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HERDING BEHAVIOR IN THE MARKET FOR CLEAN AND DIRTY CRYPTOCURRENCIES

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ABSTRACT: *In this article, we study the herding behavior of two types of cryptocurrencies, called dirty and clean, based on their energy consumption levels. Empirical results reveal that herding behavior generally only exists in the dirty cryptocurrency market and is more pronounced during bear market periods, high trading volume days, and high trading days. volatility. Moreover, we observe herding behavior in the cryptocurrency market only during the period of the Covid-19 pandemic.*

KEYWORDS: Herd behavior, Cryptocurrencies, Covid-19, Russia-Ukraine War.

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INTRODUCTION

Cryptocurrencies have recently become a popular topic of discussion among investors, portfolio managers, policymakers and academics due to their different characteristics and high performance. The theory of efficient markets suggests that price formation in markets is based on fundamental factors; however, this theory cannot explain the volatility of speculative markets (**Javaira and Hassan, 2015**). Therefore, excessive volatility in cryptocurrency markets could be explained by behavioral factors, such as herding behavior. Herding behavior refers to the investor's tendency to imitate the behavior of other investors.

It is essential to study herd behavior in cryptocurrency markets because the value of cryptocurrencies depends heavily on individuals' beliefs and decisions rather than fundamental factors (**Kumar, 2021).** Furthermore, the study of herd behavior is vital because it can lead to bubbles or stock market crashes (**Lux, 1995**).

A number of articles have studied the presence of herding behavior in the cryptocurrency market. **Stavros and Vassilios (2019)** extracted daily data for eight cryptocurrencies over a sample period from 2015 to 2018 and found the absence of clustering in the cryptocurrency market. Consistent with the above studies, **Silva et al. (2019)** also analyzed herding behavior in the digital currency market using the 50 most liquid cryptocurrencies during the same sample period from 2015 to 2018.

They found a weak herd effect in the currency market digital. **Ballis and Drakos (2020)** study herding behavior in six major cryptocurrencies between 2015 and 2018. The results of the CSAD model indicate clustering among investors in the largest sector of the cryptocurrency market, which becomes stronger over time the rise of the market.

A similar result is found by **Kallinterakis and Wang (2019),** who, using data for 296 cryptocurrencies, provide evidence of a herd that intensifies during days of market rise, low volatility, and volume pupil. Contrary to the results of **Ballis and Drakos (2020), Vidal-Thomas et al. (2019)** conclude that herding is only present during market declines by examining a set of 65 digital currencies. **Bouri et al. (2019)** use the static CSAD model and sliding windows approach to examine herding behavior in 14 cryptocurrencies from 2013 to 2018. Their CSAD model results reveal no evidence of herding, while the sliding windows approach shows significant herding behavior.

Yarovaya et al. (2021) study the presence of herding behavior in cryptocurrency markets during the Covid-19 pandemic. They conclude that the Covid-19 pandemic does not amplify the herding trend in the cryptocurrency markets. Based on a sample of the top 43 cryptocurrencies by market capitalization between 2013 and 2020,

Youssef and Waked (2022) find significant evidence of herding behavior for the entire sample period only in periods of high volatility. Additionally, during the COVID-19 crisis, the results suggest that investors in the cryptocurrency market are following the consensus.

Our study attempts to uncover the difference in market dynamics of two distinct types of cryptocurrencies based on their fundamental difference in energy consumption and efficiency, called Dirty and Clean, from a perspective closely that of the herd to establish whether there are distinct patterns, which adds to the literature from a new perspective.

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The remainder of this article is structured as follows: We present the data and empirical methodology in Section 2 and discuss the results in Section 3. Finally, we conclude our study in Section 4.

DATA AND METHODOLOGY

Data

We studied patterns of herding behavior in a sample of 6 of the top "Dirty" cryptocurrencies (Bitcoin, Ethereum, Bitcoin Cash, Ethereum Classic, Litecoin) as well as 8 clean "Clean" cryptocurrencies (Cardano, Cosmos, Hedera, Polygon, Ripple, Stellar, Tron, VeChain), all ranked in the top 50 in terms of market capitalization according to CoinMarketCap data. Similar to Ren and Lucey (2022), dirty cryptocurrencies are so called due to their reliance on PoW algorithms for consensus, which requires enormous energy flows to support mining activities and transaction, while clean cryptocurrencies are built on different types of energy-efficient consensus algorithms. including Proof-of-Stake (PoS), Proof-of-Authority (PoA), Ripple Protocol, Stellar Protocol and a few other alternatives. This analysis covered the period from October 1, 2019 to December 31, 2023.

The period examined encompasses several major global events that could influence investors in cryptocurrencies. These events include the Covid-19 pandemic (March 11, 2020-February 23, 2022) and more recently, the Russian invasion (February 24, 2022-December 31, 2023).

To detect herding behavior, we first use the absolute transverse deviation (CSAD) of yields, proposed by Chang et al. (2000) and calculated as follows:

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

Where: N is the number of clean or dirty cryptocurrencies in the respective market portfolio, R_(i,t) is the logarithmic return of the individual clean or dirty cryptocurrency i in the respective portfolio at time t, R_(m,t) is the return on the market portfolio at time t. Chang et al. (2000) propose the following model to estimate the herd on the market:

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

A significant negative value of γ_2 indicates the presence of a herd (Chang et al., 2000).

Chiang and Zheng (2010) propose the following equations to detect herding under rising and falling market conditions:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2(1 - D^{up})\left|R_{m,t}\right| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t \quad (3)$$

With: D^up= 1 when R_(m,t) > 0 and 0 otherwise. Negative estimates of coefficients γ_3 and γ_4 reflect the presence of asymmetric mimetic behavior in bullish and bearish markets.

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The following equations can be used to estimate herding behavior during high and low trading volumes:

$$CSAD_t = \alpha + \gamma_1 D^{volume}\left|R_{m,t}\right| + \gamma_2(1 - D^{volume})\left|R_{m,t}\right| + \gamma_3 D^{volume}(R_{m,t})^2 + \gamma_4(1 - D^{volume})(R_{m,t})^2 + \varepsilon_t \quad (4)$$

With: 〖D〗^volume= 1 when the trading volume of day t is greater than the moving average of the trading volume of the last 30 days, and 0 otherwise.

The following equations can be used to estimate herding behavior during periods of high and low market volatility:

$$CSAD_t = \alpha + \gamma_1 D^{volatilité}\left|R_{m,t}\right| + \gamma_2(1 - D^{volatilité})\left|R_{m,t}\right| + \gamma_3 D^{volatilité}(R_{m,t})^2 + \gamma_4\left(1 - D^{volatilité}\right)(R_{m,t})^2 + \varepsilon_t \quad (5)$$

With: D^volatility = 1 when the volatility of day t is greater than the moving average of the last 30 days, and 0 otherwise. We use a measure of historical volatility proposed by Garman and Klass (1980) . The expression of the Garman and Klass (1980) measure is as follows:

$$Volatilité = \left[\frac{1}{2}(Ln\frac{H_t}{L_t})^2 - (2Ln2 - 1)(Ln\frac{C_t}{O_t})^2\right]$$

Where H_t and L_t are respectively the maximum and minimum prices reached on day t by the cryptocurrency, while C_t and O_t are, respectively, the closing and opening prices of cryptocurrency on day t.

The following regression model is used to determine whether the two recent stock market crises, namely, the Covid-19 pandemic and the Russian invasion of Ukraine have caused herd behavior:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \gamma_3 D^{crisis} R_{m,t}^2 + \varepsilon_t \quad (6)$$

With D^crisis designates the dummy variable which is worth 1 on crisis days and 0 otherwise. The two crises unfold in distinct regressions. A significant and negative γ_3 coefficient means that the crisis in question caused herd behavior.

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EMPIRICAL RESULTS

Table 1 presents the results of herding behavior in both types of cryptocurrencies during the full sample period. The coefficient

γ_1 is significantly positive in cryptocurrency markets, indicating that 〖CSAD〗_t is an increasing function of absolute market returns |R_(m,t)|. According to the CCK model, herd behavior is only evident if the coefficient γ_2 turns out to be statistically significant and negative. The results in Table 1 show that herd behavior only exists in the dirty cryptocurrency market captured by a significantly negative coefficient γ_2.

Table 1 : Herd behavior throughout the sampling period (equation (2)).

Market	α	γ_1	γ_2	Adj. R^2
Dirty Crypto	0.001494*** (0.0000)	0.042115*** (0.0000)	**-0.040040**** **(0.0484)**	0.2806
Clean Crypto	0.004423*** (0.0000)	0.050083*** (0.0000)	0.143977*** (0.0018)	0.2721

***, ** denote the 1% and 5% significance levels, respectively.

Table 2 presents the estimated coefficients of equation (3), in which we test the existence of herding behavior conditioned on rising and falling market days. The results in Table 3 confirm that the degree of breeding varies depending on market conditions.

Herd behavior in the dirty cryptocurrency market only occurs in bear markets, because only the coefficient γ_4 is significantly negative at the 5% threshold.

No evidence of herding is found in clean rising and falling cryptocurrency markets.

Table 2: Asymmetric herding behavior using Eq. (3).

Market	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Dirty Crypto	0.001533*** (0.0000)	0.034839*** (0.0001)	0.044850*** (0.0000)	0.007402 (0.9149)	**-0.048171**** **(0.0248)**	0.3345
Clean Crypto	0.004384*** (0.0000)	0.048319*** (0.0015)	0.059195*** (0.0000)	0.086729 (0.5207)	0.126110*** (0.0091)	0.3191

***, ** denote the 1% and 5% significance levels, respectively.

The results presented in Table 3 show that the coefficient γ_3 is negative and statistically significant in dirty cryptocurrencies, this means that herding behavior was present during periods of high transaction volume.

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Table 3: Herd behavior during high/low volume periods (equation 4).

Market	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Dirty Crypto	0.001709*** (0.0000)	0.044384*** (0.0000)	0.008938 (0.4407)	**-0.050262**** **(0.0156)**	0.231632* (0.0587)	0.3016
Clean Crypto	0.004324*** (0.0000)	0.048297*** (0.0000)	0.049115*** (0.0000)	0.131457 (0.1008)	0.158743*** (0.0007)	0.2820

***, **, * denote the 1% and 5% significance levels, respectively.

Looking at the results presented in Table 4, we observe significant herding behavior only during periods of high volatility in the dirty cryptocurrency market (the coefficient γ_2 is negative and statistically significant). Our findings are consistent with those of Youssef (2020), who concludes that cryptocurrency market rallying increases with volatility.

Table 4: Herding behavior during periods of high/low volatility (equation 5).

Market	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Dirty Crypto	0.001709*** (0.0000)	0.044384*** (0.0000)	0.008938 (0.4407)	**-0.050262**** **(0.0156)**	0.231632* (0.0587)	0.3004
Clean Crypto	0.004324*** (0.0000)	0.048297*** (0.0000)	0.049115*** (0.0000)	0.131457 (0.1008)	0.158743*** (0.0007)	0.2970

***, **, * désignent les niveaux de signification de 1%, 5% et 10%, respectivement.

Table 5 presents the results of herd behavior during crisis periods. The herd phenomenon is only evident during the crisis period if the coefficient γ_3 turns out to be statistically negative. The results of Panel A reveal that the coefficient γ_3 is negative and statistically significant, which proves the presence of herd behavior only in the own cryptocurrency market during the Covid-19 period.

These results can be explained by the nature of traders in the cryptocurrency market, who are young and lack knowledge and experience, guided by market sentiment and therefore tend to flock together to avoid losses during trading periods. stress. Referring to Panel B, the γ_3 coefficients also show anti-herding behavior in both cryptocurrency markets during the crisis caused by the Russian invasion of Ukraine in 2022.

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Table 5: Herd behavior during periods of crises (equation 6).

Market	α	γ_1	γ_2	γ_3	Adj. R^2
Panel A : Covid-19 Crisis					
Dirty Crypto	0.001517*** (0.0000)	0.040278*** (0.0000)	0.001699 (0.9771)	0.035167 (0.4900)	0.2803
Clean Crypto	0.004462*** (0.0000)	0.046062*** (0.0000)	0.265309** (0.0213)	**-0.4275**** **(0.0440)**	0.2732
Panel B : Russia-Ukraine Conflict					
Dirty Crypto	0.001549*** (0.0000)	0.037572*** (0.0000)	0.031823 (0.1236)	0.115027** (0.0435)	0.2802
Clean Crypto	0.004428*** (0.0000)	0.049609*** (0.0000)	0.144701*** (0.0018)	0.018431 (0.8634)	0.2718

***, ** denote the 1% and 5% significance levels, respectively.

CONCLUSION

The environmental sustainability of cryptocurrencies is the subject of significant debate. The present study attempts to comprehensively investigate the herding behavior in two categories of cryptocurrency markets, namely, clean cryptocurrencies (Clean) and dirty cryptocurrencies (Dirty) in normal, asymmetric and of crisis.

Empirical results reveal that herding behavior only exists in the cryptocurrency market and is more pronounced during periods of bear markets, high volatility, and high dirty trading volume.

The results of this study show the absence of herd behavior in the market for clean cryptocurrencies. In addition, the Covid-19 pandemic amplifies the herding trend in these markets.

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