Herding in Crypto-Economy: Green vs. Dirty Cryptos

Vladimir Guimarães Farias Sodré [a]

[a] School of Public Policy and Government, Getulio Vargas Foundation, SGAN 602 Módulos A, B, C, Asa Norte, Brasília 70830-020, Brazil, sodre.vladimir@gmail.com.

Abstract. In this paper, we investigate the herding behaviour of cryptocurrencies, dividing them into two main groups: the clean (sustainable) cryptocurrencies and the dirty (non-sustainable) cryptocurrencies, classified according to their energy efficiency levels. The main goal of this work is to develop a preliminary study of the herding behaviour in the cryptocurrency industry. We used different models and methodologies in order to verify the existence of herding in the crypto market, and also to compare herding behaviours between the clean and the dirty cryptocurrencies. Our main questions are as follows. Is there herding in crypto? How do both markets (clean and dirty cryptos) compare in terms of herding effects? We used different methodologies and compared the results with the still early academic work in the area, since not many researchers studied the herding effects separately in the dirty and clean crypto segments. We used a five-year analysis period to study herding processes in the crypto market from 2017 to 2022. Our empirical results initially do not detect herding behaviour in both crypto markets, but with a deeper investigation, using a two-stage Markov-switching methodology, we verified the herding behaviour in the dirty cryptos and did not find herding behaviour in the clean crypto market. This result is consistent with the work by Lucey and Ren [9].

Keywords: herding, cryptocurrencies, clean crypto, dirty crypto, Huber-White, Newey-West, Markov-switching, regime-switching, CSSD, CSAD

1. Introduction

Bitcoin is the first decentralised virtual currency and has a lifespan of less than 15 years. By the end of 2022 there were more than 1000 different cryptocurrency coins in circulation. The total market capitalisation for all crypto assets at the beginning of 2021 was close to 3 trillion US dollars. The high profitability of this market also reflects the huge volatility of this asset. As in many other financial markets, it is reasonable to expect herding behaviour in the crypto market. That is, investors tend to follow the trading movements of others, which could be completely irrational, instead of trading based on economic and financial fundamentals.

Therefore, studying herding effects in financial markets is crucial to understanding market dynamics, assessing market efficiency, managing risk, and informing policy decisions. Provides valuable insights into investor behaviour and the functioning of financial markets, contributing to the development of more robust and resilient financial systems. Among other things, understanding herding behaviour helps researchers evaluate the efficiency and rationality of financial markets. If markets consistently exhibit herding behaviour, it may suggest that market participants are not making decisions based on rational analysis of fundamental information, but instead follow the crowd or react emotionally to market movements. This challenges the efficient market hypothesis and highlights potential inefficiencies in market pricing. Herding behaviour can exacerbate systemic risk and lead to market instability.

If many investors follow the same strategy or trade based on similar signals, it increases the likelihood of large-scale market movements and systemic crises. Understanding herding effects helps regulators and market participants identify and mitigate these sources of systemic risk. Therefore, central banks and regulators may need to take into account the potential impact of herding on market stability and asset prices when formulating policy responses to economic developments.

Hence, a number of papers have investigated the presence of herding behaviour in the cryptocurrency market. However, their results are not often homogeneous due to differences in the market portfolio used, time frames, and methodology.

For example, Vidal-Tomás et al. [11] discovered the existence of herding behaviour in crypto market downturns from January 2015 to December 2017 using 65 cryptocurrencies. However, their results using equal-weighted portfolio are consistent with value-weighted approach only after excluding the largest player, Bitcoin. Kallinterakis and Wang [7] found a consistent herding of the top 296 cryptocurrencies using an equal-weighted portfolio, but rejected herding when using a value-weighted portfolio.

Furthermore, previous studies treat all cryptocurrencies as the same, but these assets are actually intrinsically different, especially from a sustainability perspective [5], [6]. The energy consumption of activities related to conventional cryptocurrencies such as Bitcoin and Ethereum is huge and has attracted much criticism [8].

Using a value-weighted approach, we divided the crypto market into sustainable (clean cryptos) and not sustainable (dirty cryptos) cryptocurrencies using data from a 5-year period trying to answer 2 questions: Is there herding in crypto? How do both markets (clean and dirty cryptos) compare regarding the herding behaviour?

2. Data and Methodology

2.1 Data

We collected daily closing price data for eight major dirty cryptos (Bitcoin, Ethereum, Bitcoin Cash, Ethereum Classic, Litecoin, Monera, Dogecoin and Binance Coin) and six clean cryptocurrencies (Cardano, Ripple, Stellar, Tron, Nano and Iota) ranked in the top 50 by market capitalisation from CoinMarketCap, spanning from October 2017 to December 2022. According to Lucey and Ren [8], dirty cryptocurrencies are determined based on their reliance on Proof-of-Work (PoW) algorithms for consensus, which requires huge energy capacity to support mining and transaction activities, while clean cryptocurrencies are built on different kinds of energy-efficient consensus algorithms, including Proof-of-Stake (PoS), Proof-of-Authority (PoA) and others.

2.2 Methodology

Christie and Huang [4] suggested that the degree of dispersion of the asset returns in a market portfolio, defined in the Equation 1, can be used to detect the existence of herding behaviour in that market:

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

The CSSD approach has been criticised for its high sensitivity to outliers, as it squares the difference between individual and market returns when calculating dispersions, and its limited use in the spells of normal market [8]. To correct for this, Chang et al. [3] proposed the use of cross-sectional absolute deviation of returns in measuring dispersions, expressed as:

$$CSAD_{\mathrm{m,t}} = \frac{\sum_{i=1}^{N}|r_{\mathrm{i,t}} - r_{\mathrm{m,t}}|}{N} \quad (2)$$

A general quadratic regression of $CSAD_{\mathrm{m,t}}$ on market returns was then built to discover the presence of herding behaviour in the full sample:

$$CSAD_{\mathrm{t}} = \beta_0 + \beta_1 * |R_{\mathrm{m,t}}| + \beta_2 * R^2_{\mathrm{m,t}} + \varepsilon_{\mathrm{t}} \quad (3)$$

$$CSAD_{\mathrm{t}} = \beta_0 + \beta_1 * |R_{\mathrm{m,t}}| + \beta_2 * R^2_{\mathrm{m,t}} + \beta_3 * CSAD_{\mathrm{t-1}} + \varepsilon_{\mathrm{t}} \quad (4)$$

As suggested by Chang et al. [3], the effects of the herding behaviour would lead to a non-linear relationship between $CSAD_{\mathrm{m,t}}$ and $R_{\mathrm{m,t}}$ which is inferred by a significantly negative coefficient β_2.

Therefore, we used the models described above to test herding in clean and dirty cryptos. We go further, testing the robustness of the results including the $CSAD_{\mathrm{t-1}}$ term in the regression to control for autocorrelation in the time series (Equation 4).

We also analysed the dynamics of the herding coefficients of the clean and dirty markets, using a 240-day rolling window regression in the data, to observe the behaviour of the herding coefficient through the time. Finally, we verify herding in two stages using the Markov-Switching methodology in two stages, as in Youssef and Waked [12]:

$$CSAD_{\mathrm{t}} = \beta_{0,\mathrm{st}} + \beta_{1,\mathrm{st}} * |R_{\mathrm{m,t}}| + \beta_{2,\mathrm{st}} * R^2_{\mathrm{m,t}} + \varepsilon_{\mathrm{t,st}} ,$$

$$\varepsilon_{\mathrm{t,st}}\ \mathrm{N}\ (0, \sigma^2_{\mathrm{st}}) \quad (5)$$

Where st 1,2 follows a two-state Markov process that represents a tranquil period (low volatility) and a crisis period (high volatility).

3. Results

We measured herding in the clean crypto industry evaluating the model as in Equation 3, using the methods: standard OLS; OLS with Huber-White-Hinkely heteroskedasticity consistent covariance matrix; OLS with Newey-West heteroskedasticity consistent covariance matrix; and using GARCH models, in order to verify the robustness of our findings.

The results in Table 1 demonstrate consistency for anti-herding behaviour in clean cryptocurrencies, according to the findings of Lucey and Ren [9].

We can verify that the β_2 coefficient is statistically significant in almost all equations with a positive relation with the dispersion of the returns, which implies an anti-herding behaviour inside this market, in the evaluation period.

Therefore, we develop the robustness check using the model as in Equation 4, which reinforced the robustness of our achievements. Both equations, 3 and 4, showed that the methodology with Huber-White standard errors does not provide significant coefficients for the herding parameter, contrary to the other methods we used.

Tab. 1 – Herding – Clean Cryptos

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{CLt} = \beta_0 + \beta_1 * \lvert R_{CLm,t} \rvert + \beta_2 * R^2_{CLm,t} + \varepsilon_t$, OLS				
β_0	0,0099	0,0009	10,6914	0,0000
β_1	0,8867	0,0130	68,0309	0,0000
β_2	0,2446	0,0187	13,0793	0,0000

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{CLt} = \beta_0 + \beta_1 * \lvert R_{CLm,t} \rvert + \beta_2 * R^2_{CLm,t} + \varepsilon_t$, OLS HW				
β_0	0,0099	0,0014	7,3070	0,0000
β_1	0,8867	0,0396	22,3953	0,0000
β_2	0,2446	0,0986	2,4818	0,0132

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{CLt} = \beta_0 + \beta_1 * \lvert R_{CLm,t} \rvert + \beta_2 * R^2_{CLm,t} + \varepsilon_t$, OLS NW				
β_0	0,0099	0,0016	6,2281	0,0000
β_1	0,8867	0,0435	20,3683	0,0000
β_2	0,2446	0,0923	2,6502	0,0081

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{CLt} = \beta_0 + \beta_1 * \lvert R_{CLm,t} \rvert + \beta_2 * R^2_{CLm,t} + \varepsilon_t$, GARCH				
β_0	0,0040	0,0004	10,6112	0,0000
β_1	0,9982	0,0072	138,1916	0,0000
β_2	0,0703	0,0193	3,6448	0,0003

Therefore, we used several models and methods to attest to the anti-herding behaviour in clean cryptocurrencies. The study by Lucey and Ren [9] achieved the same results for clean crypto, but using a narrower time period.

We use a value-weighted portfolio, which means that we consider the market capitalisation of each cryptocurrency when analysing its volatility. This method makes more sense for us, in the way that the coins show great differences in their market capitalisation. Therefore, we preferred to consider the market cap of the assets in order to increase the soundness of the results.

Through the outcomes in Table 1, we verified that the intensity of the anti-herding stays around 0,25 in most of the results. The calculations using the lagged term of the dispersion (Equation 4) did not show significance for this term, as mentioned.

Table 2 shows the outcomes for the evaluation of the dirty cryptos. Observing the results, we find out that there is no herding behaviour, as well. Nevertheless, we observe that the anti-herding intensity in dirty cryptos is much weaker than that in the clean cryptos. The anti-herding intensity in the dirty cryptos segment is around 0,01, in most of the results, when the anti-herding intensity observed in the clean cryptos market is about 0,25, which is an effect 25 times stronger in the the clean cryptos sector than in the dirty cryptos segment. We also ran Equation 4 for the dirty market and the results were similar to those using Equation 3.

Tab. 2 – Herding – Dirty Cryptos

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{DTt} = \beta_0 + \beta_1 * \lvert R_{DTm,t} \rvert + \beta_2 * R^2_{DTm,t} + \varepsilon_t$, OLS				
β_0	0,0369	0,0033	11,2082	0,0000
β_1	1,2602	0,0096	130,8785	0,0000
β_2	0,0109	0,0039	2,8057	0,0051

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{DTt} = \beta_0 + \beta_1 * \lvert R_{DTm,t} \rvert + \beta_2 * R^2_{DTm,t} + \varepsilon_t$, OLS HW				
β_0	0,0369	0,0036	10,1947	0,0000
β_1	1,2602	0,0143	88,2575	0,0000
β_2	0,0109	0,0056	1,9707	0,0489

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{DTt} = \beta_0 + \beta_1 * \lvert R_{DTm,t} \rvert + \beta_2 * R^2_{DTm,t} + \varepsilon_t$, OLS NW				
β_0	0,0369	0,0047	7,8944	0,0000
β_1	1,2602	0,0192	65,8004	0,0000
β_2	0,0109	0,0053	2,0717	0,0384

Variable	Coeff.	Std. Error	t-statistics	Prob.
$CSAD_{DTt} = \beta_0 + \beta_1 * \lvert R_{DTm,t} \rvert + \beta_2 * R^2_{DTm,t} + \varepsilon_t$, GARCH				
β_0	0,0239	0,0022	10,9128	0,0000
β_1	1,2704	0,0063	202,0309	0,0000
β_2	0,0127	0,0035	3,6097	0,0003

Following this preliminary analysis, which shows evidence of stronger anti-herding effects in clean cryptos, backing up the findings from academia, and weaker anti-herding signals for the dirty cryptos, we drew the graphs below of the herding dynamics through the time, to have a time perspective of this process.

In Figure 1, we plotted the herding behaviour of clean cryptos, during the study period. The blue line is the herding coefficient for the clean cryptos, and the green and red lines represent the 95% confidence interval for this coefficient. As explained previously, the negative value of the coefficient for the squared return indicates herding behaviour within this market. In the clean crypto market, we observe that the blue line is positive most of the time, which is consistent with our previous outcomes indicating anti-herding movements in this market.

In Figure 2, it is possible to observe a period with consistent negative values for the herding coefficient, indicating herding behaviour for dirty cryptos.

Thus, we used a Markov-Switching model with two regimes, as in Equation 5, to detect herding.

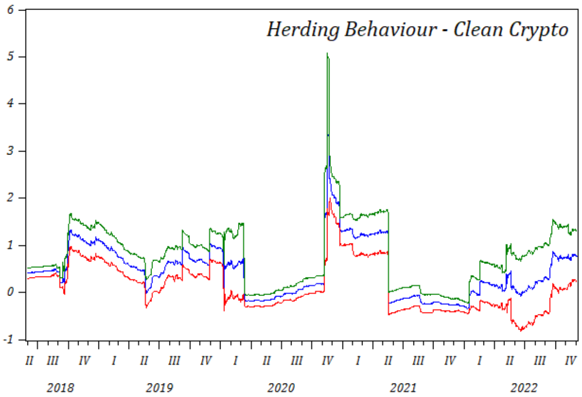

Fig. 1 – Herding behaviour – Clean Cryptos

The results in Table 3 show no evidence of herding behaviour in both regimes for the clean cryptos, strengthening our preliminary findings.

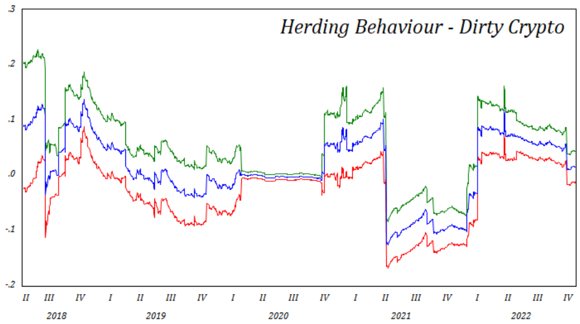

Fig. 2 – Herding behaviour – Dirty Cryptos

Using the same methodology for the dirty crypto market, we achieved the results in Table 4. In our results, we realised that the value of coefficient β_2 is negative and statistically significant in the first regime, indicating the herding behaviour of dirty cryptos, when analysed in a two-regime model. This fact can occur because the switching-regimes model can isolate two distinct processes occurring in the time period. When we run the model in just one regime, these distinct behaviours may not be captured. We checked the robustness of these results using the lagged term of the dispersion in the model, and the results supported our findings.

Tab. 3 – Markov-switching model – Clean Cryptos

$CSAD_{CLt} = \beta_0 + \beta_1 * |R_{CLm,t}| + \beta_2 * R^2_{CLm,t} + \varepsilon_{t,st}$, $\varepsilon_{t,st}$ N(0, σ^2_{st})

Variable	*Coeff.*	*Std. Error*	*z-statistics*	*Prob.*
		Regime 1		
β_0	0,0883	0,0063	14,1325	0,0000
β_1	1,0121	0,0329	30,7743	0,0000
β_2	0,2126	0,0287	7,4203	0,0000
		Regime 2		
β_0	0,0097	0,0007	14,7954	0,0000
β_1	0,8530	0,0103	82,7061	0,0000
β_2	0,0752	0,0178	4,2315	0,0000

Tab. 4 – Markov-switching model – Dirty Cryptos

$CSAD_{DTt} = \beta_0 + \beta_1 * |R_{DTm,t}| + \beta_2 * R^2_{DTm,t} + \varepsilon_{t,st}$, $\varepsilon_{t,st}$ N(0, σ^2_{st})

Variable	*Coeff.*	*Std. Error*	*z-statistics*	*Prob.*
		Regime 1		
β_0	0,0219	0,0034	6,3983	0,0000
β_1	1,3347	0,0235	56,7864	0,0000
β_2	-0,0869	0,0221	-3,9329	0,0001
		Regime 2		
β_0	0,4048	0,0968	4,1813	0,0000
β_1	1,2248	0,1145	10,6998	0,0000
β_2	0,0093	0,0182	0,5116	0,6090

Thus, the above results show the herding of dirty cryptos in the first regime, which represents the period of the crypto bubble burst, in 2021. This result is also consistent with Lucey and Ren [9], who found herding in dirty crypto, mainly in periods of greater volatility in the market.

Finally, our outcomes, obtained for a longer period of time (5 years) compared with the usual works in the area, proved very consistent with the literature, including the reference paper in analysing herding behaviour in the crypto market for clean and dirty cryptos. Empirical results from Lucey and Ren [9] revealed that herding generally exists only in the dirty cryptocurrency market and is more significant in down markets, supporting our analysis in two regimes.

4. Conclusions

We found evidence of herding behaviour in dirty cryptos. The results for clean cryptos remain consistent with no herding behaviour. These outcomes are consistent with the reference paper in the field, which performed these analyses in a narrower time window.

Our analysis in two regimes is consistent with herding behaviour for dirty cryptos in the first regime, which represents the period of crypto bubble burst, in 2021. This result indicates that herding occurs mainly in periods of more volatility of the market. We did not find herding processes in clean cryptos. These outcomes find support in the literature, as mentioned throughout the text.

For a continuation of our work, we suggest the following:

- analysis of asymmetric herding, which means analysing herding behaviour when the market is in the 10% upside and in the 10% downturn;

- spillover analysis, which means analysing the contagion of one market in another one; in this way, it is possible to analyse the effect of the crypto market in other markets, like the energy market, for example;

- deeper analysis of herding in turmoil, in financial and crypto-crisis moments vs. tranquil periods.

References

[1] Bikhchandani S., Sharma S. Herd behaviour in financial markets. *IMF Staff Paper*. 2001; 47(3):279-310.

[2] Bouri E., Gupta R., Roubaud D. Herding behaviour in cryptocurrencies. *Finance Research Letter*. 2019; 29:216–221.

[3] Chang E.C., Cheng J.W., Khorana A. An examination of herd behaviour in equity markets: An international perspective. *Journal of Banking and Finance*. 2000; 24(10):1651–1679.

[4] Christie W.G., Huang R.D. Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*. 1995; 51(4):31–37.

[5] Corbet S., Lucey B., Yarovaya L. Bitcoin-energy markets interrelationships - New evidence. *Resources Policy*. 2021; 70:101916.

[6] Gallersdörfer U., Klaaßen L., Stoll C. Energy consumption of cryptocurrencies beyond bitcoin. *Joule*. 2020; 4(9):1843–1846.

[7] Kallinterakis V., Wang Y. Do investors herd in cryptocurrencies – and why? *Research in International Business and Finance*. 2019; 50:240–245.

[8] Lucey B., Ren B. A clean, green haven? – Examining the relationship between clean energy, clean and dirty cryptocurrencies. *Energy Economics*. 2022; 105951.

[9] Lucey B., Ren B. Do clean and dirty cryptocurrency markets herd differently? *Finance Research Letters*. 2022; 47:102795.

[10] Stavroyiannis S., Babalos V. Herding behaviour in cryptocurrencies revisited: Novel evidence from a TVP model. *Journal of Behavioural and Experimental Finance*. 2019; 22:57–63.

[11] Vidal-Tomás D., Ibáñez A.M., Farinós J.E. Herding in the cryptocurrency market: CSSD and CSAD approaches. *Finance Research Letters*. 2019; 30:181–186.

[12] Youssef M., Waked S.S. Herding behaviour in the cryptocurrency market during COVID-19 pandemic: The role of media coverage. *The North American Journal of Economics and Finance*. 2022; 62:101752.

[13] Youssef M. What drives herding behaviour in the cryptocurrency market? *Journal of Behavioural Finance*. 2020; 1–10.