HIGH SCHOOL EDITION
Journal of Student Research
Volume 12 Issue 4 (2023)

Do Cryptocurrencies Exhibit Herding Behavior? Evidence from CSSD and CSAD Approaches

Melinda Wang[1], Abhishek Dev[1#] and Qinyue Zhou[1#]

[1]Scholar Launch
[#]Advisor

ABSTRACT

This paper investigates whether herding behavior is present in the rapidly growing cryptocurrency market. It analyzes herding behavior over a 4-year period by using the daily closing price data of 16 cryptocurrencies and CSSD and CSAD. The findings indicated that with CSSD, no herding was detected for the entire time period. However, for CSAD, a weak herding effect was observed but it was statistically insignificant. The evidence further revealed that the 8 cryptocurrencies with the lowest market capitalization, both CSSD and CSAD showed a higher chance of herding behavior. Similarly, in times of higher volatility, there was a higher chance of herding behavior. It was also found that there was no herding behavior during the start of COVID-19, the FTX bankruptcy, or Google Trends. This paper has important implications for cryptocurrency investors, especially retail investors who may invest more in smaller cryptocurrencies. They should be more cautious when approaching lower market map cryptocurrencies and during times of high market volatility to prevent greater financial loss.

Introduction

There is a spectrum of rationality in assets ranging from gold and silver to modern digital assets like cryptocurrencies and non-fungible tokens (NFTs). While assets with a physical value to back them up behave more predictably, those without might act more irrationally (Calderón 2018). Among these assets, cryptocurrencies have emerged in global financial markets as an irrational market (Ballis and Drakos, 2020). We hypothesize that the cryptocurrency market experiences levels of irrationality and unpredictability, leading to a distinct behavioral pattern known as herding. Herding is where individuals tend to follow others' investment decisions rather than depend on their independent analysis (Jia et al. 2022).

The rationality of financial markets is influenced by many factors. An aspect to consider is the competitiveness of the currency, which is characterized by the size of its user base and its widespread adoption. A highly competitive currency entails a larger group of opinions where more investment strategies are made. This reduces the likelihood of investors blindly following others. Another aspect is the presence of secondary entities such as businesses utilizing the currency because it increases the currency's competitiveness and therefore, creates a more rational decision-making environment. Market capitalization, representing the total value of a cryptocurrency, also plays a significant role in rationality (Tomás et al. 2019). Similar to a market's competitiveness, a larger market capitalization suggests a more established and mature market, potentially leading to decreased irrationality and herding. The speculative nature of an asset is another factor because speculative investments often prioritize short-term gains which contribute to higher levels of irrationality. (Calderón 2018). Media coverage and public sentiment surrounding an asset can also sway investors' decision-making and lead to herding behavior (Calderón 2018).

This study focuses on finding out if there is any herding behavior within the cryptocurrency market. As retail investors increasingly invest in this market, it becomes crucial to study herding behavior. Crypto investors are typically less experienced and more susceptible to herding; their vulnerability leads to concerns about the potential loss of savings and their financial well-being.

This paper presents the results of the investigation into herding behavior across 16 prominent cryptocurrencies. The cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) methods were employed to the closing prices to assess if there is herding within the cryptocurrency market. These two methods are the gold standard for measuring herding behavior. Surprisingly, our findings indicate the absence of significant herding behavior across the analyzed cryptocurrencies, as determined by both the CSSD and CSAD measures. This may be because we are looking at only the top 16 cryptocurrencies by market cap. Additionally, cryptocurrency has been around for longer now and is not an obscure asset class anymore. However, when examining the top 8 and bottom 8 cryptocurrencies based on market capitalization, we observed a notable difference in herding behavior. The bottom 8 cryptocurrencies exhibited a higher degree of herding compared to the top 8 cryptocurrencies. Moreover, during a period of high volatility which is from March 2021 to November 2022 in our time period, there is evidence of increased herding among investors.

These results have significant implications for investors in the cryptocurrency market. Although most investors have a relatively rational decision-making approach when considering investments, those investing in smaller, less established cryptocurrencies are more susceptible to herding. Retail investors should be aware of herding behavior and its impact on their investment decisions, so they are not exposed to greater financial risk. By raising awareness of the risks associated with herding, this research contributes to creating a more informed environment in the cryptocurrency market.

Literature Review

This literature review explores many studies regarding herding behavior in cryptocurrency markets. Ballis and Drakos (2020) investigate herding behavior among the top players in crypto markets, focusing on factors of irrationality such as market capitalization, market volume, data availability, and its listing on major cryptocurrency platforms. They only use six prominent cryptocurrencies while we use 16 and they cover a three-year period from August 2015 to December 2018 while we cover a longer and more recent sample range. They use CSAD to find the herding behavior but also use the Newey West method and a GARCH model which we do not employ. They find a negative and statistically significant relationship, suggesting the presence of herding behavior. They also find that up-events follow market movements at a faster pace compared to down-events.

In a related study, Jia et al. (2022) examine the impact of extreme sentiment on herding behavior. They introduce new sentiment proxies, such as the Cryptocurrency Market Sentiment Indicator (CMSI) and Daily Happiness Sentiment (DHS) which we do not use. Their research spans from January 2016 to June 2022 and selected the largest 1000 cryptocurrencies based on capitalization values of 1 million USD or more. In contrast, we only selected 16 cryptocurrencies. The empirical analysis reveals that herding behavior is more pronounced on dysphoric (negative sentiment) days compared to euphoric (positive sentiment) days, and herding is more prevalent during downward market movements. This disagrees with Ballis and Drakos as they found more herding behavior in upward market movements. However, both papers do suggest that volatility affects herding behavior in some way. It is noted that when testing the entire time period, there is no herding behavior, which is also what we found. Additionally, larger cryptocurrencies exhibit more sensitivity to extreme sentiment conditions and show increased signs of herding behavior compared to smaller cryptocurrencies. This is different from what our data implies because we found that there are more signs of herding in smaller cryptocurrencies. We believe that smaller cryptocurrencies would mean it was newer and had less competition. Therefore, investors would have fewer opinions on it and there would be fewer strategies presented.

Another study by Calderón (2018) focuses on explaining the volatility of cryptocurrency prices from a behavioral finance perspective. It emphasizes the investors' cognitive biases, limited information processing capabilities, and weak prior knowledge. Calderón questions if cryptocurrency has a fundamental value because its store of value function is hard to measure given its great volatility. This agrees with our conclusion that crypto does not have a tangible value, and therefore, is harder to predict. The study highlights the presence of overconfidence, limited resources to process information, and media sentiment in influencing herding. Their research covers a period from April 2013 to 2018 so we have more recent data, but they include the first 100 cryptocurrencies. They also use a Markov switching model (MS) which splits the sample into regimes to find the ranges with the most volatility. There is herding when the market experiences positive returns but there is no herding when the market faces declining returns. This suggests that investors hold onto their assets despite negative returns. This contradicts the findings in the previous study by Jia et al. (2022) which found that the market is more susceptible to herding in down market movements but is consistent with Ballis and Drakos (2020). This implies that the cryptocurrency market is still unpredictable. Our research will be unique as we will be using the most recent data up to May 2023 and we will also be comparing herding behavior in terms of market capitalization and volatility combined. Additionally, we will examine if there is herding behavior during specific events.

Data Collection

The data collection involved two steps. First, a dataset containing historical price data on 23 cryptocurrencies was obtained from Kaggle. However, since the Kaggle dataset only covered cryptocurrency prices up to June 2021, we downloaded the data using Yahoo Finance (yahoo.finance.com) on June 5th, 2023. This data covered the entire period of October 9th, 2018, to May 31st, 2023. Then, the dataset was narrowed down to focus on 16 cryptocurrencies. The cryptocurrencies were chosen based on the number of days that would be counted. With the start date of October 9th, 2018, 1695 days are counted for the top 16 cryptocurrencies.

Table 1. List of cryptocurrencies and market index (CCI30) in our sample. 7 cryptocurrencies were dropped.

Date	Start date	End date	Difference	Years	Actual start date	Number of observations
BTC	4/29/2013	5/31/2023	3684	10.09	10/9/2018	1695
LTC	4/29/2013	5/31/2023	3684	10.09	10/9/2018	1695
XRP	8/5/2013	5/31/2023	3586	9.82	10/9/2018	1695
DOGE	12/16/2013	5/31/2023	3453	9.46	10/9/2018	1695
XMR	5/22/2014	5/31/2023	3296	9.03	10/9/2018	1695
XLM	8/6/2014	5/31/2023	3220	8.82	10/9/2018	1695
USDT	3/6/2015	5/31/2023	3008	8.24	10/9/2018	1695
NEM	4/2/2015	5/31/2023	2981	8.17	10/9/2018	1695
ETH	8/8/2015	5/31/2023	2853	7.82	10/9/2018	1695
IOTA	6/14/2017	5/31/2023	2177	5.96	10/9/2018	1695
EOS	7/2/2017	5/31/2023	2159	5.92	10/9/2018	1695
BNB	7/26/2017	5/31/2023	2135	5.85	10/9/2018	1695
TRON	9/14/2017	5/31/2023	2085	5.71	10/9/2018	1695
LINK	9/21/2017	5/31/2023	2078	5.69	10/9/2018	1695
ADA	10/2/2017	5/31/2023	2067	5.66	10/9/2018	1695
USDC	10/9/2018	5/31/2023	1695	4.64	10/9/2018	1695
CRO	12/15/2018	5/31/2023	1628	4.46	10/9/2018	N/A

Date	Start date	End date	Difference	Years	Actual start date	Number of observations
WBTC	1/31/2019	5/31/2023	1581	4.33	10/9/2018	N/A
ATOM	3/15/2019	5/31/2023	1538	4.21	10/9/2018	N/A
SOL	4/11/2020	5/31/2023	1145	3.14	10/9/2018	N/A
DOT	8/21/2020	5/31/2023	1013	2.78	10/9/2018	N/A
UNI	9/18/2020	5/31/2023	985	2.70	10/9/2018	N/A
AAVE	10/5/2020	5/31/2023	968	2.65	10/9/2018	N/A
CCI30	1/1/2015	5/31/2023	3072	8.42	10/9/2018	1695

To test whether market capitalization affects herding behavior, we split our sample into the top 8 and bottom 8 cryptocurrencies using the market capitalization data from July 6th, 2021. To test whether volatility affected herding in the market, the 16 data sets were graphed out as seen in Figure 1. Then, specific data periods within the entire range were found where all the prices experienced a high level of volatility and a low level of volatility. The range for high volatility is March 24th, 2021, to November 14th, 2022, and the range for low volatility is June 12th, 2019, to February 1st, 2021.

We also tested for herding behavior during the COVID-19 pandemic by using the data range of March 20th, 2020, to May 19th, 2020, and the FTX bankruptcy from November 10th, 2022, to January 9th, 2023. Then, we calculated if there was herding behavior when Google Trends for the search "BTC" was at the highest from September 1st, 2019, to October 31st, 2019. We did the same with the search "Cryptocurrency" from May 9th, 2021, to July 8th, 2021. These data ranges are 60 days.

COVID-19 was declared a pandemic in March, so we started our data in that month. FTX bankruptcy took place on November 11th, 2022, and we decided to start our data range a day before that. In April 2021, there was a huge shift in the daily price of cryptocurrencies as there is a period of rapid price growth followed by a significant market downturn as seen in Figure 1. Ponciano (2021) reported that this was from large-scale blackouts in China, leading to "massive declines in Bitcoin's mining rates." This tanked prices and spurred billions of dollars in liquidations (Ponciano 2021). Furthermore, it is important to note that certain cryptocurrencies, such as USDC and USDT exhibit lower price volatility, as shown in Figure 1o and 1p respectively. This is because they are stablecoins, which means they are backed by the USD currency, a stable asset.

Methodology

The CCI30 index was used to represent the overall market performance of cryptocurrencies. The CCI30 (CryptoCurrency Index 30), as shown at the bottom of Table 1, is a popular index that measures the performance of the top 30 cryptocurrencies by market capitalization. First, we calculated the daily returns of the 16 closing prices. Then, to analyze the herding behavior within the selected cryptocurrencies, two established metrics were utilized. First, the cross-sectional standard deviation (CSSD) created by Christie & Huang (1995) was employed:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (\mathrm{R}_{\mathrm{i,t}} - \mathrm{R}_{\mathrm{m,t}})^2}{N-1}}$$

where $\mathrm{R}_{\mathrm{i,t}}$ is the return of cryptocurrency i at time t, $\mathrm{R}_{\mathrm{m,t}}$ is the cross-sectional average return of the N returns of the equally weighted market portfolio at time t, and N is the number of stocks in the market. Once CSSD is calculated, a regression is conducted where dummy variables are created which equal 1 during extreme market movements and 0 otherwise. The extreme market movement in this case was returns below the 5th percentile and above the 95th percentile.

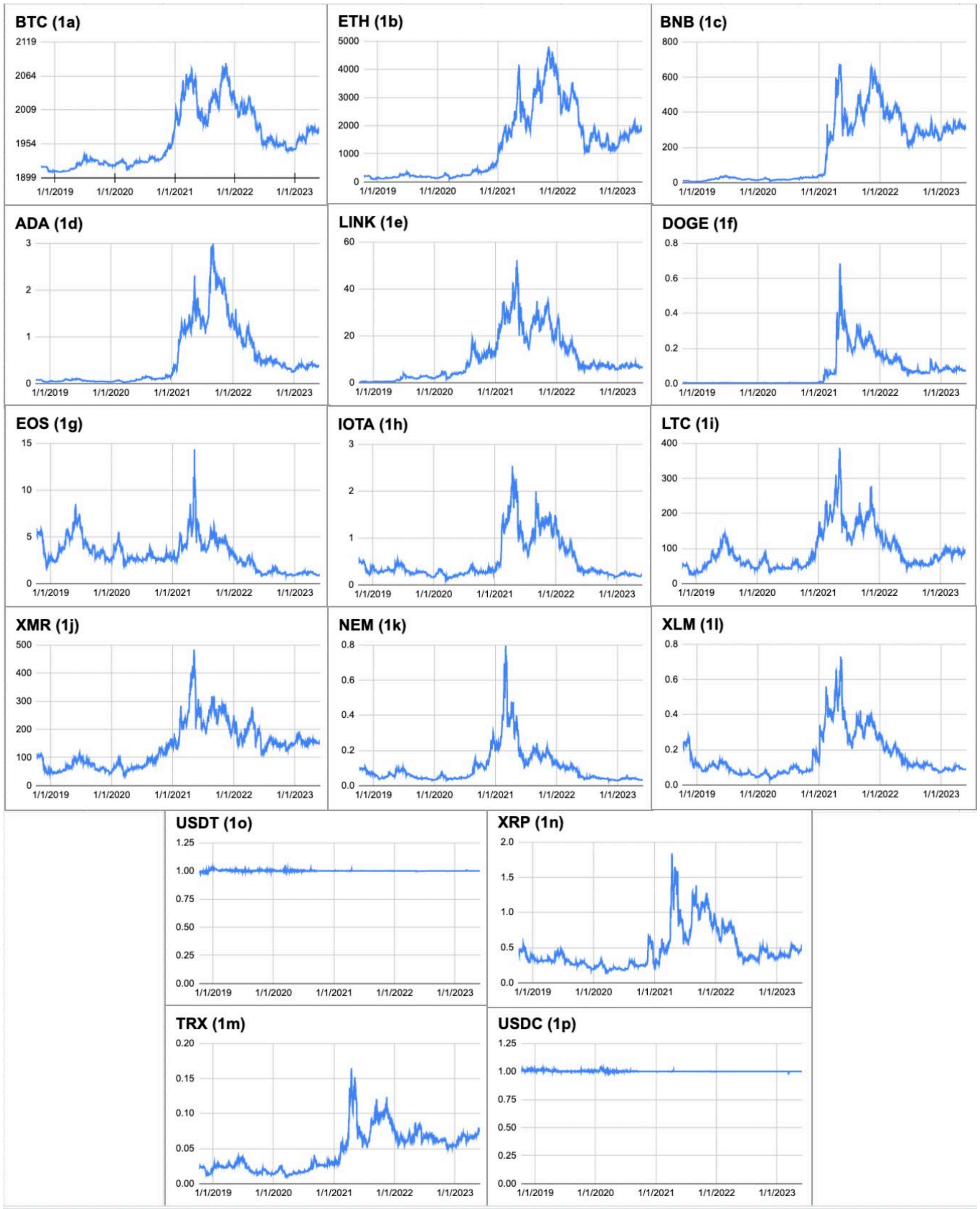

Figure 1. Time series plot of the 16 cryptocurrencies in our sample labeled with the cryptocurrency name on each panel.

Then, in a later study, Chang et al. (2000) recommended the use of the cross-sectional absolute deviation (CSAD) because CSSD is sensitive to outliers. CSSD is used on more extreme market conditions, focusing on the top and bottom 5% whereas CSAD is used on the entire datasets.

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

$\mathrm{R}_{\mathrm{i,t}}$ is the return of cryptocurrency i at time t, $\mathrm{R}_{\mathrm{m,t}}$ is the market return on day t. After CSAD was calculated, this regression was then applied:

$$CSAD_t = a + y_1\left|\mathrm{R}_{\mathrm{m,t}}\right| + y_2\mathrm{R}^2{}_{\mathrm{m,t}} + \epsilon_t$$

where $\left|\mathrm{R}_{\mathrm{m,t}}\right|$ is the absolute equally weighted market return and $\mathrm{R}^2{}_{\mathrm{m,t}}$ is the squared market return.

According to Chang et al. (2000), a statistically significant negative coefficient y_2 implies that the square market return is negatively correlated with the CSAD value, which further implies the existence of herding.

Coefficient is negative:
Null hypothesis is H0: There is no herding behavior.
Alternative hypothesis H1: There is herding behavior.

Coefficient is positive:
Null hypothesis is H0: There is herding behavior.
Alternative hypothesis H1: There is no herding behavior.

Results

The empirical analysis examines herding behavior within the cryptocurrency market using CSSD and CSAD.

Table 2. Summary of CSSD and CSAD for 16 cryptocurrencies in our sample from 2018-2023 using CCI30 as the market index.

		Coefficients	P-value
CSSD	**Right**	0.0223	0.0000
	Left	0.0325	0.0000
CSAD	**Ret^2**	-0.0641	0.4887
	Abs Ret	0.2898	0.0000
	Ret	0.0599	0.0000

In Table 2, the results demonstrate that all 16 cryptocurrencies consistently exhibited no herding behavior throughout the study period. The coefficients calculated using CSSD for both the left and right tail were positive and significant at 5%. This indicates that we can rule out the null hypothesis and that these 16 cryptocurrencies do not have herding behavior compared to the CCI30 index. The Ret^2 coefficient calculated using CSAD was negative, showing weak herding behavior, but was not significant at 5%, this means that we cannot rule out our null hypothesis, so we cannot rule out that there is no herding behavior. This suggests that crypto investors have a relatively independent decision-making approach when looking at these 16 cryptocurrencies.

Table 3. Summary of CSSD and CSAD for top 8 and bottom 8 cryptocurrencies by market cap from 2018-2023 using CCI30 as the market index.

		Top 8		Bottom 8	
		Coefficients	**P-value**	**Coefficients**	**P-value**
CSSD	**Right**	0.0363	0.0000	0.0080	0.0007
	Left	0.0430	0.0000	0.0217	0.0000
CSAD	**Ret^2**	-0.0942	0.4666	-0.0340	0.7237
	Abs Ret	0.4171	0.0000	0.1625	0.0000
	Ret	0.0714	0.0000	0.0484	0.0000

In Table 3, the top 8 and bottom 8 cryptocurrencies are split up by market capitalization and calculated. The coefficients calculated using CSSD for both the left and right tail were positive and significant at 5%. This indicates that we can rule out the null hypothesis so there is no herding behavior. The Ret^2 coefficient calculated using CSAD was negative but was not significant at 5%, this means that we cannot rule out our null hypothesis, so we cannot rule out that there is no herding behavior.

However, the results also indicated that the bottom 8 cryptocurrencies displayed a higher degree of possible herding compared to the top 8 and overall sample because the statistically significant coefficients are smaller than the top 8 samples and the overall 16 cryptocurrency sample. The results are consistent across both CSSD and CSAD. The result of Ret^2 for the bottom 8 is bigger than the top 8 sample, but it is insignificant. This finding indicates that smaller, less established cryptocurrencies are more likely to be influenced by herding even though there is no definite sign of herding due to the positive coefficients. This matches our hypothesis.

Table 4. Summary of CSSD and CSAD for 16 cryptocurrencies by volatility from 3/24/21 to 11/14/22 for high volatility and 6/12/19 to 2/1/21 for low volatility using CCI30 as the market index.

		High Volatility		Low Volatility	
		Coefficients	**P-value**	**Coefficients**	**P-value**
CSSD	**Right**	0.0199	0.0000	0.0270	0.0016
	Left	0.0258	0.0000	0.0389	0.0000
CSAD	**Ret^2**	0.2288	0.1248	-0.1715	0.2498
	Abs Ret	0.2108	0.0000	0.3432	0.0000
	Ret	0.0406	0.0000	0.0847	0.0000

Table 4 examines the relationship between volatility and herding behavior in the cryptocurrency market. The coefficients calculated using CSSD for both the left and right tail were positive and significant at 5%. This indicates that we can rule out the null hypothesis so there is no herding behavior. The Ret^2 coefficient calculated using CSAD during low volatility was negative but was not significant at 5%; this means that we cannot rule out our null hypothesis, so we cannot rule out that there is no herding behavior in times of low volatility. The rest of the results for CSAD are positive and significant so there are no signs of herding behavior.

Although all the samples using CSSD and CSAD show signs of no herding, the statistically significant coefficients of higher volatility are consistently smaller than the coefficients in Table 2. The only one that is not consistent is Ret^2 but it is insignificant. Similarly, the statistically significant coefficients of low volatility are bigger than the coefficients of CSSD and CSAD in Table 2. This suggests that higher levels of volatility can be associated with a greater degree of herding behavior, and investors should be cautious when investing in them.

Table 5. Summary of CSSD and CSAD for 16 cryptocurrencies by top 8 and bottom 8 cryptocurrencies and by volatility from 3/24/21 to 11/14/22 for high volatility and 6/12/19-2/1/21 for low volatility using CCI30 as the market index.

		Top 8 w/ High Volatility		**Top 8 w/ Low Volatility**	
		Coefficients	**P-value**	**Coefficients**	**P-value**
CSSD	**Right**	0.0330	0.0000	0.0419	0.0005
	Left	0.0359	0.0000	0.0469	0.0001
CSAD	**Ret^2**	0.0800	0.6663	-0.1597	0.4873
	Abs Ret	0.3548	0.0000	0.4652	0.0000
	Ret	0.0534	0.0000	0.0919	0.0000

		Bottom 8 w/ High volatility		**Bottom 8 w/ Low volatility**	
		Coefficients	**P-value**	**Coefficients**	**P-value**
CSSD	**Right**	0.0064	0.0354	0.0121	0.0095
	Left	0.0143	0.0000	0.0321	0.0000
CSAD	**Ret^2**	0.3775	0.0272	-0.1833	0.1742
	Abs Ret	0.0669	0.0188	0.2212	0.0000
	Ret	0.0278	0.0053	0.0776	0.0000

Table 5 examines the relationship between volatility, market capitalization, and herding behavior in the cryptocurrency market. The coefficients calculated using CSSD in Table 5 for both the top and bottom 8 were positive and significant at 5%. This indicates that we can rule out the null hypothesis so there is no herding behavior. The Ret^2 coefficient calculated using CSAD in the low volatility was negative but was not significant at 5%, meaning that we cannot rule out our null hypothesis, that there is no herding behavior.

Although all the samples using CSSD and CSAD show signs of no herding, the sample with the higher volatility in both the top 8 and bottom 8 consistently had a smaller coefficient than the coefficients in Table 2, based on CSSD and CSAD. The sample with the higher volatility in Table 5 also consistently had a smaller significant coefficient than the coefficients in Table 3. However, the statistically significant coefficients under low volatility in Table 5 were inconsistent in terms of bigger or smaller coefficients compared to Table 2. This suggests that higher levels of volatility were associated with a greater degree of herding, while lower volatility levels were inconsistent. This further shows that at higher levels of volatility, herding behavior could be more present, and investors should be cautious when investing in those times.

Table 6. Summary of CSSD and CSAD for 16 cryptocurrencies using a 60-day period after the start date of each time period of interest. Covid-19 pandemic from 3/20/2020 to 5/19/2020, FTX Bankruptcy from 11/10/2022 to 1/9/2023, highest Google Trend of search "BTC" from 9/1/2019 to 10/31/2019, and Highest Google Trend of search "Cryptocurrency" from 5/9/2021 to 7/8/2021, using CCI30 as the market index.

COVID-19 Pandemic			
		Coefficients	**P-value**
CSSD	**Right**	0.0144	0.0079
	Left	0.0182	0.0000
CSAD	**Ret^2**	-0.1536	0.8289
	Abs Ret	0.1998	0.0025
	Ret	0.0361	0.0098

FTX Bankruptcy			
		Coefficients	**P-value**
CSSD	**Right**	0.0190	0.0135
	Left	0.0485	0.0000
CSAD	**Ret^2**	-0.6415	0.1184
	Abs Ret	0.3188	0.0000
	Ret	0.0076	0.7110

Highest Google Trend "BTC"			
		Coefficients	**P-value**
CSSD	**Right**	0.0505	0.0000
	Left	0.0426	0.0001
CSAD	**Ret^2**	0.0144	0.8223
	Abs Ret	0.3073	0.0007
	Ret	0.0585	0.0192

Highest Google Trend "Cryptocurrency"			
		Coefficients	**P-value**
CSSD	**Right**	0.0268	0.0002
	Left	0.0352	0.0000
CSAD	**Ret^2**	0.2003	0.3925
	Abs Ret	0.2218	0.0002
	Ret	0.0425	0.0119

In Table 6, we attempt to find if there is a correlation between world events and trends and cryptocurrency prices. From the start of the COVID-19 pandemic, March 20th, 2020, to 60 days later, the coefficients calculated using CSSD for both the left and right tail were positive and significant at 5%. This indicates that we can rule out our null hypothesis and that there is no herding behavior. The R^2 coefficient calculated using CSAD was negative, showing weak herding behavior, but was not significant at 5%, this means that we cannot rule out our null hypothesis, so we cannot rule out that there is no herding behavior. However, we find that the coefficients are consistently smaller than Table 2, implying that there could be a higher chance of herding during the first 60 days of the COVID-19 pandemic.

The same results were found for the first 60 days after the FTX bankruptcy on November 11th, 2022. However, the results are inconsistently smaller or larger than the coefficients in Table 2, meaning there is no certainty that the FTX bankruptcy could signal a change in herding behavior. For both the highest Google trend search for "BTC" and "Cryptocurrency," all the coefficients are either positive and significant, ruling out the null hypothesis that there is herding, or positive and insignificant, not able to rule out the null. These findings are also inconsistent with the hypothesis that there is more herding behavior when trends fluctuate because the coefficients are not collectively bigger or smaller than those in Table 2.

It is important to note that there is also a difference between the CSAD and CSSD coefficient levels. When they are both significant, the coefficient on CSSD is consistently lower than that of CSAD and closer to 0. This implies that the model is predicting more herding behavior when it focuses on the more extreme market conditions (top and bottom 5%), where the volatility would also be higher.

Discussion

Contrary to popular expectations, our analysis, past academic research papers, and current evidence do not support the existence of herding in the cryptocurrency space. However, our research indicates that there are situations such as a lower market cap or higher volatility where there is a higher chance of herding behavior.

However, when studying specific events such as the FTX bankruptcy, there was no consistent statistically significant herding behavior. This was seen similarly when trying to find the correlation between Google trends and the cryptocurrency market. This could be because we used the next 60 days from the start date, and this window could either be too small or too large. The market may correct itself very quickly or in some cases, the market would need more time to adapt. The use of USDC and USDT, stablecoins, could have also affected the analysis because they are backed by a stable asset.

Similar to Jia et al. (2022) we found no herding when we analyzed the entire sample and we also found that volatility affects herding behavior. The difference in our results compared to Ballis and Drakos (2020) which found herding behavior and increased herding behavior in up-events could potentially be due to the different methodological parameters. Their study looked at fewer cryptocurrencies, over a shorter time period and was confined to the years 2015-2018, when the crypto market was still nascent and highly volatile. They also used the Newey-West model and a GARCH model which we do not. Calderón (2018) got a similar result to us, but we do not use the Markov switching model that they use when finding volatility. This limitation of graphing the t-series instead of using the model could potentially mean less refined and efficient outcomes.

Another interesting point to consider is the rapid maturation of the cryptocurrency market. As the trading volume rises and secondary entities like businesses get involved, there is a growth in the market's sophistication. With this maturity comes an increase in access to information and the ability to make more rational choices. Although this could reduce the likelihood of herding, we need to be careful when investing in smaller cryptocurrencies and look out for times when there is high volatility in the price. Smaller assets that could be more influenced by herding behavior can cause additional risks and market fluctuations. As herding is more pronounced in smaller and less established cryptocurrencies, investors should practice increased judgment and research before emerging themselves in these assets.

Conclusion

Our research provides valuable insights into the behavior of investors in this new but rapidly evolving market. By using the CSSD and CSAD metrics, our paper contributes to the existing literature as it finds positive, significant evidence that there is no herding in a large group of cryptocurrencies over a recent period of 4 years. However, it does find a higher chance of herding in times of high volatility and lower market cap, even though the coefficients are still positive. It also finds that from a period of two months, there seems to be a lack of correlation between Google search trends and herding behavior, along with huge market events like the FTX bankruptcy.

In contrast to our hypothesis, these findings suggest that there is a low level of herding behavior, and market participants are displaying more rational decisions. Throughout the last decade, it seems that the market has been able to mature at a quick pace. This accelerated maturation can be attributed to various factors such as the minimal barriers to entry for retail investors and globalization. Moreover, the advancement of digital technologies and the accessibility of information could also have created this group of more informed investors.

Future Work

For future work, first, it is crucial to explore alternative methodologies as well. Despite the popularity of the CSSD and CSAD methodologies, there may be other metrics that are more efficient. In particular, the Newey West model and the GARCH model should be explored as many other research papers employ these methods. These approaches have much more complexity involved. Expanding the number of cryptocurrencies used such as including the top 100 by market capitalization would also offer a more comprehensive perspective on herding behavior. We could also measure the correlation between gold, silver, and oil prices and herding behavior for cryptocurrencies. To go even further, we can try to measure if there is a causal relationship between them.

References

Ballis, A., & Drakos, K. (2020). Testing for herding in the cryptocurrency market. *Finance Research Letters*, 33, 101210. https://doi.org/10.1016/j.frl.2019.06.008

Calderón, O. P. (2018). Herding behavior in cryptocurrency markets. *arXiv preprint arXiv:1806.11348.*

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679. https://doi.org/10.1016/S0378-4266(99)00096-5

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: do individual returns herd around the market?. *Financial Analysts Journal*, 51(4), 31-37. https://doi.org/10.2469/faj.v51.n4.1918

Jia, B., Shen, D., & Zhang, W. (2022). Extreme sentiment and herding: Evidence from the cryptocurrency market. *Research in International Business and Finance*, *63*, 101770. https://doi.org/10.1016/j.ribaf.2022.101770

Ponciano, J. (2021, April 18). *Crypto Flash Crash Wiped Out $300 Billion In Less Than 24 Hours, Spurring Massive Bitcoin Liquidations*. Forbes. https://www.forbes.com/sites/jonathanponciano/2021/04/18/crypto-flash-crash-wiped-out-300-billion-in-less-than-24-hours-spurring-massive-bitcoin-liquidations/?sh=3b7189082c89.

Rajkumar, S. (2021). *Cryptocurrency Historical Prices* (Version 3) [Data set]. Kaggle. https://www.kaggle.com/datasets/sudalairajkumar/cryptocurrencypricehistory

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Herding in the cryptocurrency market: CSSD and CSAD approaches. F*inance Research Letters*, 30, 181-186. https://doi.org/10.1016/j.frl.2018.09.008