russia–Ukraine Conflict 24/02/2022	86.93	0.0000	2.50	0.0579
Israëli–Palestinian Conflict 07/10/2023	30.07	0.0000	14.62	0.0000

In fact, herding behavior among cryptocurrency investors is observed only during the COVID-19 pandemic and only for clean cryptocurrencies, which could be explained by the heightened perception of these assets as “ethical” or sustainable during a health crisis. Conversely, during other crises (geopolitical or macroeconomic), reactions are divergent and non-herding, even though the negative γ_1 coefficients indicate some form of coordination that is not accompanied by a decrease in dispersion ($\gamma_2 > 0$). The Chow test (Table 10) applied to structural breakpoints in herding behavior reveals a clear differentiation between so-called “clean” and “dirty” cryptocurrencies in response to recent geopolitical shocks. For “clean” cryptocurrencies, the F-statistics are consistently high and significant (*p*-values effectively zero) during the various crises studied the COVID-19 pandemic (both at the onset and over the full period), the Russia-Ukraine war, and the Israeli-Palestinian conflict indicating major structural breaks in the dynamics of investor behavior. These breaks confirm that exogenous events significantly altered the formation process of herding behavior for these assets. In contrast, for “dirty” cryptocurrencies, the Chow test does not detect significant structural breaks during the initial and full periods of the COVID-19 crisis (*p*-values of 0.2775 and 0.1073 respectively), corroborating our finding of no notable evolution in herding behavior for these assets in that context. During the Russia-Ukraine war, the break is borderline significant ($p = 0.0579$), suggesting a possible but weak structural change. Only the Israeli–Palestinian conflict triggers a clear and significant break for this segment ($p = 0.0000$), indicating that this crisis had a more pronounced and unprecedented impact on investor behavior in energy-intensive cryptocurrencies. These conclusions confirm that “clean” cryptocurrencies are more sensitive to major exogenous events, leading to structural changes in investor herding, particularly during health and geopolitical crises. Conversely, the “dirty” segment exhibits greater behavioral inertia, with fewer and less pronounced breaks, consistent with the absence of herding behavior observed in previous analyses. Our results corroborate the findings of Kaiser and Stöckl (2020) and Bouri et al. (2019), which highlight stronger herding during crisis periods.

4. Conclusion

This study explored the dynamics of herding behavior in the cryptocurrency market across various periods of geopolitical and economic turmoil, including the COVID-19 pandemic, the Russo-Ukrainian war, and the Israeli-Palestinian conflict. By applying CSSD and CSAD methodologies to a panel of 17 major cryptocurrencies from December 2019 to December 2024, we identified context-dependent patterns of investor behavior. Overall, the findings show that herding tendencies emerge primarily during periods marked by heightened economic uncertainty, as reflected by the inclusion of sentiment indices. These patterns are especially noticeable in clean cryptocurrencies, which appear more sensitive to major external shocks. The findings imply that herding does not consistently occur across all market phases or during every shock. There were no consistent indications of herding during other geopolitical crises, although investor behavior did exhibit some convergence during the COVID-19 period, especially for clean assets. Furthermore, the asymmetric analysis indicates no discernible difference in herding between rising and falling markets.

Structural break analysis further reinforces the idea that clean cryptocurrencies are more prone to behavioral shifts during stress events. These insights underscore the heterogeneous nature of the cryptocurrency market and highlight the importance of considering both asset-specific characteristics and the nature of external shocks when evaluating market behavior. For policymakers and investors, these findings suggest that behavioral responses in crypto markets are primarily driven by crisis-induced sentiment rather than by price trends alone, warranting close monitoring especially in the case of assets promoted as environmentally sustainable.

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Declaration of Competing Interest

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix1

Descriptive Statistics of Cryptocurrency Returns over the Period from 30/12/2019 to 31/12/2024

Dirty equal weights

	CSAD	CSSD	R_{mT}	$\|R_{mt}\|$	R_{mt}^2	$\sum R_{it}$	D^{DOWN}	D^{UP}	SENT	COVID-19	Ukraine-Russia Conflict	Israel-Palestine conflict
Mean	0.015277	0.060556	0.002058	0.027082	0.001606	0.012348	0.050301	0.050301	-0.073203	0.361400	0.569710	0.247130
Median	0.012156	0.040790	0.002518	0.018242	0.000333	0.015108	0.000000	0.000000	-0.036290	0.000000	1.000000	0.000000
Maximum	0.149084	0.884652	0.254573	0.395628	0.156522	1.527437	1.000000	1.000000	0.301323	1.000000	1.000000	1.000000
Minimum	0.001459	3.16E-05	-0.395628	1.42E-05	2.00E-10	-2.373770	0.000000	0.000000	-0.667066	0.000000	0.000000	0.000000
Std. Dev.	0.012973	0.066053	0.040027	0.029540	0.005626	0.240163	0.218625	0.218625	0.198982	0.480537	0.495252	0.431461
Skewness	4.167690	3.439095	-0.685343	3.439095	16.00283	-0.685343	4.115021	4.115021	-1.059873	0.577013	-0.281591	1.172480
Kurtosis	30.61457	26.61515	13.46820	26.61515	372.4580	13.46820	17.93340	17.93340	3.864853	1.332944	1.079294	2.374710
Jarque-Bera	63408.61	46104.89	8494.326	46104.89	10480442	8494.326	22156.81	22156.81	399.4303	313.2812	305.3125	448.8539
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	27.94153	110.7576	3.763989	49.53233	2.936518	22.58394	92.00000	92.00000	-133.8886	661.0000	1042.000	452.0000
Sum Sq. Dev.	0.307658	7.975507	2.928772	1.595101	0.057862	105.4358	87.37233	87.37233	72.37738	422.1148	448.3619	340.2974
Observations	1829	1829	1829	1829	1829	1829	1829	1829	1829	1829	1829	1829

Clean equal weights

	CSAD	CSSD	R_{mT}	$\|R_{mt}\|$	R_{mt}^2	$\sum R_{it}$	D^{DOWN}	D^{UP}	SENT	COVID-19	Ukraine-Russia Conflict	Israel-Palestine conflict
Mean	0.020204	0.097956	0.002362	0.030976	0.002045	0.025981	0.050301	0.050301	-0.073203	0.361400	0.569710	0.247130
Median	0.015823	0.067112	0.003580	0.021223	0.000450	0.039384	0.000000	0.000000	-0.036290	0.000000	1.000000	0.000000
Maximum	0.200971	1.313326	0.209227	0.415310	0.172483	2.301494	1.000000	1.000000	0.301323	1.000000	1.000000	1.000000
Minimum	0.002787	2.26E-05	-0.415310	7.16E-06	5.13E-11	-4.568412	0.000000	0.000000	-0.667066	0.000000	0.000000	0.000000
Std. Dev.	0.016070	0.104194	0.045168	0.032949	0.006509	0.496843	0.218625	0.218625	0.198982	0.480537	0.495252	0.431461
Skewness	3.815172	3.120360	-0.565453	3.120360	14.26977	-0.565453	4.115021	4.115021	-1.059873	0.577013	-0.281591	1.172480
Kurtosis	27.25257	21.68936	11.29161	21.68936	314.8392	11.29161	17.93340	17.93340	3.864853	1.332944	1.079294	2.374710
Jarque-Bera	49261.76	29587.04	5336.856	29587.04	7472849.	5336.856	22156.81	22156.81	399.4303	313.2812	305.3125	448.8539
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	36.95399	179.1607	4.319992	56.65560	3.739514	47.51991	92.00000	92.00000	-133.8886	661.0000	1042.000	452.0000
Sum Sq. Dev.	0.472072	19.84535	3.729310	1.984535	0.077441	451.2465	87.37233	87.37233	72.37738	422.1148	448.3619	340.2974
Observations	1829	1829	1829	1829	1829	1829	1829	1829	1829	1829	1829	1829