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HERDING IN CRYPTOCURRENCIES: CSSD AND CSAD APPROACHES

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Abstract:
This paper uses CSSD developed by Christie and Huang (1995) and CSAD developed by Chang, Cheng, and Khorana (2000) to test for herding in cryptocurrencies over the period 21/09/2018-21/09/2022. Two sets of cryptocurrencies were considered, one containing the 34 largest cryptocurrencies by market capitalisation and the other containing 15 cryptocurrencies with market capitalisations under $200 million. Any cryptocurrencies launched after 21/09/2018 were excluded from the samples in the interests of consistency. Using CSSD, no herding was detected while with CSAD a weak herding effect was observed, though the results were not statistically significant. This paper has important implications for cryptocurrency investors, researchers, and policymakers.

Keywords:
herding, cryptocurrencies, bitcoin, digital currencies.

1. INTRODUCTION

Based on a little-known procedure called proof-of-work which was initially intended to reduce spam emails (Back, 2002), Bitcoin has become a household name and a regular news story. Developed by the pseudonymous (Nakamoto, 2008), using HashCash's novel idea to prevent abuse of unmetered internet services, Bitcoin has sparked an entire new class of investment assets. Cryptocurrencies are famed for their volatility and risk, perhaps best exemplified by the precipitous collapse of LUNA in May this year: With the cryptocurrency's price dropping from $85 per coin to a few fractions of a cent in a matter of days. On the other hand, cryptocurrencies offer the potential for investors to receive excess returns which makes them an attractive asset class for investors with high risk-appetites.

The efficient-market hypothesis holds that as returns increase or decrease, the dispersion of those returns should increase or decrease in a linear fashion. Whether this holds true in all situations has become a topic for research since the mid 1990's. Researchers have questioned this notion using various methods to detect a phenomenon known as herding. Herding occurs when the dispersion of returns reduces in comparison with market returns. This was theorized to occur in extreme market conditions, both in bear and bull markets and would demonstrate that investors are rallying around a consensus instead of trading based on fundamental information. Testing for herding has become a popular field of research with studies conducted on various asset classes in numerous of countries over the years since methodologies for testing it were first developed.

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Herding as a concept can be classed with the wider movement towards behavioural economics in recent years. Behavioural economists posit that social and psychological factors, amongst other things, influence the decisions of economic agents. The idea that economic agents are not completely rational at all times is a direct challenge to much of classical economic theory. Therefore, herding when discovered in data, can be used to question conventional economic thinking.

Testing cryptocurrencies for evidence of herding is a relatively new field. This is partially because cryptocurrencies are a recent class, with many of the top 100 cryptocurrencies established in the last 4 years or so. This paper uses cross-sectional standard deviation and cross-sectional absolute deviation in order to test for herding using two sets of cryptocurrency data. One set is comprised of the largest cryptocurrencies by market capitalisation and one set of cryptocurrencies with market capitalisations of under $200 million as of 21/09/2022.

2. LITERATURE REVIEW

(Christie & Huang, 1995) proposed the CSSD method of detecting herding. Dummy variables are used to detect extreme market movements and a regression is conducted in order to test for herding.

(Chang, Cheng, & Khorana, 2000) developed the work of the previous authors, proposing the CSAD method of detecting herding. CSAD improves CSSD as it includes the entire dataset, not just the arbitrarily defined "extreme movements". CSAD and its variants are the most popular way to test for herding in research.

Since the developments of these methodologies, herding has become a popular topic of research with various asset classes analysed for the presence of herding in a great number of countries. In general, the research results have been mixed on the existence of herding. For example, (Chang, Cheng, & Khorana, 2000) analysed intraday Australian equities and found no evidence of herding using both CSSD and CSAD. In contrast, (Economou, Katsikas, & Vickers, 2016) tested for herding on the Athens stock exchange and discovered strong evidence thereof during the sovereign debt crisis.

As pertains to cryptocurrencies, testing markets for herding is a relatively new field of research and results have again been mixed. For example, (da Gama Silva, Klotzle, Pinto, & Gomes, 2019) discovered evidence of herding in the cryptocurrency market using the CSSD model but not the CSAD owing to the low P-value of the result. In addition, (Kyriazis, 2020) discovered evidence of herding using the CSAD method during bull markets. (Poyser, 2018) also discovered evidence of herding using an asymmetrical CSAD approach, noting that market stress often led to investors abandoning rational information. (Kumar A. S., 2018) discovered substantial evidence of herding but found no evidence that the effect was exacerbated by Coronavirus.

In contrast, (Vidal-Tomás, Ibáñez, & Farinós, 2019) find no evidence of herding and state that investor behaviour is not in contradiction with rational asset pricing models, they did however find some evidence of herding during down markets. In addition, (Bouri, Gupta, & Roubaud, 2019) discovered the presence of an anti-herding effect in their static model. They did; however, find some evidence of herding when a rolling window regression was conducted. Equally, (Stavroyiannis & Babalos, 2019), found that herding does not exist when a time-varying model was employed. The authors did find some evidence of herding during up market days.

One would expect that if herding were to be found anywhere, that place would be in the market for cryptocurrencies. As an asset class, they are extremely volatile and prone to days with extreme market movements. There is also a documented tendency for investors to purchase cryptocurrencies when they see the price going up, often referred to colloquially as "fear of missing out" (FOMO). Given the unclear evidence of herding in cryptocurrency markets, this paper attempts to contribute to existing research by helping to resolve the question of whether herding as a phenomenon occurs in cryptocurrencies.

3. RESEARCH METHODOLOGY

Two datasets of cryptocurrencies were collected with data spanning 4 years from 21/09/2018-21/09/2022. The first set contains the 33 largest cryptocurrencies by market capitalisation and the second containing a set of 15 cryptocurrencies with market caps below $200 million. Any cryptocurrencies launched after 21/09/2018 were excluded from the datasets in the interests of consistency. All data was retrieved from CoinMarketCap, and Bitcoin was used as a proxy for market return for the purposes of this research.

In order to test the two datasets for herding, a variety of methodologies were used. Firstly, the cross-sectional standard deviation approach (CSSD) developed by (Christie & Huang, 1995) was employed. CSSD is defined as follows:

$$CSSD = \sqrt{\sum_{i=1}^{n}}$$

where $R_{i,t}$ is the return of cryptocurrency i on day t, R_m is the average return on day t and n is the number of cryptocurrencies in the sample. Once the CSSD is calculated, a regression is conducted on the data. The regression is as follows:

$$CSSD_t = \acute{a} + \hat{a}^L D_t^L + \hat{a}^U D_t^U + \mathring{a}_t$$

where both D_t^L and D_t^U are dummy variables which equal 1 during extreme market movements and 0 otherwise. For the purposes of this study, extreme market movements were identified as returns below the 5th percentile and above the 95th percentile.

There have been some criticisms of the CSSD model; primarily owing the arbitrary nature of defining "extreme" and the model's sensitivity to outliers. As such, the CSAD model developed by (Chang, Cheng, & Khorana, 2000) is a more widely used methodology for detecting herding. CSAD is defined as follows:

$$CSAD_{it} = \frac{1}{n}\sum_{i=1}^{n}\left|R_{it} - R_{mt}\right|$$

where $R_{i,t}$ is the return of cryptocurrency *i* on day *t* and R_{mr} is the market return on day *t*. After the cross-sectional absolute deviation was calculated, the following regression was applied to the data

The above regression was also conducted using a rolling window of 7 days and 30 days to test for differing levels of herding during different timeframes.

Finally, an additional regression was conducted to test for asymmetrical herding in the CSAD dataset. The regression is defined as follows

$$CSAD_{i.t} = \tilde{a}_0 + \tilde{a}_1 R_{mt} + \tilde{a}_2\left|R_{mt}\right| + \tilde{a}_3 R_{mt}^2 + \mathring{a}_{i.t}$$

where **1**-***D*** and ***D*** are dummy variables which are equal to 1 depending on whether the market is up or down respectively.

4. EMPIRICAL RESULTS AND DISCUSSION

The results of the CSSD approach showed no evidence whatsoever of herding with both sets of D_t^L and D_t^U coefficients being positive. This is consistent with the findings of (Ren & Lucey, 2022) and (Vidal-Tomás, Ibáñez, & Farinós, 2019) as pertains to use of the CSSD model to detect herding. In contrast, (da Gama Silva, Klotzle, Pinto, & Gomes, 2019) did find evidence of herding using the CSSD model. The positive β1 coefficients indicate that dispersion increases in the lower tail of both datasets with the positive β2 coefficients demonstrating the same result is present in the upper tail of both datasets. This would seem to disprove the idea that there is a strong herding effect, at least at the day trading level of cryptocurrencies. Considering the differences between the CSAD and CSSD results, the lack of herding when using the CSSD methodology may partially explain the fact that fewer researchers now use CSSD with many opting to use the CSAD model and its variants.

Table 1. CSSD regression for small market cap cryptocurrencies

	Coefficients	Standard Error	t Stat	P-value
α	0.059915207	0.001061453	56.446	0
β1	0.075320857	0.004628432	16.274	7.6563E-55
β2	0.033819881	0.004628432	7.307	4.482E-13

Table 2. CSSD regression for large market cap cryptocurrencies

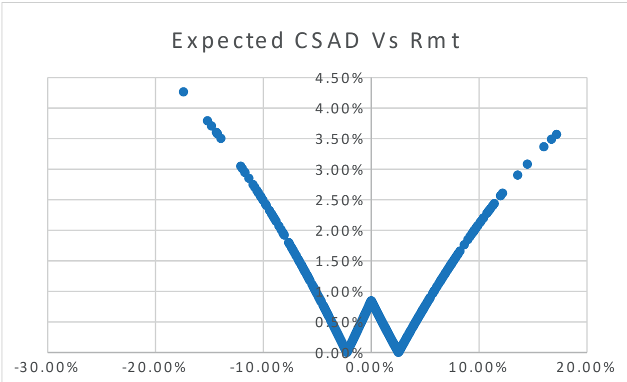
	Coefficients	Standard Error	t Stat	P-value
α	0.05037	0.000802	62.82747	0
β1	0.075679	0.003496	21.6483	2.42E-90
β2	0.048756	0.003496	13.94688	1.36E-41

In contrast, the results of the CSAD approach with the static model detected herding in both datasets, but the results were not statistically significant in either case with P-values of 0.46 and 0.53 respectively. Equally, the results for the asymmetrical herding regression indicate the presence of herding during up market days, but the results are again not statistically significant with P-values of 0.4 and 0.46 respectively. Finally, the rolling regression windows of 30 days and 7 days do not detect negative r_{mt}^2 coefficients for the dataset with high market capitalisations but does find some evidence of herding in the dataset with smaller market capitalisations using a 7-day rolling window. The bowing effect in figure 1 demonstrates a slight reduction in return dispersion during extreme market movements. It is also possible to note that this effect is more pronounced during bull periods than in bear periods.

Table 3. Asymmetrical Herding Regression Results for Large Cap Cryptocurrencies

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.026067	0.000659	39.54321	6.8E-233
(1-D) * RMT	0.237048	0.043948	5.39382	8.04E-08
D * RMT	-0.24857	0.026163	-9.50058	8.24E-21
(1-D) * Rmt^2	0.534279	0.428173	1.247811	0.212301
D * Rmt^2	-0.08619	0.102847	-0.83802	0.402156

Figure 1. Absolute Rmt for large cap cryptocurrencies



These results are consistent with the research of a number of authors, including (da Gama Silva, Klotzle, Pinto, & Gomes, 2019) and (Bouri, Gupta, & Roubaud, 2019) where weak evidence of herding was discovered using static models. What is surprising about this research is that the asymmetrical herding measure and rolling window regressions also find only weak evidence of herding.

These findings would seem to imply that the cryptocurrency market is more efficient than it might be thought at first glance. Traders are unlikely to experience long-term irrationality in the form of herding when investing in cryptocurrencies.

Despite that, the weak, but ubiquitous, herding effect discovered using the CSAD methodology means that expanding this research using other methodologies may yield statistically significant evidence of herding. Two potential options could be introducing Markov-switching into the model to test for potential time-varying herding effects or the use of quantile regression as an additional measure. As pertains to policymakers, adequate regulation of cryptocurrencies as an investment asset is a necessary next step. The volatility of cryptocurrencies necessitates that investors receive the proper rights and protections when they elect to invest in this asset class.

5. CONCLUSION

Cryptocurrencies have developed into a popular class of assets in recent years owing to their potential to offer investors excess returns. The existence of herding in cryptocurrency markets is a much-debated topic in academic research. This paper contributes to existing literature insofar as it finds weak, statistically insignificant evidence of herding using both the CSSD and CSAD methodologies. It is of particular interest that the herding effect captured using the asymmetrical model is also statistically insignificant. One would expect stronger herding during bull markets as excited investors experience fear of missing out (FOMO), and abandon their own opinions about an asset in order to cash in on a bull market.

Future research should focus on establishing whether herding occurs in cryptocurrencies over longer time frames, as much of the research shows either weak evidence of herding or herding during specific market conditions over short periods of time.

6. LITERATURE

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