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Does cryptocurrency exhibit herding behavior?

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I. Introduction

Cryptocurrency is an intriguing market to study due to its volatility and global impact. Its decentralized nature challenges traditional financial systems, offering insights into the future of finance and technology. The market's continuous evolution and regulatory uncertainties create a dynamic environment for analysis and allow for unique challenges and opportunities to understand investor behavior.

We want to study investor behavior in this market as there may be herding present in the cryptocurrency market due to the unfamiliarity of this sector for many investors. We expect more herding to be present in the cryptocurrency markets than in other markets such as stocks because this market is still relatively new and continues to grow at a rapid rate which leads investors to rely on signals from the crowd, resulting in increased herding behavior.

The 5 research papers studied resulted found weak to moderate evidence of herding in investor behavior. These studies suggest that investors often deviated from the rational asset pricing benchmark and instead, chose to follow the consensus during market stress situations. These findings imply that there is a great speculative aspect and that the cryptocurrency market is not efficient.

We looked at 16 major cryptocurrencies from 10/9/2018 to 7/6/2021 to investigate if there was any herding present in the cryptocurrency market in this period. Herding refers to the public not considering an individual stock's fundamentals and following the general market trend or following the actions of big investors. We investigated the presence of herding using the Cross-Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD). Although CSSD and CSAD are both incredibly useful tools in identifying herding behavior, it is widely accepted that CSAD is the more accurate method and serves as more conclusive evidence.

To investigate if there was any significant difference in herding behavior in the early vs late halves of our time period, which is suspected due to the impacts of the COVID-19 pandemic in the latter half of the period, we compare the CSSD and CSAD results for the two halves to look for any difference in herding behavior between the two time frames.

II. Literature Review:

i) ***Herding behavior and contagion in the cryptocurrency market***

Silva, Vitor, et.al 2019 evaluates the prices of 50 cryptocurrencies from the time period March 2015 to November 2018. The methodology used for detecting herding behavior in this study included cross-sectional absolute deviation and cross-sectional standard deviation. The results showed herding behavior with periods of extreme herd behavior as well.

This study used currencies that were chosen based on the highest market cap, liquidity, and also data availability. Since the data collected for our study is for the time frame of October 2018 to July 2021 there is very little overlap between the time frames of the two studies. Our study uses data for 16 of the largest cryptocurrencies that were public before October 2018.

ii) ***Herding in the cryptocurrency market: CSSD and CSAD approaches***

Bouri et al. 2019 used 65 different cryptocurrencies from the time period of 1st January 2015 to 31st December 2017. This study used the CSSD and CSAD methodologies and distinguished between up and down markets. The results show that while there is herding this can only be applied to the bitcoin asset and does not apply to all cryptocurrencies.

To examine herding, this study evaluates herding in the smaller currencies against the larger ones, while our study distinguishes herding by looking at the earlier half of our time frame against the latter. Two different strategies have been employed to determine the effects of herding behavior and its presence in the cryptocurrency market.

iii) ***Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty.***

Gurdgiev and O'Loughlin 2020 studied the time period from January 1, 2017, to April 2, 2019. The study used 10 of the biggest cryptocurrencies in the market based on the market capitalization of the currencies. The method used for this was sentimental analysis to model the effects of public sentiment on investment markets. The results show that investor sentiment can predict the price direction of cryptocurrencies, a direct impact of herding biases.

This study examines the difference in herding in the bull market from January 1, 2017, to December 18, 2018, and the bear market from December 19, 2018, through April 2, 2019. This is different from our study as we examine the effects of herding in the early was late halves of our time frame by splitting the data points down the middle having equal halves and evaluating CSSD and CSAD for these two different categories.

iv) ***Herding Behavior in Cryptocurrencies***

Poyser 2018 focuses on 14 of the largest cryptocurrencies based on the highest market capitalizations for cryptocurrencies who price data spans at least 2 years in the time period of 4/28/2013 - 05/02/2018. The methodology used to measure herding in this study is cross-sectional absolute deviation (CSAD).

The time period for this study comes prior to the time period for ours and there is no overlap between the two. This study looks for evidence of herding throughout the time period, whereas our study also looks at the difference in herding between early vs late halves of the time period.

v) ***Herding Behavior in cryptocurrency market***

Vidal-Tomás, et al 2019 employs methodology present in Chang, Cheng and Korena and uses CSSD to identify herding in cryptocurrency markets. Data was collected for the first 100 leading cryptocurrencies, which make up approximately 96% of the total cryptocurrency market capitalization. The time period runs from April 29, 2013 to April 3, 2018.

This study employs a slightly different methodology than us as we use the CSSD regression from Christie and Huang. We also use the same start dates for all cryptocurrencies for which data was collected as opposed to different start dates for price observations as used in this study.

III. Methods:

We got the historical prices for 23 cryptocurrencies from Kaggle[1] and we focused on closing price for each cryptocurrency. We got the market index from CCi30[2].

The CCi30 is a rules-based index designed to objectively measure the overall growth, daily and long-term movement of the blockchain sector. It does so by tracking the 30 largest cryptocurrencies by market capitalization, excluding stablecoins. It serves as a tool for passive investors to participate in this asset class, and as an industry benchmark for investment managers. The CCi30 is used by investors to gauge the overall health and direction of the cryptocurrency market and is commonly used to compare the performance of individual cryptocurrencies against broader market trends.

Weighted Average Market Capitalization Formula:

$$M^*(t) = \frac{\sum_{i=0}^{\infty} M(T\ -\ i\ )e^{-ai}}{\sum_{i=0}^{\infty} e^{-ai}}$$

where *M(t)* is the actual market cap at time *t*, *M* is the adjusted market cap, and α is the decay rate of the exponential moving average, set with a half-life of 3 days.

Constituents Weight Calculation Formula:

$$w_0(t) = \frac{\sqrt{M_0^*(t)}}{\sum_{i=0}^{N} \sqrt{M_i^*(t)}}$$

where M_i* is the adjusted market capitalization of a specified cryptocurrency at time *t* and M_0^* is the market capitalization of a particular cryptocurrency.

Index Value Calculation Formula:

$$I_t = \sum_{j=1}^{30} W_j \frac{P_j(t)}{P_j(0)}$$

Where I_t is the value of the index at time *t*, W_j is the weight of the *j*th name in the index, and P_j is the price of the *j*th name as a function of time.

We used this data to evaluate the cross-sectional standard and absolute deviation of many of the major cryptocurrencies to be able to measure if there is any herding behavior present in these currencies.

1000 data points were taken from each selected cryptocurrency, with each data point as the closing price for the currency on each day from 10/9/2018 - 7/6/2021. These dates were chosen as we found an overlap in dates for 16 of the largest cryptocurrencies by market capitalization.

[1] https://www.kaggle.com/datasets/sudalairajkumar/cryptocurrencypricehistory

[2] https://cci30.com/

CSSD and CSAD

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

$$CSSD_t = \alpha + a_1 D_t^L + a_2 D_t^U + \varepsilon_t$$

Where D_t^L = 1 if the market returns are at the lower end of the distribution and D_t^L = 0 otherwise, and D_t^U=1 if the market returns are at the upper end of the distribution and D_t^U=0 otherwise.

If the dispersion is low in the presence of large market changes, that is, when the estimated alphas are negative and statistically significant, the occurrence of herding behavior is assumed.

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

$$CSAD_{i,t} = \alpha_0 + a_1\left|R_{m,t}\right| + \alpha_2 R_{m,t}^2 + \varepsilon_t$$

Where $R_{i,t}$ and $R_{m,t}$ is the return on cryptocurrency and the value of a weighted average (based on their percentage of total market capitalization) of all 16 cryptocurrencies returns for period t, respectively; N is the number of cryptocurrencies in the portfolio at time t.

Chang et. al developed CSAD based on the CAPM (Capital Asset Pricing Model) model, assuming that the returns' dispersion is linearly related to the market returns. Therefore, in the absence of herding behavior we can expect a positive and significant estimate for the a_1
coefficient. On the other hand, if we observe herding behavior in days of extreme market movements, it is expected that the cross-sectional dispersion of stock returns will decrease or increase to a lesser extent than the market return. In this situation, when the estimated a_2
coefficient is negative and statistically significant; we assume herding behavior has occurred.

Name	Start date	End date	Number of days
Bitcoin	4/29/13	7/6/21	2990
Litecoin	4/29/13	7/6/21	2990
XRP	8/5/13	7/6/21	2892
DodgeCoin	12/16/13	7/6/21	2759
Monero	5/22/14	7/6/21	2602
Stellar	8/6/14	7/6/21	2526
Tether	2/26/15	7/6/21	2322
Nem	4/2/15	7/6/21	2287
Ethereum	8/8/15	7/6/21	2159
IOTA	6/14/17	7/6/21	1483
EOS	7/2/17	7/6/21	1465
Binance coin	7/26/17	7/6/21	1441
Tron	9/14/17	7/6/21	1391
ChainLink	9/21/17	7/6/21	1384
Cardano	10/2/17	7/6/21	1373
USD Coin	10/9/18	7/6/21	1001

Table 1. Start and End Dates for each of 16 cryptocurrencies studied

IV. Results:

	LEFT	RIGHT	Intercept
Coefficient	0.02310	0.03942	0.03181
Standard error	0.00524	0.00524	0.00120
t-stat	4.40937	7.52590	26.48631
p-value	0.00	0.00	0.00

Table 2. CSSD for 16 cryptocurrencies from 10/9/2018 to 7/6/2021.

	RET^2	ABS RET	RET	Intercept
Coefficient	-0.16621	0.32511	0.07431	0.01420
Standard error	0.12000	0.02345	0.01014	0.00067
t-stat	-1.38510	13.86289	7.32505	21.19234
p-value	16.63%	0.00%	0.00%	0.00%

Table 3. CSAD for 16 cryptocurrencies from 10/9/2018 to 7/6/2021.

	Early			Late		
	LEFT	RIGHT	Intercept	LEFT	RIGHT	Intercept
Coefficient	0.02224	0.03716	0.02583	0.02178	0.03779	0.03808
Standard error	0.00302	0.00325	0.00063	0.00929	0.00887	0.00231
t-stat	7.36261	11.42281	40.95253	2.34485	4.26061	16.49086
p-value	0.00000	0.00000	0.00000	0.01943	0.00002	0.00000

Table 4. CSSD for 16 cryptocurrencies for early (10/9/2018 - 2/21/2020) and late (2/22/2020 - 7/6/2021) periods.

	Early				Late			
	RET^2	ABS RET	RET	Intercept	RET^2	ABS RET	RET	Intercept
Coefficient	0.48207	0.21643	0.05352	0.01335	-0.24547	0.34868	0.08020	0.01632
Standard error	0.23783	0.02900	0.00827	0.00055	0.17704	0.03979	0.01719	0.00125
t-stat	2.0270	7.4645	6.4707	24.1642	-1.3865	8.7629	4.6645	13.0644
p-value	4.32%	0.00%	0.00%	0.00%	16.62%	0.00%	0.00%	0.00%

Table 5. CSAD for 16 cryptocurrencies for early (10/9/2018 - 2/21/2020) and late (2/22/2020 -7/6/2021) periods.

II. Discussion:

Looking at Table 2, which includes the CSSD for the entire period, since the coefficients are positive, and the p-values are less than the significant level at $\alpha = 0.05$ which suggests that no herding is present in the market. The coefficient in the left tail and right tail increases, suggesting that the investors do not herd towards the market signal or the opinion of key investors.

The CSAD regression in Table 3 shows that the coefficient for RET^2 is negative, which would suggest that herding is present, however, the p-value is not significant and therefore we cannot conclude if the coefficient is negative due to random chance.

Table 4 compares the results for CSSD for the 2 halves of our time period. No significant difference is present between the two time frames, which suggests that herding was significantly prevalent in either of the two time frames as the coefficients are positive in each and the p-values are significant.

The comparison of CSAD results between the time frames in Table 5 shows some variation in coefficients. The RET^2 coefficient is positive and significant for the early half of the period, however, the coefficient is negative but not significant for the late half of the period, so we cannot rule out herding or market rationality. This shows some evidence of herding but due to our limited sample size, we may not have enough statistical power to get a significant result.

III. Conclusion:

Using CSSD and CSAD regressions, we examined herding behavior in the cryptocurrency market over the period from October 9, 2018, to July 6, 2021. Our analysis was not able to rule out the presence of herding or market rationality. Both CSSD and CSAD regressions failed to identify statistically significant relationships between dispersion measures and individual stock returns. As such, we lack sufficient evidence to conclude that investors in the cryptocurrency market demonstrated herding behavior during the specified period.

These findings contribute to the ongoing discourse about market behavior in the newly evolving market of digital assets. Future research with a greater number of cryptocurrencies over a long time horizon may allow us to have enough statistical power to observe whether there is herding in the cryptocurrency market. Moreover, alternative methodologies would need to be employed to gain sufficient evidence to conclude whether the market behaved rationally or if investors followed the general market trend or were swayed by the opinion of key investors.

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