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Do clean and dirty cryptocurrency markets herd differently?

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ABSTRACT

In this paper, we investigate the herding behaviour of two types of cryptocurrencies, referred to as "black/dirty" and "green/clean" based on their energy usage levels. Empirical results reveal that herding generally exists only in the dirty cryptocurrency market, and is more significant in down markets. Moreover, we find that clean cryptocurrencies do herd, but with dirty cryptocurrencies, when the two markets are both positive. Our findings are robust across value- and equal-weighted portfolios and provide valuable insights to investors and policy makers.

1. Introduction

It has only been 13 years since the birth of Bitcoin, the first decentralised virtual currency, and as of the time of writing (November 2021) there are more than 1000 different cryptocurrency coins in circulation. If we calculate for all crypto assets, including stablecoins and tokens, the total market capitalisation of over 7000 kinds is worth more than 2.6 trillion U.S. Dollar.[1]

Investing in cryptocurrencies can be extremely rewarding, but this reflects the extremely volatile nature of the asset. As in many other financial markets, we could reasonably expect the herding phenomenon to be observed in the crypto market. That is, investors tend to follow others' moves or mimic others' trading decisions, which could be completely irrational or somewhat rational (Bikhchandani and Sharma, 2001). A number of papers have investigated the presence of herding behaviour in the cryptocurrency market as well as its possible driving forces (see, e.g., Bouri et al. (2019), Poyser (2018), Vidal-Tomás et al. (2019), Youssef (2020), Amirat and Alwafi (2020), Stavroyiannis and Babalos (2019) and Kallinterakis and Wang (2019), etc.). However, their results are not always consistent due to differences in constructing the market portfolio, assets under investigation and time frames. For example, Vidal-Tomás et al. (2019) discovered the existence of herding behaviour in crypto market downturns from January 2015 to December 2017 using 65 cryptocurrencies. However, their results of using equal-weighted portfolio are consistent to value-weighted approach only after excluding the largest player, Bitcoin. Kallinterakis and Wang (2019) found significant herding of top 296 cryptocurrencies from December 2013 to July 2018 using equal-weighted portfolio, but the herding was insignificant and vanished when using value-weighted portfolio with and without Bitcoin, respectively.

Moreover, past studies treat all cryptocurrencies as the same, but these assets are actually different intrinsically, especially from a sustainability perspective (Corbet et al., 2021; Gallersdörfer et al., 2020). The energy consumption of activities related to

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[1] Obtained from CoinMarketCap at https://www.coinmarketcap.com on Nov 17, 2021.

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conventional cryptocurrencies such as Bitcoin and Ethereum is huge and has attracted much negative commentary.[2] Gallersdörfer et al. (2020) studied the top 20 Proof-of-Work (PoW) based cryptocurrencies beyond Bitcoin. They found that the estimated energy consumption of these cryptos are all extremely high, even in conservative modelling. Both Corbet et al. (2021) and Gallersdörfer et al. (2020) suggested that future practitioners should distinguish between cryptocurrencies that are built on energy-intensive or energy-efficient algorithms. In fact, there exist a number of energy-efficient cryptocurrencies with more being developed, such as Cardano, Ripple, and IOTA which have or had been the top 10 cryptocurrencies by market capitalisation. The estimated energy consumption of Cardano, XRP, IOTA is 0.5479, 0.0079, and 0.00011 KWh per transaction, respectively, compared to the 707 KWh per transaction of Bitcoin.[3] With policy globally moving towards greater environmentally conscious actions, more environmentally conscious investors are perhaps likely to switch from energy-intensive cryptocurrencies to [altcoins] that are more sustainable.

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, termed black ("dirty") and green ("clean"), from a narrow perspective – herding – to establish if there are distinct patterns, which adds to the literature from a novel angle. If clean cryptocurrencies display different characteristics from dirty, this might provide opportunities for investors or regulators to increase usage of cleaner cryptocurrencies. However, if the two markets display similar dynamics then, given the larger size of the dirty market it is likely that the still predominantly retail crypto investors will, at the margin, prefer trading dirty cryptocurrencies.

The remainder of this paper is structured as follows. We describe the data in Section 2. We present the empirical methodology and discuss the results in Section 3, followed by Section 4 where we check the robustness of previous results. Finally, we conclude and address implications of our study in Section 5.

2. Data

We collected daily closing price data for 6 major "dirty" (Bitcoin, Ethereum, Bitcoin Cash, Ethereum Classic, Litcoin, and Monera)[4] and 12 "clean" cryptocurrencies (Cardano, Ripple, Polygon, Algorand, Stellar, VeChain, TRON, Cosmos, Hedera, Tezos, EOS, and IOTA)[5] ranked in the top 50 by market capitalisation[6] from CoinMarketCap, spanning from November 1, 2019 to November 1, 2021.[7] Similar to Ren and Lucey (2022), the dirty cryptocurrencies are so termed based on their reliance on PoW algorithms for consensus which requires tremendous energy inflows 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), Ripple Protocol, Stellar Protocol, and some other alternatives. We calculated the respective value-weighted portfolio returns based on end of day market capitalisation of these assets.

3. Empirical analysis

We tested whether the phenomenon of herding exists in the clean and dirty cryptocurrency markets using both cross-sectional standard deviation of returns (CSSD) approach introduced in Christie and Huang (1995) and the cross-sectional absolute deviation of returns (CSAD) approach proposed in Chang et al. (2000).

Christie and Huang (1995) suggested that the degree of the dispersion of asset returns in a market portfolio can be used to detect the existence of herding behaviour in that market, which in our case is defined as:

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

where N is the number of clean or dirty cryptocurrencies in the respective market portfolio, $R_{i,t}$ is the logarithmic return of individual clean or dirty cryptocurrency i in the respective portfolio at time t, $R_{m,t}$ is the market portfolio return at time t.

According to Christie and Huang (1995), herding in the market usually leads to low return dispersions, but low dispersions are not necessarily attributable to herds. Hence, it is hard to verify the presence of herds with the use of the return dispersion (CSSD) during the condition of a normal market. It is reasonable to test the presence of herding under market stress as rational investors

[2] https://digiconomist.net/bitcoin-energy-consumption and https://digiconomist.net/ethereum-energy-consumption.

[3] https://www.trgdatacenters.com/most-environment-friendly-cryptocurrencies.

[4] Dogecoin was not selected because: 1. Dogecoin was originally created as a meme coin without other uses; 2. its energy consumption is debated as Dogecoin can be mined in parallel with other coins such as Litecoin without using additional power, which makes its actual energy consumption hard to define and estimate; 3. it has been more highly influenced/boosted by Musk's social media comments rather than the market dynamics.

[5] The "clean" cryptos are selected based on the market capitalisation status as well as recent media attention. We first screened the most frequently discussed energy-efficient cryptos on the internet, examples are on https://www.leafscore.com/blog/the-9-most-sustainable-cryptocurrencies-for-2021/ (retrieved in November of 2021), https://finance.yahoo.com/news/15-environmentally-sustainable-cryptocurrencies-invest-224849569.html, https://www.thetimes.co.uk/money-mentor/article/eco-friendly-cryptocurrencies/, etc. Second, we excluded cryptos that were not in top 50 or did not have a full two-year data when we conducted the analysis. In this process, Solana, Polkadot, Avalanche, Chia, and some others were not considered as they came to the market much later. Binance Coin was not selected as it shares a completely different nature as a derivative of the Binance Exchange, historically built on Ethereum blockchain, and began to support its own staking in 2020. IOTA was the last pick and the smallest player which ranked 48th when we conducted this analysis. However, it ranked as 18th largest cryptocurrency as of November 3, 2019.

[6] On November 5, 2021 when we retrieved the data.

[7] As we define "dirty" and "clean" cryptocurrencies based on their energy consumption, we prefer using coins than tokens as tokens using others' blockchain technology are not that comparable to coins such as Bitcoin on energy issues. We excluded stablecoins also because their volatilities are slight on a daily basis.

Table 1
Regression results of $CSSD_{m,t}$ on dummy variables of value-weighted average market return extremes.

Market	α_0	α_1	α_2
Clean crypto	0.0427*** (0.0000)	0.0478*** (0.0000)	0.0210*** (0.0000)
Dirty crypto	0.0251*** (0.0000)	0.0168*** (0.0000)	0.0247*** (0.0000)

Notes:
1. Eq. (2) was used.
***Denotes the rejection of the null hypothesis at the 1% significance level.

Table 2
Regression results of $CSAD_{m,t}$ on unconditional value-weighted average market returns.

Market	γ_0	γ_1	γ_2
Clean crypto	0.0228*** (0.0000)	0.2160*** (0.0000)	0.3641*** (0.0009)
Dirty crypto	0.0124*** (0.0000)	0.2598*** (0.0000)	**−0.3048***** (0.0017)

Notes:
1. Eq. (4) was used.
***Denotes the rejection of the null hypothesis at the 1% significance level.

are sensitive to outliers and should react differently to the market, causing the dispersion to increase. In other words, herding exists if the level of dispersions is low during extreme market movements. We followed Christie and Huang (1995) and examined the presence of herding in extreme tails of return distribution:

$$CSSD_{m,t} = \alpha_0 + \alpha_1 D^{UT}_{m,t} + \alpha_2 D^{LT}_{m,t} + \epsilon_t, \tag{2}$$

where $D^{UT}_{m,t}$ and $D^{UT}_{m,t}$ are dummy variables with values of 1 if the market return at time t is in the upper or lower tails and 0 otherwise. A significantly negative coefficient α_1 or α_2 indicates the presence of herding during extreme up or down market condition, respectively.

Table 1 reports the estimation results of herding using the CSSD approach using 5% extreme tails.[8] The α_1 and α_2 for both clean and dirty crypto portfolios are significantly positive, which indeed indicates that no herding effect is found during the periods of extreme market movements in either of markets.

The CSSD approach has been criticised for its high sensitivity to outliers as it squares the difference between individual and market returns when calculating the dispersions, and its limited use in the spells of normal market. To correct this, Chang et al. (2000) proposed the use of cross-sectional absolute deviation of returns in measuring the dispersions, expressed as:

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

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

$$CSAD_{m,t} = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R^2_{m,t} + \epsilon_t, \tag{4}$$

As suggested by Chang et al. (2000), herd effects would lead to a non-linear relationship between $CSAD_{m,t}$ and the $R_{m,t}$, which is inferred by a significantly negative coefficient γ_2.

From the CSAD approach we obtained opposite results to those in the CSSD approach with respect to different types of cryptocurrencies as shown in Table 2. Specifically, herding behaviour only exists in the dirty cryptocurrency market, captured by a significantly negative coefficient of the $R^2_{m,t}$ term (−0.3048***).

It is reasonable to assume that investors may react differently to upward and downward trends, so we divided the market into up and down states to investigate the potential asymmetric herding behaviour in two market conditions following (Chang et al., 2000):

$$CSAD^{UP}_{m,t} = \gamma_0 + \gamma_1 \left| R^{UP}_{m,t} \right| + \gamma_2 \left(R^{UP}_{m,t} \right)^2 + \epsilon_t, \tag{5}$$

$$CSAD^{DOWN}_{m,t} = \gamma_0 + \gamma_1 \left| R^{DOWN}_{m,t} \right| + \gamma_2 \left(R^{DOWN}_{m,t} \right)^2 + \epsilon_t, \tag{6}$$

where $\left| R^{UP}_{m,t} \right|$ and $\left| R^{DOWN}_{m,t} \right|$ are positive and negative market returns, respectively.

[8] Our results remain robust for 1% and 10% extreme tails, albeit the 1% sample is small. All results are available upon request.

Table 3
Regression results of $CSAD_{m,t}$ on asymmetric value-weighted average market returns.

Market	γ_0	γ_1	γ_2
Panel A: Positive market returns			
Clean crypto	0.0237*** (0.0000)	0.2158*** (0.0000)	0.9890*** (0.0004)
Dirty crypto	0.0147*** (0.0000)	0.0981* 0.0975	0.9925* (0.0587)
Panel B: Negative market returns			
Clean crypto	0.0248*** (0.0000)	0.0476 (0.1880)	0.6666*** (0.0000)
Dirty crypto	0.0117*** (0.0000)	0.3141*** (0.0000)	**−0.4350***** (0.0010)

Notes:
1. Eqs. (5) and (6) were used in Panel A and B, respectively.
*Denote the rejections of the null hypothesis at the 10% significance level.
***Denote the rejections of the null hypothesis at the 1% significance level.

Results from Table 3 confirms that the degree of herding varies from market conditions. Herding behaviour in dirty cryptocurrency market only presents in down markets as only the coefficient of $(R_{m,t}^{DOWN})^2$ (γ_2) is significantly negative (−0.4350***). No evidence of herding is found in either rising and falling clean cryptocurrency markets as both γ_2 are significantly positive, which is consistent with the previous results with the use of a generalised formula.

So far, evidence indicates that there are herds in dirty cryptocurrencies, but not in clean cryptocurrencies. Since the dirty cryptocurrencies have been dominating the market for years especially Bitcoin and Ethereum which share much larger market capitalisation and greater attention than other folks and any clean cryptocurrencies, we further tested the possibility that clean cryptocurrency investors may tend to follow the dynamics of the dirty cryptocurrency market (γ_4) rather than their own (γ_2):

$$CSAD_{c,t} = \gamma_0 + \gamma_1 \left|R_{c,t}\right| + \gamma_2 R_{c,t}^2 + \gamma_3 CSAD_{d,t} + \gamma_4 R_{d,t}^2 \epsilon_t, \tag{7}$$

where subscription c refers to clean cryptocurrencies, while d is for dirty ones.

Additionally, similar to the methodology used in single market analysis, we tested the above relationship under asymmetric market conditions. For example, Eqs. (8) and (9) allow us to examine whether clean cryptocurrencies asymmetrically herd with the dirty cryptocurrencies (γ_4 and γ_5), and whether this is conditioned on the market status of dirty crypto market ($R_{d,t}^{UP}$ and $R_{d,t}^{DOWN}$).

$$CSAD_{c,t}^{UP} = \gamma_0 + \gamma_1 \left|R_{c,t}^{UP}\right| + \gamma_2 (R_{c,t}^{UP})^2 + \gamma_3 CSAD_{d,t} + \gamma_4 D_c^{UP} (R_{d,t}^{UP})^2 + \gamma_5 D_c^{UP} (R_{d,t}^{DOWN})^2 + \epsilon_t \tag{8}$$

$$CSAD_{c,t}^{DOWN} = \gamma_0 + \gamma_1 \left|R_{c,t}^{DOWN}\right| + \gamma_2 (R_{c,t}^{DOWN})^2 + \gamma_3 CSAD_{d,t} + \gamma_4 D_c^{DOWN} (R_{d,t}^{UP})^2 + \gamma_5 D_c^{DOWN} (R_{d,t}^{DOWN})^2 + \epsilon_t \tag{9}$$

where dummy variables $D_{c,t}^{UP}$ and $D_{c,t}^{DOWN}$ are equal to 1 when clean crypto market return at t is positive or negative, respectively.

Interestingly, we found that the performance in dirty cryptocurrency market does affect investors' behaviour in clean cryptocurrency market. As presented in the Panel A of Table 4, although investors do not herd in clean cryptocurrencies as γ_2 is significantly positive (0.6927***), they herd with information provided in price movements of dirty cryptocurrency, captured by a negative and statistically significant coefficient γ_4 (−0.3852***). Specifically, if we look at the Panel B and C, we find that clean cryptocurrency investors only herd towards dirty crypto market when both markets are positively rewarded as only coefficient γ_4 in Eq. (8) is significantly negative (−1.6619***). We cannot conclude that clean crypto investors herd with the dirty crypto market when both markets are falling as γ_5 in Eq. (9) is negative but not statistically significant. Nevertheless, it can be observed that when the two markets diverge, the behaviour of clean crypto investors is more likely to be driven by the performance of dirty cryptocurrencies as the values of γ_5 (7.4689***) and γ_4 (3.2001**) are much larger than those of γ_2 (0.7762*** and 0.7358***) in Panel B and C, respectively (Table 4).

4. Robustness check

We have shown a difference in herding patterns in dirty and clean cryptocurrency markets, taking into account the size effect (Kallinterakis and Wang, 2019; Vidal-Tomás et al., 2019) by using value-weighted portfolios . However, emphasising weights on large participants may diminish the effects of noisy movements created by small ones. To ensure that our results are robust, we re-performed tests using equal-weighted portfolios of dirty and clean cryptocurrencies.

For the clean crypto market, results are consistent with previous findings when we employed the CSSD approach (Table 5). When we applied the CSAD approach, results became slightly different (apart from those in Table 7). Specifically, the γ_2 for clean cryptocurrency becomes negative (−0.1007) but not statistically significant (see Table 6). Such change results probably because

Table 4
Regression results of $CSAD_{c,t}$ on unconditional and asymmetric value-weighted market returns.

Market	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
Panel A: Unconditional market returns						
Clean crypto	0.0231*** (0.0000)	0.1770*** (0.0000)	0.6927*** (0.0000)	0.0417 (0.3290)	**−0.3852***** (0.0001)	
Panel B: Positive market returns						
Clean crypto	0.0202*** (0.0000)	0.2849*** (0.0000)	0.7762*** (0.0032)	0.1801*** (0.0009)	**−1.6619***** (0.0000)	7.4689*** (0.0001)
Panel C: Negative market returns						
Clean crypto	0.0240*** (0.0000)	0.0412 (0.2919)	0.7358*** (0.0000)	0.0255 (0.6831)	3.2001** (0.0189)	−0.0852 (0.4389)

Notes:
1. Eqs. (7), (8), and (9) were used in Panel A, B and C, respectively.
**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 5
Regression results of $CSSD_{m,t}$ on dummy variables of equal-weighted average market return extremes.

Market	α_0	α_1	α_2
Clean crypto	0.0395*** (0.0000)	0.0429*** (0.0000)	0.0228*** (0.0000)
Dirty crypto	0.0200*** (0.0000)	0.0302*** (0.0000)	0.0143*** (0.0000)

Notes:
1. Eq. (2) was used.
***Denotes the rejection of the null hypothesis at the 1% significance level.

Table 6
Regression results of $CSAD_{m,t}$ on unconditional equal-weighted average market returns.

Market	γ_0	γ_1	γ_2
Clean crypto	0.0219*** (0.0000)	0.2344*** (0.0000)	−0.1007 (0.1990)
Dirty crypto	0.0091*** (0.0000)	0.2496*** (0.0000)	**−0.2761***** (0.0000)

Notes:
1. Eq. (4) was used.
***Denotes the rejection of the null hypothesis at the 1% significance level.

the relation between $CSAD_{c,t}^{UP}$ and $(R_{c,t}^{UP})^2$ is no longer significantly positive but insignificantly negative (−0.2259). Another minor difference is that the γ_2 and γ_4 in the Panel C of Table 8 are not statistically significant anymore.

Moreover, the signs of γ_2 and γ_5 are changed, which indicates the dispersions of clean crypto returns are affected by dirty crypto price movements which however makes sense as we have weakened the influence of larger participants on market returns. Regarding dirty crypto market, results are same.

Overall, we can draw the same conclusions in regard to herding regardless of using either equal-weighted or value-weighted portfolios as our market proxy.

5. Conclusions

The environmental sustainability of cryptocurrencies is a subject of significant debate. We found compelling evidence of herd investing in dirty cryptocurrencies, which is asymmetric and more pronounced in down than in up markets. More interestingly, although we did not find the presence of herds in clean crypto market, we did find that clean crypto investors herd to dirty crypto markets, especially when both markets are generating positive returns. In other words, investors in clean cryptocurrencies tend to follow the actions of dirty crypto investors in up markets, even as the set of clean cryptocurrencies is expanding and a significant number of the most valuable cryptocurrencies are clean coins. Our results are robust across value- and equal-weighted portfolios. These findings suggest that policy efforts to shift investors towards cleaner cryptocurrencies may founder for so long as dirty cryptocurrencies remain dominant in size and salience.

Table 7
Regression results of $CSAD_{m,t}$ on asymmetric equal-weighted average market returns.

Market	γ_0	γ_1	γ_2
Panel A: Positive market returns			
Clean crypto	0.0212*** (0.0000)	0.3341*** (0.0000)	−0.2259 (0.6210)
Dirty crypto	0.0107*** (0.0000)	0.1822*** 0.0002	0.8053** (0.0137)
Panel B: Negative market returns			
Clean crypto	0.0219*** (0.0000)	0.1269*** (0.0000)	0.1354* (0.0946)
Dirty crypto	0.0094*** (0.0000)	0.1720*** (0.0000)	**−0.1387**** (0.0140)

Notes:
1. Eqs. (5) and (6) were used in Panel A and B, respectively.
*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
Regression results of $CSAD_{c,t}$ on unconditional and asymmetric equal-weighted market returns.

Market	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
Panel A: Unconditional market returns						
Clean crypto	0.0200*** (0.0000)	0.1598*** (0.0000)	0.8967*** (0.0000)	0.2419*** (0.0002)	**−0.8952***** (0.0000)	
Panel B: Positive market returns						
Clean crypto	0.0161*** (0.0000)	0.2707*** (0.0000)	1.2907** (0.0102)	0.4120*** (0.0000)	**−1.9123***** (0.0000)	14.4398*** (0.0000)
Panel C: Negative market returns						
Clean crypto	0.0208*** (0.0000)	0.1234*** (0.0003)	−0.0319 (0.9196)	0.0689 (0.3504)	2.2970 (0.2118)	0.1604 (0.5752)

Notes:
1. Eqs. (7), (8), and (9) were used in Panel A, B and C, respectively.
**Denote the rejections of the null hypothesis at the 5% significance level.
***Denote the rejections of the null hypothesis at the 1% significance level.

CRediT authorship contribution statement

Boru Ren: Data curation, Econometrics, Writing – original draft & revision. **Brian Lucey:** Conceptualisation, Editorial curation, Writing – final draft & revision.

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References

Amirat, A., Alwafi, W., 2020. Does herding behavior exist in cryptocurrency market? Cogent Econ. Finance 8 (1), 1735680.
Bikhchandani, S., Sharma, S., 2001. Herd behavior in financial markets. IMF Staff Pap. 47 (3).
Bouri, E., Gupta, R., Roubaud, D., 2019. Herding behaviour in cryptocurrencies. Finance Res. Lett. 29, 216–221.
Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. Financ. 24 (10), 1651–1679.
Christie, W.G., Huang, R.D., 1995. Following the pied piper: Do individual returns herd around the market? Financ. Anal. J. 51 (4), 31–37.
Corbet, S., Lucey, B., Yarovaya, L., 2021. Bitcoin-energy markets interrelationships - New evidence. Resour. Policy 70, 101916.
Gallersdörfer, U., Klaaßen, L., Stoll, C., 2020. Energy consumption of cryptocurrencies beyond bitcoin. Joule 4 (9), 1843–1846.
Kallinterakis, V., Wang, Y., 2019. Do investors herd in cryptocurrencies – and why? Res. Int. Bus. Finance 50, 240–245.
Poyser, O., 2018. Herding behavior in cryptocurrency markets. arXiv preprint arXiv:1806.11348.
Ren, B., Lucey, B., 2022. A clean, green haven?–Examining the relationship between clean energy, clean and dirty cryptocurrencies. Energy Econ. 105951.
Stavroyiannis, S., Babalos, V., 2019. Herding behavior in cryptocurrencies revisited: Novel evidence from a TVP model. J. Behav. Exp. Finance 22, 57–63.
Vidal-Tomás, D., Ibáñez, A.M., Farinós, J.E., 2019. Herding in the cryptocurrency market: CSSD and CSAD approaches. Finance Res. Lett. 30, 181–186.
Youssef, M., 2020. What drives herding behavior in the cryptocurrency market? J. Behav. Finance 1–10.