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HERDING BEHAVIOR IN VOLATILE MARKET REGIMES: AN IN-DEPTH ANALYSIS OF COINS, TOKENS, PANDEMIC, PENNY, AND PRICEY CRYPTOCURRENCIES

Rayenda Khresna Brahmana
School of Economics, Finance, and Accounting, Coventry University

Muhammad Arsalan Hashmi
Institute of Business & Health Management, Dow University of Health Sciences, Karachi, Pakistan

Abdullah
College of Management Sciences, Karachi Institute of Economics & Technology, Karachi, Pakistan

Josephine Tan-Hwang Yau♣
Faculty of Economics & Business, Universiti Malaysia Sarawak
Corresponding author, Email: ythjosephine@unimas.my

ABSTRACT

This study comprehensively analyzes herding behavior in the cryptocurrency market. First, we conduct an in-depth investigation of herding behavior in the overall cryptocurrency market. Second, we form several groups of cryptocurrencies according to their characteristics and analyze whether each group behaves similarly in volatile market regimes. Third, we investigate whether herding existed in each cryptocurrency group before and during the COVID-19 pandemic. Using a sample of 227 cryptocurrencies constituting nearly 95% of market capitalization, we reveal that herding behavior was absent in the overall sample and sub-samples comprising cryptocurrency groups. Further, the anti-herding behavior implies a contrarian response to the crowd. This anti-herding can be explained from two views: rational behavior of taking profit from market irrationality and irrational behavior due to fear or recency bias.

Keywords: Cryptocurrency, herding, coins, tokens, COVID-19.

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1. INTRODUCTION

Surging as the new hype among investors, the market activity of cryptocurrency has attracted academics, policymakers, regulators, and hedge funds to exploit the opportunity of cryptocurrency as a new asset class. Empirically, there is an abundance of findings related to market dynamics (Urquhart, 2018; Corbet et al., 2020), regulation (Feinstein & Werbach, 2021; Yadav et al., 2020), portfolio management (Jiang & Liang, 2017; Boako et al., 2019, and efficiency (Urquhart, 2016; Urquhart, 2017) of these cryptocurrencies. A systematic analysis by Corbet et al. (2019) provides a comprehensive literature analysis of this matter.

From the perspective of market dynamics and efficiency, the proponent of behavioral finance attributes the fluctuation in cryptocurrency returns to investor behavior, famously known as herding. It posits that investors irrationally imitate the decisions of other investors while ignoring their unique investment strategies. Cryptocurrency investors irrationally respond to the bullish and bearish markets by following the collective consensus. As a result, investors are exposed to inefficient prices in cryptocurrency markets, resulting in an irrational momentum strategy. Unfortunately, prior literature provides mixed findings related to herding behavior in the cryptocurrency market. The existing literature indicates that some studies have found assertive herding behavior under different circumstances, while others report an absence of herd behavior. Appendix C provides a summary of selected influential literature on herding in cryptocurrencies.

One reason for the mixed findings of cryptocurrency herding behavior is that prior studies have only focused on selected renowned cryptocurrencies like Bitcoin while ignoring the majority of over 200 liquid cryptocurrencies. Furthermore, a few studies that have analyzed multiple cryptocurrencies have pooled all cryptocurrencies assuming that they behave in a similar manner (i.e.,

♣ Corresponding author, Email: ythjosephine@unimas.my

Kallinterakis and Wang, 2019; Omane-Adjepong et al., 2021). To the best of our knowledge, no prior study distinguishes between coins, tokens, big-capitalization, small-capitalization, pricey, and penny cryptocurrencies. Furthermore, no previous study has investigated herding while considering the trading volume and investors' familiarity with cryptocurrency coins and tokens that may exhibit different investor behavior.
Additionally, the COVID-19 pandemic has opened an opportunity for developers to issue more cryptocurrencies (such as pandemic cryptocurrency), which may behave differently as compared to their counterparts. Given the different behavior of various cryptocurrencies, a more comprehensive understanding of how the cryptocurrency market behaves is critical to the digital finance literature. However, this critical topic has not received direct attention in the current literature.

In view of the abovementioned gap, this study comprehensively analyzes the behavior of several types of cryptocurrencies. To achieve this objective, we categorize the cryptocurrencies of our sample into four groups based on type, market capitalization, price, and time of issue. The first group, categorized based on type, is divided into coins and tokens. The second group, categorized based on market capitalization, consists of Big-5 cryptocurrencies and others. Further, we group the cryptocurrencies according to their prices, i.e., pricey and penny. Lastly, we formed a group of cryptocurrencies initiated during the COVID-19 pandemic. Appendix A presents the definitions of each group.

The existing literature comprehensively analyzes herding in cryptocurrency types is scarce and remains a black box. We argue that different types of cryptocurrencies exhibit different market behavior in volatile market regimes. Figure 1 presents the risk and reward of each cryptocurrency group, which indicates a substantial difference in the risk and reward relationship of several cryptocurrency groups such as coins, tokens, penny, big-5, and pricey. Given the above discussion and the gap in the literature, this study has several objectives. First, we conduct an in-depth investigation of herding behavior in the overall cryptocurrency market. Second, we form several groups of cryptocurrencies according to their characteristics and analyze whether each group has similar behavior in volatile market regimes. Third, we investigate whether herding was present in each cryptocurrency group before and during the COVID-19 pandemic.

Our study is different from the recent influential studies on cryptocurrency herding, such as Philippas et al. (2020), Yarovaya et al. (2021), Corbet et al. (2020), and other empirical findings (see Appendix C), which analyzed herding behavior in cryptocurrency markets. However, these studies did not separately analyze cryptocurrency herding in various groups like coins, tokens, pennies, and pricey cryptocurrencies. In addition, these studies used a relatively small sample comprising only popular cryptocurrencies. Similarly, most existing studies do not analyze how the COVID-19 pandemic has affected investor behavior toward cryptocurrencies.

The study has several unique contributions. First, we analyzed data for over 200 active cryptocurrencies, unlike most earlier literature focusing on a few cryptocurrencies at a time. Second, we categorize these cryptocurrencies into four distinct groups based on type, market capitalization, price, and time of issue. Third, we find novel evidence that different groups of cryptocurrencies exhibit different market behavior. Fourth, we find no systematic evidence of herding behavior, suggesting that several cryptocurrencies follow the rational asset pricing hypothesis.

The remainder of the paper is structured as follows. The subsequent section provides a literature review. It is followed by the methodology, results, and discussion. The last section concludes the study by highlighting the main findings, limitations, and suggestions for future research.

2. LITERATURE REVIEW

Conventional finance theories suggest that investors and other market participants always make rational investment decisions. These rational decisions assume that investors have perfect information in the market that they can use for detailed analysis before making investment decisions (Malkiel and Fama, 1970). On the contrary, the proponents of behavioral finance argue that investors are human beings, and their investment decisions are affected by human psychology and emotions (Easley and Kleinberg, 2012; Brahmana et al., 2012b; Shiller, 2003). Moreover, behavioral finance theorists believe investors do not always make rational investment decisions. Their decision-making is affected by emotions, sentiments, and behavioral biases, which sometimes lead to market volatility (Kahneman and Tversky, 1973; Shleifer and Summers, 1990). One such phenomenon frequently observed among investors is referred to as herding. Herding or herd behavior occurs when investors irrationally replicate or follow the investment decisions of other market participants while ignoring their own beliefs and analysis (Shiller, 2003; Brahmana et al., 2012b; Easley and Kleinberg, 2012; Bikhchandani and Sharma, 2000). Prior studies have argued that herding causes asset prices to deviate from their fundamental values, creating unnecessary volatility and noise in financial markets (Kumar, 2020).

This study intends to comprehensively examine the herding behavior of cryptocurrencies. Cryptocurrency is a digital currency based on blockchain technology and was introduced as a substitute for paper money that operates in a decentralized environment without the supervision of central banks or government regulations (Urquhart & Yarovaya, 2020). Cryptocurrency takes many forms, such as coins and tokens, which may be used for payments and speculative trading. Unlike other financial assets, the value of cryptocurrency is not based on fundamentals but on the participation level of its users, such as developers and miners (Urquhart & Yarovaya, 2020). The movement in the value of cryptocurrency results from changes in the participation and perception of its users. The perception of cryptocurrency users is heavily dependent upon information circulating on social media and news channels (Kumar, 2020). Due to the heavy reliance on unreliable information and lack of technical knowledge of cryptocurrencies, investors may follow other market participants, leading to herding and market volatility (Bouri et al., 2018; Vidal-Tomás et al., 2018).

Coins and tokens are two forms of cryptocurrencies that are pretty distinct. Coins represent virtual money based on blockchain technology which utilizes encryption and provides a store of value. Coins also have monetary characteristics, including durability, portability, and acceptability. Contrarily, tokens are a form of cryptocurrency that can be solely utilized as a means of payment for a specific project issue. Further, it allows user participation in a network. Therefore, coins are essentially digital currencies used for buying and selling, while tokens are typically used in the context of a specific project. Unlike conventional financial instruments, cryptocurrencies operate in a decentralized environment without government or central bank intervention. Moreover, cryptocurrency markets are different from traditional currency markets as the former is largely unaffected by changing political and economic forces. Thus, the price of cryptocurrency coins and tokens will likely be affected by several factors, such as market capitalization, media coverage, and integration with existing e-commerce infrastructure.

The unique features and forms of cryptocurrencies have attracted the attention of academic researchers. Existing research has focused on cryptocurrency valuation, investor behavior, trading strategies, and other market dynamics. Several recent studies have analyzed herd behavior using various cryptocurrencies. It is argued that herding behavior is prevalent during stressful periods when the market exhibits bearish and bullish trends, such as booms, recessions, and pandemics (Vidal-Tomas et al., 2019). Several studies have found evidence of herding in cryptocurrencies under different market conditions; for instance, Silva et al. (2019) found herding under bearish market conditions using a dataset comprising 50 cryptocurrencies. Haryanto et al. (2019) found that changes in Bitcoin prices drive herding behavior in the cryptocurrency market. Similarly, Ballis and Drakos (2019) suggest herd behavior was prevalent under bullish market conditions in six leading crypto-currencies.

Further, Kumar (2020) found that stressful market conditions and volatility lead to rampant herding among cryptocurrency market participants. Mandaci and Cagli (2021) analyzed several cryptocurrencies during the COVID-19 pandemic and found herding behavior among investors. Likewise, Rubbaniy et al. (2021) investigated the presence of herding behavior in a dataset of 101 crypto-currencies during the COVID-19 pandemic and found evidence of herding during extreme bullish and bearish market scenarios. Contrarily, numerous studies did not find evidence of herding in the cryptocurrency market. For instance, Stavros and Vassilios (2019) found no evidence of herding in a sample of eight cryptocurrencies. Likewise, Silva et al. (2019) investigated 50 cryptocurrencies but documented weak evidence of herd behavior among investors. Similarly, Yarovaya et al. (2021) studied a sample of nine cryptocurrencies during the COVID-19 pandemic and found no evidence of herding behavior.

3. METHODOLOGY

3.1 Data

The study used daily prices of 227 cryptocurrencies from January 1, 2019, to May 31, 2021. The data was extracted from the cryptocurrency market website, i.e., coinmarketcap.com. The daily price data was used to calculate daily returns after applying the log transformation. By 2021, there will be over 6,500 cryptocurrencies available in the market; however, not all cryptocurrencies fit our selection criteria. We used two criteria for selecting cryptocurrencies for the study. First, we included those cryptocurrencies with a liquid trading volume during the sample period. Second, we include cryptocurrencies that are actively traded. The final sample comprises 227 cryptocurrencies, constituting over 95% of the market capitalization of the cryptocurrencies. Following the seminal paper of Christie and Huang (1995), we calculate dispersion using the Cross-Sectional Standard Dispersion (CSSD) and Cross-Sectional Absolute Standard Deviation (CSAD) methods.

3.2 Herding Model Specification

Herding literature is divided into two approaches in terms of exploring the existence of the behaviour. The first stream is a micro-data-based model pioneered by Lakonishok et al. (1992) and Sias (2004). This approach takes intraday trading data, which is difficult to acquire such data in cryptocurrencies. Meanwhile, the second stream is the aggregate-data-based model, coined by Christie and Huang (1995). This approach uses the cross-sectional standard deviation of returns to capture herd behavior. They introduced Cross-Sectional Standard Dispersion (CSSD) and Cross-Sectional Absolute Standard Deviations (CSAD) measures based on a normal distribution framework. Much herding research employs this model to capture the behavior.

Hence, our study used the dispersion approach of Christie and Huang (1995) and Chang et al. (2000) for analyzing herd behavior among cryptocurrency investors. These studies argue that investors may react rationally or adopt herd behavior when there is a large movement in prices. Rational asset pricing predicts an increase of dispersion during large price movements because each cryptocurrency differs in its sensitivity to the cryptocurrency market. Contrarily, herding behavior leads to a decrease in dispersion during large price movements. Prior literature suggests a negative relationship exists between extreme returns and the level of dispersion if investors adopt herd behavior. This theoretical model is commonly used in the herding literature, while alternative models by Bohl et al. (2014) and Lee (2017) are rarely used. Following Christie and Huang (1995) and Chang et al. (2000), we estimate the following model:

$$S_t = \alpha_1 + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t$$

Where, S_t is the portfolio return dispersion, measured by Cross-Sectional Standard Dispersion (CSSD) and Cross-Sectional Absolute Standard Deviations (CSAD). D^U is a dummy variable for the upper bound, taking a value of 1 if the market return on day *t* lies in the 95th percentile of the return distribution and 0 otherwise. D^L is a dummy variable for the lower bound, taking a value of 1 if the market return on day *t* lies in the 5th percentile of the return distribution and 0 otherwise.

3.3 Cross-Sectional Standard Dispersion (CSSD)

The first measurement for dispersion in cryptocurrencies returns is Cross-Sectional Standard Dispersion (CSSD), which is calculated by the following expression:

$$CSSD = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}}$$

Where, r_i is the observed return of cryptocurrency *i* and $\bar{r}$ is the cross-sectional average of the *n* returns in the portfolio. This approach was introduced by Christie and Huang (1995) to quantify the degree to which cryptocurrency returns tend to move compared to portfolio returns, which capture herd behavior.

3.4 Cross-Sectional Absolute Standard Deviations (CSAD)

The second measure of dispersion that is used in the study for capturing herd behavior is the Cross-Sectional Absolute Standard Deviation (CSAD). CSSD can be calculated using the formula:

$$CSAD = \frac{\sum_{i=1}^{n}|r_i - \bar{r}|}{n}$$

4. RESULTS

4.1. Descriptive Statistics

Table 1 presents the summary statistics for the relevant groups in the sample comprising the mean, standard deviation, and the number of cryptocurrencies. The portfolio's mean return comprising all cryptocurrencies is 3.571%, consistent with Parveen et al. (2021), with a mean portfolio return of 3.5% for 2015-2020. However, our mean portfolio return was lower than Kumar's (2020), which reports a mean return of 5.37% for 100 cryptocurrencies during the period 2013-2019. Further, Kallinterakis and Wang (2019) reported mean returns of 0.15% in a sample of 296 cryptocurrencies from 2013 to 2018. It suggests that the mean return of cryptocurrencies may vary according to the market cycle and the sample. Our findings support the view that different cycles will result in different levels of dispersion in cryptocurrencies. For instance, Parveen et al. (2021) report that CSAD during the COVID-19 pandemic was higher than CSAD in the pre-pandemic period.

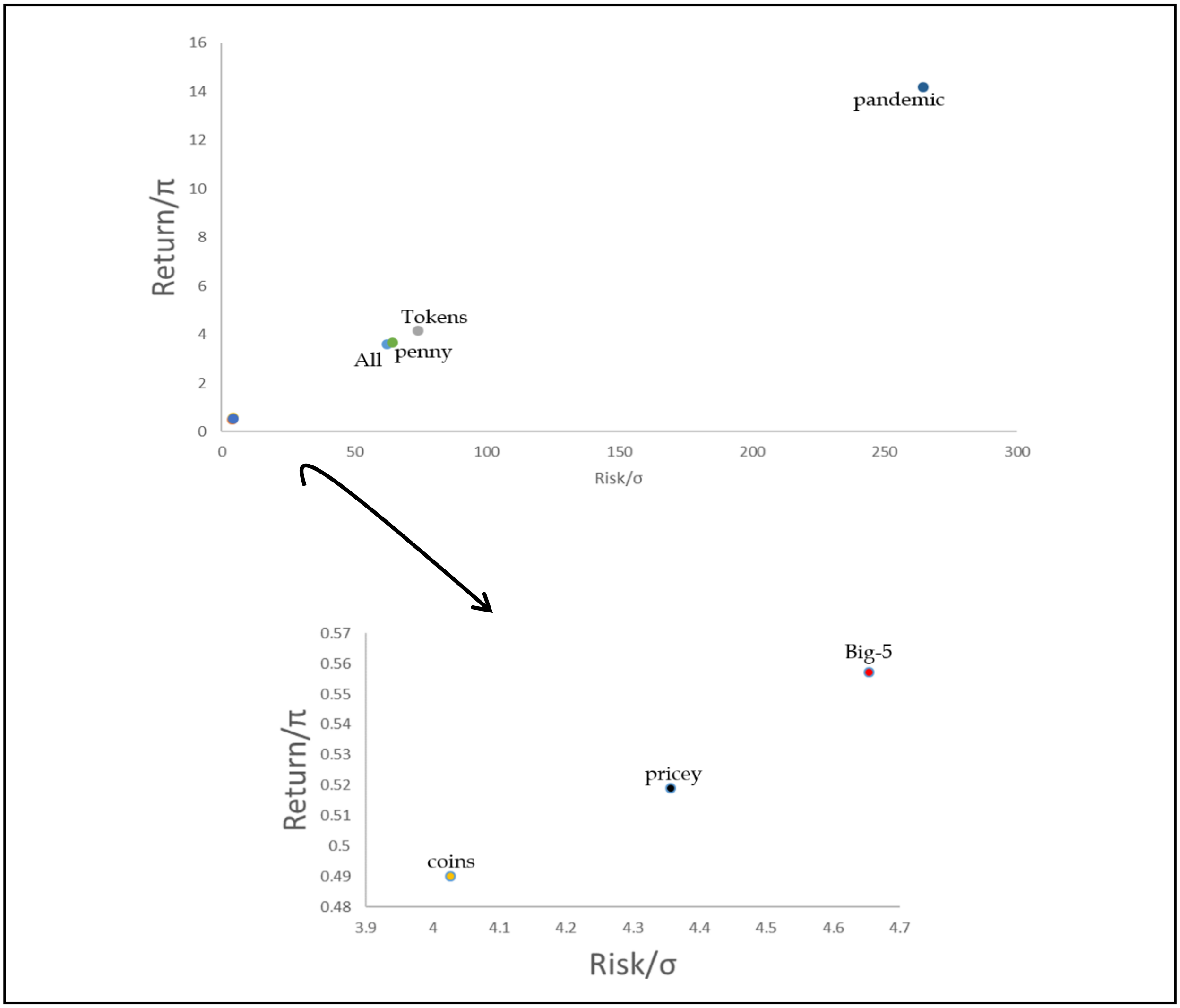
We split the cryptocurrency sample into several categories for detailed analysis, including coins, tokens, big-5, pandemic, pricey, and penny cryptocurrencies. Appendix A provides the definition of each type of cryptocurrency in the sample. The results in Table 1 suggest that each cryptocurrency group's mean return and standard deviation are different. For instance, coins and tokens have a mean portfolio return of 0.49% and 4.15% and a standard deviation of 4.027% and 74.247%, respectively. The results provide some interesting facts. First, the portfolio return of tokens was nine times higher than the return of coins. Second, the risk of tokens was eighteen times higher than the risk of coins. Further, coins' risk and return values are similar to the big-5 group, with a mean return of 0.557% and a standard deviation of 4.654%, respectively.

Table 1: Summary Statistics

	Mean (%)	Standard deviation (%)	Number of Cryptocurrencies
All Cryptocurrencies			227
Portfolio Return	3.571	62.493	
CSSD	50.101	789.953	
CSAD	11.993	62.867	
Coins			30
Portfolio Return	0.490	4.027	
CSSD	8.023	4.910	
CSAD	4.935	2.415	
Tokens			197
Portfolio Return	4.151	74.247	
CSSD	51.738	858.592	
CSAD	13.103	147.493	
Big-5			5
Portfolio Return	0.557	4.654	
CSSD	1.858	2.850	
CSAD	0.845	0.809	
Others			222
Portfolio Return	3.666	64.534	
CSSD	48.798	800.603	
CSAD	2.566	2.336	
Pandemic			121
Portfolio Return	14.180	264.571	
CSSD	107.429	1854.655	
CSAD	3.129	4.964	
Pricey			6
Portfolio Return	0.519	4.357	
CSSD	0.492	1.601	
CSAD	1.321	0.589	
Penny			221
Portfolio Return	3.671	64.534	
CSSD	48.843	800.605	
CSAD	2.572	2.336	

Further, Table 1 presents the mean returns and dispersion of various groups such as a pandemic, pricey, and penny cryptocurrencies. The results are interesting and unique. For instance, the pandemic cryptocurrency group offers the highest mean portfolio return of 14.180%. Contrarily, the pricey cryptocurrency group offers relatively low mean returns of approximately 0.519%, similar to the cryptocurrency coins and big-5 groups. In addition, the mean portfolio return for the penny cryptocurrency group is 3.671%, which is higher than its counterpart, i.e., the pricey cryptocurrency group. Figure 1 presents the risk-reward diagram for all portfolio groups in the sample.

Figure 1: Risk and Reward for Various Cryptocurrency Groups



4.2. Herding Results

We estimate the regression models for both CSSD and CSAD using OLS with heteroscedasticity-consistent standard errors. Table 2 presents the regression results for each cryptocurrency group. A negative and statistically significant coefficient of D_U implies that investors follow each other, representing herding during the bullish market. Furthermore, a negative and statistically significant DL coefficient implies uniformity in investor decisions or herding behavior during a bearish market. Contrarily, if the coefficients of D_U and D_L are positive and statistically significant, it represents an absence of herding behavior.

The results in Table 2 do not provide evidence of herding behavior among cryptocurrency investors. However, the positive and significant coefficients of D_U and D_L imply that cryptocurrency investors make rational investment decisions and do not follow herd behavior. This finding is consistent with several other studies documenting herd behavior's absence (Bouri et al., 2019; Gümüş et al., 2019; Kumar, 2020). Further, the results are consistent in several cryptocurrency groups, i.e., coins, Big-5, pandemic, pricey, and other cryptocurrencies. Overall, the results indicate that cryptocurrency investors do not follow herd behavior and make independent and rational investment decisions. Thus, our findings corroborate the viewpoint that cryptocurrency markets behave efficiently and rationally.

Table 2: Regression Results

	CSSD			CSAD		
	A	**D_U**	**D_L**	**A**	**D_U**	**D_L**
All cryptocurrencies	12.34***	742.31	6.66***	8.60***	59.26	7.99***
	(59.84)	(1.40)	(6.64)	(121.11)	(1.40)	(9.54)
Coins	7.85***	2.10***	1.28	4.83***	1.42***	0.58
	(44.61)	(2.86)	(1.31)	(56.01)	(3.48)	(1.35)
Tokens	44.17	-29.15	179.85	11.90**	-3.66	27.64
	(1.43)	(-0.94)	(0.84)	(2.21)	(-0.68)	(0.83)
Big-5	1.55***	5.38***	0.76*	0.78***	1.08***	0.27**
	(20.21)	(5.04)	(1.75)	(28.98)	(5.41)	(2.17)
Others	10.05***	8.89***	0.83*	2.39***	3.28**	0.25***
	(70.00)	(3.97)	(1.79)	(184.45)	(2.17)	(4.24)
Pandemic	13.01***	25.53***	2.66***	2.79***	1.85***	0.40***
	(38.52)	(5.27)	(3.37)	(102.55)	(6.34)	(5.88)
Pricey	2.52***	1.33***	4.51***	1.23***	0.48***	0.96***
	(30.96)	(3.03)	(5.69)	(65.84)	(5.48)	(8.06)
Penny	50.84*	-8.77	-40.04	2.57***	-0.01	0.07
	(1.74)	(-1.34)	(-1.37)	(30.10)	(-0.38)	(0.66)

***Note:** ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.3. *Robustness Check*

We perform a series of robustness checks to ensure the reliability of our findings. Prior studies suggest herding behavior is pronounced, especially during stressful periods like recessions, financial crises, and pandemics (Jalal et al., 2020; Mandaci and Cagli, 2021). Therefore, in order to validate our results, we divided the full sample into two sub-samples comprising pre-COVID and during COVID periods. Furthermore, different researchers have used different approaches for investigating herding behavior. Consequently, to cross-validate our findings, we used an alternative approach for analyzing herd behavior, i.e., the market beta approach.

4.3.1 Robustness check: Pre-COVID-19 and Covid-19 Pandemic Periods

Recent research has analyzed the adverse effects of the COVID-19 pandemic on various aspects, such as stock returns, investor behavior, and firm performance (Mishra et al., 2020; He et al., 2020; Phan and Narayan, 2020). The COVID-19 pandemic caused major disruption in business activities globally as most countries imposed comprehensive travel restrictions and strict lockdowns. The pandemic has led to extreme uncertainty and fear among governments, businesses, and investors. It is expected that the COVID-19 pandemic would have significantly affected investor sentiments and perception, which may result in behavioral anomalies, such as herding. Given the adverse effects of COVID-19, several researchers have analyzed herding behavior in various markets such as equities, bonds, and cryptocurrencies (Mnif et al., 2020; Yarayova et al., 2021; Gu et al., 2020). To address the above concerns, we re-estimate the herding model for two sub-periods: (1) before the COVID-19 pandemic (January 1, 2019 to March 2020); and (ii) during the COVID-19 pandemic (April 2020 to May 2021).

Table 3 presents the results during the pre-COVID-19 and during COVID-19 periods. The results suggest that investors make rational investment decisions and do not adopt herding behavior in all cryptocurrency groups. Rational investor behavior is prevalent across all market conditions, i.e., bearish, bullish, and pandemics. A possible reason for this finding is that cryptocurrency prices are not based on fundamentals but on user participation and social media news (Katsiampa et al., 2019; Shen et al., 2019). Overall, the results corroborate our earlier findings suggesting the absence of herd behavior in cryptocurrencies.

Table 3: Regression Results Before and During COVID-19 Pandemic Periods

	CSSD				CSAD			
	D_U	D_L	D_U	D_L	D_U	D_L	D_U	D_L
	Pre-Pandemic		During Pandemic		Pre-Pandemic		During Pandemic	
All cryptocurrencies	44.287	6.828***	1129.573	6.627***	4.82	7.685***	89.347	8.362***
	(1.152)	(4.949)	(1.379)	(4.705)	(1.157)	(5.905)	(1.372)	(8.362)
Coins	0.2	0.433	3.310***	2.292	0.502	0.047	2.020***	1.211
	(0.307)	(0.522)	(3.212)	(1.298)	(1.349)	(0.135)	(3.396)	(1.554)
Tokens	0.963	-2.009	-60.385	362.054	1.05	-0.41	-8.999	55.756
	(0.393)	(-1.060)	(-0.980)	(0.859)	(1.249)	(-0.860)	(-0.840)	(0.843)
Big-5	0.39	0.481*	7.282***	0.919	0.179	0.263*	1.258***	0.225*
	(1.219)	(1.806)	(5.916)	(1.359)	(1.027)	(1.852)	(8.006)	(1.660)
Others	5.920***	0.274***	10.134***	1.560***	1.242**	0.214***	4.362**	0.315***
	(3.379)	(2.517)	(3.092)	(2.738)	(2.213)	(3.023)	(1.960)	(3.894)
Pricey	1.853**	4.503***	0.999**	4.502***	0.661***	0.926***	0.336***	0.924***
	(2.130)	(2.874)	(2.217)	(4.900)	(3.769)	(3.716)	(3.864)	(6.874)
Penny	-1.554	-1.423	-71.441	-72.57	0.117	0.148	0.169	0.014
	(-0.889)	(-0.801)	(-1.266)	(-1.336)	(1.529)	(1.513)	(0.944)	(0.079)

***Note:** ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.3.2 Robustness check: alternative thresholds

Prior cryptocurrencies research used the 5% threshold to capture the tail distribution of cryptocurrencies' return, which portrays the market behavior and rational expectations. However, solely relying on the 5% criterion might not align with the definition of the arbitrary extreme market. Given the extreme tail of cryptocurrencies, we use the threshold of 1%, consistent with the seminal work of Christie and Huang (1995). Therefore, we isolate the dispersion level further by using the 1% criterion. The D_U and D_L are redefined as follows: (i) D_U is a dummy variable taking a value of 1 if the market return lies in the 1% upper tail of the return dispersion and 0 otherwise, (ii) D_L is a dummy variable taking a value of 1 if the market return lies in the 1% lower tail of return dispersion, and 0 otherwise. Table 4 presents the results, which align with our earlier findings. The results reveal that herding is not present in all cryptocurrency groups. Our results imply that cryptocurrencies do not exhibit herding behavior in extreme market conditions.

Table 4: Regression Results at the 1% threshold

	CSSD		CSAD	
	D_U	D_L	D_U	D_L
All cryptocurrencies	3429.75	13.532***	272.378	14.373***
	(1.514)	(4.084)	(1.511)	(5.210)
Coins	13.310***	1.482*	6.984***	1.820*
	(4.462)	(1.680)	(6.731)	(1.652)
Tokens	3720.486	2.764	633.118	2.752*
	(1.510)	(1.041)	(1.492)	(1.782)
Big-5	6.460**	2.818*	1.168**	0.707**
	(2.167)	(1.828)	(2.490)	(2.136)
Others	8.911**	10.441**	5.633*	6.272*
	(2.216)	(2.331)	(1.877)	(1.890)
Pricey	2.328**	8.121***	0.595***	1.471***
	(2.411)	(3.392)	(3.794)	(4.821)
Penny	-38.065	-37.665	0.058	0.146
	(-1.339)	(-1.324)	(0.454)	(1.612)

***Note:** ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.4. Explanation of the cryptocurrencies anti-herding and its investing implication

Overall, the results show anti-herding behavior, supporting the findings from Ajaz and Kumar (2018) and Yarayova et al. (2020). It contradicts the general herding perspective, whereas investors follow the flock in cryptocurrencies during market stress regimes. They argue that a significantly bullish or bearish cryptocurrency market is due to herding behavior from other investors by mimicking the market leaders. However, this argument is empirically proven not necessarily true. We find the presence of rational asset pricing in cryptocurrency markets, meaning that investors rationally enter the market.

We explain this anti-herding behavior in three ways. The first explanation is the long-term equilibrium value. This anti-herding behavior occurred as a systematic adjustment from previous herding behavior, specifically from 2017-2018. It also explains why previous research with a sample period of 2015-2018 would conclude the herding. Meanwhile, those with samples from 2019-2020 would conclude the anti-herding. The irrational pricing has moved to rational pricing, resulting in anti-herding behavior.

Second, it affirms the contrarian behavior of the investors against the prevailing market sentiments (Kosc et al., 2019). Investors believe market sentiment during extreme events is evidence of irrationality, leading to mispriced assets. Investors aim to exploit these market inefficiencies by taking a contrarian approach and profit from the eventual price correction.

Lastly, we explain the anti-herding from the irrational behavior itself. Cryptocurrencies investors have anchored the market behavior from previous experiences, where bullish (bearish) market signals exit (entry) points (Dhawan & Putniņš, 2023). It drives the overconfidence bias of the investors by disregarding or downplaying the prevailing market sentiment. They may believe they have superior knowledge or abilities, leading them to make investment decisions that go against the consensus, even without solid evidence to support their views. Further, during periods of market euphoria, anti-herding can occur due to regret aversion when investors take positions against the prevailing trend based on unfounded optimism or the belief that the market will suddenly reverse (Haryanto et al., 2020). This behavior is driven by irrational exuberance and the desire to profit from a potential market correction.

5. CONCLUSION

This study analyzes the herding behavior of over 200 cryptocurrencies, representing nearly 95% of trading volume in the cryptocurrency market from January 1, 2019, to May 31, 2021. We analyze herding behavior using two commonly used approaches in the literature: CSSD and CSAD. The findings show the anti-herding behavior among cryptocurrency investors even during volatile market regimes. Our results can be seen as a rational response to market dynamics or an irrational response to the fear of missing out.

This research has several implications. First, regulators and policymakers should consider developing a well-regulated market for cryptocurrencies to provide a viable investment avenue and safeguard the interests of investors. Moreover, investors should carefully evaluate a cryptocurrency before making investment decisions, as cryptocurrencies are not based on fundamentals. In addition, investors should distinguish between different types of cryptocurrencies, such as coins, tokens, and other cryptocurrencies, to make viable investment strategies.

To the best of our knowledge, this study is unique and novel. It comprehensively analyzes investor behavior toward various types of cryptocurrencies during an era that has exhibited phenomenal returns for digital currencies like Bitcoin. However, this study has several limitations. For instance, Christie & Huang's (1995) model focuses on aggregate herding instead of "alpha play" sentiments. Anecdotally, influencers such as Elon Musk, Vitaly Butterin, Michael Saylor, Roger Ver, Anthony Pompliano, John McAfee, or Andreas Antonopoulos can be the "alpha" in cryptocurrencies, and the investors may flock towards their sentiment.

Additionally, sentiment analysis might play a significant contribution to this topic. For example, the difference-in-difference method can be applied whenever there are positive or negative sentiments and investigate how it may influence herding behavior. Future research may engage this influencer herding to reveal more comprehensive research on this area. Nevertheless, this study provides a strong premise for further research in this area, which may be beneficial for institutional investors, regulators, and policymakers in understanding cryptocurrency market behavior.

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REFERENCES

Ajaz, T., & Kumar, A. S. (2018). Herding in crypto-currency markets. *Annals of Financial Economics*, *13*(2), 1850006.

Amirat, A., & Alwafi, W. (2020). Does herding behavior exist in cryptocurrency market? *Cogent Economics & Finance*, *8*(1), 1735680.

Ballis, A., & Drakos, K. (2020). Testing for herding in the cryptocurrency market. *Finance Research Letters*, *33*, 101210.

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff papers*, *47*(3), 279-310.

Boako, G., Tiwari, A. K., & Roubaud, D. (2019). Vine copula-based dependence and portfolio value-at-risk analysis of the cryptocurrency market. *International Economics*, *158*, 77-90.

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*(55), 5935-5949.

Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters*, *29*, 216-221.

Brahmana, R., Hooy, C. W., & Ahmad, Z. (2012). Psychological factors on irrational financial decision making: Case of day‐of‐the week anomaly. *Humanomics*, *28*(4), 236-257.

Brahmana, R., Hooy, C. W., & Ahmad, Z. (2012). The role of herd behviour in determining the investor's Monday irrationality. *Asian Academy of Management Journal of Accounting & Finance*, *8*(2).

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.

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.

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*, 101554.

Corbet, S., Larkin, C., Lucey, B., & Yarovaya, L. (2020). KODAKCoin: a blockchain revolution or exploiting a potential cryptocurrency bubble?. *Applied Economics Letters*, *27*(7), 518-524.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182-199.

da Gama Silva, P. V. J., Klotzle, M. C., Pinto, A. C. F., & Gomes, L. L. (2019). Herding behavior and contagion in the cryptocurrency market. *Journal of Behavioral and Experimental Finance*, *22*, 41-50.

Dhawan, A., & Putniņš, T. J. (2023). A new wolf in town? Pump-and-dump manipulation in cryptocurrency markets. *Review of Finance*, *27*(3), 935-975.

Easley, D., & Kleinberg, J. (2012). Networks, crowds, and markets. *Cambridge Books*.

Feinstein, B. D., & Werbach, K. (2021). The impact of cryptocurrency regulation on trading markets. *Journal of Financial Regulation*, *7*(1), 48-99.

Gu, X., Ying, S., Zhang, W., Tao, Y., 2020. How do firms respond to COVID-19? First evidence from Suzhou, China. *Emerging Markets Finance and Trade*, *56*(10), 2181–2197.

Gümüş, G. K., Gümüş, Y., & Çimen, A. (2019). Herding behaviour in cryptocurrency market: CSSD and CSAD analysis. In *Blockchain Economics and Financial Market Innovation* (pp. 103-114). Springer, Cham.

Haryanto, S., Subroto, A., & Ulpah, M. (2020). Disposition effect and herding behavior in the cryptocurrency market. *Journal of Industrial and Business Economics*, *47*(1), 115-132.

Haryanto, S., Subroto, A., & Ulpah, M. (2020). Disposition effect and herding behavior in the cryptocurrency market. *Journal of Industrial and Business Economics*, *47*, 115-132.

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID–19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, *56*(10), 2198-2212.

Jalal, R. N. U. D., Sargiacomo, M., Sahar, N. U., & Fayyaz, U. E. (2020). Herding behavior and cryptocurrency: Market asymmetries, inter-dependency and intra-dependency. *The Journal of Asian Finance, Economics, and Business*, *7*(7), 27-34.

Jiang, Z., & Liang, J. (2017, September). Cryptocurrency portfolio management with deep reinforcement learning. In *2017 Intelligent Systems Conference (IntelliSys)* (pp. 905-913). IEEE.

Kallinterakis, V., & Wang, Y. (2019). Do investors herd in cryptocurrencies–and why? *Research in International Business and Finance*, *50*, 240-245.

Katsiampa, P., Moutsianas, K., & Urquhart, A. (2019). Information demand and cryptocurrency market activity. *Economics Letters*, *185*, 108714.

Kosc, K., Sakowski, P., & Ślepaczuk, R. (2019). Momentum and contrarian effects on the cryptocurrency market. *Physica A: Statistical Mechanics and its Applications*, *523*, 691-701.

Kumar, A. (2020). Empirical investigation of herding in cryptocurrency market under different market regimes. *Review of Behavioral Finance*, *13*(3), 297-308.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of financial economics*, *32*(1), 23-43.

Lee, K. (2017). Herd behavior of the overall market: Evidence based on the cross-sectional comovement of returns. *The North American Journal of Economics and Finance*, *42*, 266-284.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*, 383– 417.

Mandaci, P. E., & Cagli, E. C. (2021). Herding intensity and volatility in cryptocurrency markets during the COVID-19. *Finance Research Letters*, 102382.

Mishra, A. K., Rath, B. N., & Dash, A. K. (2020). Does the Indian financial market nosedive because of the COVID-19 outbreak, in comparison to after demonetisation and the GST?. *Emerging Markets Finance and Trade*, *56*(10), 2162-2180.

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance Research Letters*, *36*, 101647.

Omane-Adjepong, M., Paul Alagidede, I., Lyimo, A. G., & Tweneboah, G. (2021). Herding behaviour in cryptocurrency and emerging financial markets. *Cogent Economics & Finance*, *9*(1), 1933681.

Papadamou, S., Kyriazis, N. A., & Tzeremes, P. G. (2021). Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets. *The North American Journal of Economics and Finance*, *56*, 101343.

Parveen, S., Satti, Z.W., Subhan, Q.A., Riaz, N., Baber, S.F. and Bashir, T. (2021), “Examining investors’ sentiments, behavioral biases and investment decisions during COVID-19 in the emerging stock market: a case of Pakistan stock market”, *Journal of Economic and Administrative Sciences*

Phan, D. H. B., & Narayan, P. K. (2020). Country responses and the reaction of the stock market to COVID-19—A preliminary exposition. *Emerging Markets Finance and Trade*, *56*(10), 2138-2150.

Philippas, D., Philippas, N., Tziogkidis, P., & Rjiba, H. (2020). Signal-herding in cryptocurrencies. *Journal of International Financial Markets, Institutions and Money*, *65*, 101191.

Raimundo Júnior, G. D. S., Palazzi, R. B., Tavares, R. D. S., & Klotzle, M. C. (2022). Market stress and herding: a new approach to the cryptocurrency market. *Journal of Behavioral Finance*, 23(1), 43-57.

Rubbaniy, G., Polyzos, S., Rizvi, S. K. A., & Tessema, A. (2021). COVID-19, lockdowns and herding towards a cryptocurrency market-specific implied volatility index. *Economics Letters*, *207*, 110017.

Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict Bitcoin?. *Economics Letters*, *174*, 118-122.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of economic perspectives*, *17*(1), 83-104.

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic perspectives*, *4*(2), 19-33.

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies*, *17*(1), 165-206.

Stavroyiannis, S., & Babalos, V. (2019). Herding behavior in cryptocurrencies revisited: novel evidence from a TVP model. *Journal of Behavioral and Experimental Finance*, *22*, 57-63.

Susana, D., Kavisanmathi, J. K., & Sreejith, S. (2020, December). Does herding behaviour among traders increase during COVID 19 pandemic? Evidence from the cryptocurrency market. In *International Working Conference on Transfer and Diffusion of IT* (pp. 178-189). Springer, Cham.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, *5*(2), 207-232.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, *148*, 80-82.

Urquhart, A. (2017). Price clustering in Bitcoin. *Economics letters*, *159*, 145-148.

Urquhart, A. (2018). What causes the attention of Bitcoin?. *Economics Letters*, *166*, 40-44.

Urquhart, A., & Yarovaya, L. (2020). Introduction to cryptocurrencies. In *Cryptocurrency and Blockchain Technology* (pp. 1-8). De Gruyter.

Vidal-Tomás, D., & Ibañez, A. (2018). Semi-strong efficiency of Bitcoin. *Finance Research Letters*, *27*, 259-265.

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Herding in the cryptocurrency market: CSSD and CSAD approaches. *Finance Research Letters*, *30*, 181-186.

W Senarathne, C., & Jianguo, W. (2020). Herd behaviour in the cryptocurrency market: Fundamental vs. spurious herding. *The European Journal of Applied Economics*, *17*(1), 20-36.

Yadav, S. P., Agrawal, K. K., Bhati, B. S., Al-Turjman, F., & Mostarda, L. (2020). Blockchain-based cryptocurrency regulation: an overview. *Computational Economics*, 1-17.

Yarovaya, L., Matkovskyy, R., & Jalan, A. (2021). The effects of a “black swan” event (COVID-19) on herding behavior in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*, 101321.

APPENDICES

Appendix-A Cryptocurrency Groups and Definitions

Terms	Definition
1. All cryptocurrency	227 liquid and active cryptocurrencies.
2. Coins	A type of cryptocurrency based on Blockchain technology that acts as a digital currency.
3. Tokens	A type of cryptocurrency issued by the project as a method of payment inside a project’s ecosystem that gives the holder a right to participate in the network.
4. Big-5	Five major cryptocurrencies ranked by Coinbase from 1 to 5.
5. Others	All other cryptocurrencies after excluding the Big-5.
6. Pandemic	Cryptocurrencies were issued during the Covid-19 pandemic.
6. Pricey	Cryptocurrencies with a price greater than 1 dollar within the span of the research period.
7. Penny	Cryptocurrencies with a price of less than 1 dollar within the span of the research period.

Appendix B List of Cryptocurrencies

Category	Cryptocurrencies
Pandemic	AAB, ALBT, ALN, ALPACA, ALY, AME, ANRX, ARGON, ARPA, ASKO, BASID, BEPRO, BHAO, BLANK, BOSON, BPLC, BREW, BUY, BYN, BZRX, COMBO, CTSI, CUDOS, CVR, CZRX, DEC, DERI, DF, DHT, DOWS, DPR, DRS, DUCK, DVC, DVI, DYP, EARNX, ESD, EVZ, FINE, FRONT, GOF, GOM2, HARD, HOGE, IBP, IDEA, IDV, JMC, JST, JULD, KAI, KDAG, KEYFI, KGO, KING, LABS, LAYER, LINA, LMT, MBL, MBN, MIST, MOON, MXX, NFT, NRU, NVT, OM, ORAO, ORC, PAID, PBR, PHA, PLA, PNT, PRQ, PTF, RAI, RAMP, RFI, RFUEL, SAFEMOON, SAKE, SAND, SFP, SFUND, SHIB, SHOPX, SIG, SKL, SMG, SOTA, SPA, SPARTA, STC, STPL, STPT, SWAP, TARA, TITAN, TNC, TOWER, TRXDOWN, TXL, UDO, UFT, UMB, UNISTAKE, UNW, URQA, USDJ, VRT, WOZX, XPN, XTZBEAR, XTZBULL, YFIUP, ZDEX, ZEFU, ZKS
Penny	AAB, AENS, AIT, AKRO, ALBT, ALN, ALPACA, ALY, AME, ANRX, AOA, APIX, ARGON, ARPA, ASKO, AST, ATP, BAAS, BASID, BEPRO, BHAO, BHP, BLANK, BORA, BOSON, BOX, BPLC, BREW, BTMX, BUY, BYN, BZRX, CELR, CHZ, CLBK, CNNS, COCOS, COMBO, COS, COTI, CRO, CTSI, CUDOS, CVR, CZRX, DAC, DEC, DERI, DEXA, DF, DHT, DOWS, DPR, DRS, DUCK, DVC, DVI, DYP, EARNX, EDG, EGG, EGT, EKT, EPS, ESD, EVZ, FAIR, FCT, FET, FINE, FLETA, FOR, FRONT, GARD, GEEK, GET, GOF, GOM2, GXC, HARD, HIT, HMR, HOGE, HUM, IBP, IDEA, IDEX, IDRT, IDV, IOTX, ISR, JMC, JST, JULD, KAI, KAN, KDAG, KEYFI KGO, KING, LABS, LAMB, LAYER, LCX, LET, LINA, LINKA, LMT, MBL, MBN, MCT, META, MIST, MIX, MOC, MOON, MTV, MVP, MX, MXX, MYST, NFT, NKN, NRU, NVT, OAX, OBSR, OCEAN, OGN, OM, ONE, ONT, ONX, ORAO, ORC, PAID, PAY, PBR, PEAK, PEG, PERL, PHA, PLA, PLF, PNT, POLY, PRQ, PST, PTF, PVT, RAMP, RFI, RFUEL, RSR, SAFEMOON, SAKE, SALT, SAND, SFP, SFUND, SHIB, SHOPX, SIG, SIX, SKL, SMG, SMT, SNT, SOTA, SPA, SPARTA, STC, STMX, STPL, STPT, SUB, SUTER, SWAP, TARA, TEL, FBX, TITAN, TMTG, TNC, TOK, TOWER, TRAC, TROY, TRXDOWN, TRY, TT, TXL, UDO, UFT, UGAS, UMB, UNISTAKE, UNW, UOS, URQA, USDJ, USDT, VRT, VSYS, WIKEN, WIN, WOZX WPP, WTC, XMX, XPN, XRP, XSR, XTZBEAR, XTZBULL, XUC, YFIUP, YOU, ZDEX, ZEFU, ZKS
Big-5	ADA, BNB, BTC, ETH, XRP
Coin	ADA, BHP, BNB, BTC, COTI, EDG, ETH, FAIR, GXC, IOTX, JMC, KAI, LTC, META, MIX, NKN, NVT, OBSR, ONE, ONT, ONX, PEG, PHA, RFUEL, TNC, TRXDOWN, TT, UNW, VSYS, XRP
Tokens	AAB, AENS, AIT, AKRO, ALBT, ALN, ALPACA, ALY, AME, ANRX, AOA, APIX, ARGON, ARPA, ASKO, AST, ATP, BAAS, BASID, BEPRO, BHAO, BHAO, BLANK, BORA, BOSON, BOX, BPLC, BREW, BTMX, BUY, BYN, BZRX, CELR, CHZ, CLBK, CNNS, COCOS, COMBO, COS, CRO, CTSI, CUDOS, CVR, CZRX, DAC, DEC, DERI, DEXA, DF, DHT, DOWS, DPR, DRS, DUCK, DVC, DVI, DYP, EARNX, EGG, EGT, EKT, EPS, ESD, EVZ, FCT, FET, FINE, FLETA, FOR, FRONT, GARD, GET, GOF, GOM2, HARD, HIT, HMR, HOGE, HUM, IBP, IDEA, IDEX, IDRT, IDV, ISR, JST, JULD, KAN, KDAG, KEYFI, KGO, KING, LABS, LAMB, LAYER, LCX, LEASH LET, LINA, LINKA, LMT, MBL, MBN, MCT, MIST, MOC, MOON, MTV, MVP, MX, MXX, MYST, NFT, NRU, OAX, OCEAN, OGN, OM, ORAO, ORC, PAID, PAY, PBR, PEAK, PERL, PLA, PLF, PNT, POLY, PRQ, PST, PTF, PVT, RAI, RAMP, RFI, RSR, SAFEMOON, AKE, SALT, SAND, SFP, SFUND, SHIB, HOPX, SIG, SIX, SKL, SMG, SMT, SNT, SOTA, SPA, SPARTA, STC, STMX, STPL, STPT, SUB, SUTER SWAP, TARA, TEL, TFBX, TITAN, TMTG, TOK, TOWER, TRAC, TROY, TRY, TXL, UDO, UFT, UGAS, UMB, UNISTAKE, UOS, URQA, USDJ, USDT, VRT, WIKEN, WIN, WOZX, WPP, WTC, XMX, XPN, XSR, XTZBEAR, XTZBULL, XUC, YFIUP, YOU, ZDEX, ZEFU, ZKS
Pricey	ADA, BNB, BTC, ETH, LTC, RAI

Appendix C Summary of Influential Studies on Cryptocurrency Herding

Author (Year)	Cryptocurrencies	Period	Herding Methods	Findings
Ajaz and Kumar (2018)	6 major cryptocurrencies and CCI 30 index	2015-2018	CSAD	Market volatility is found to have no significant impact on herding behavior.
Amirat and Alwafi (2020)	Big 20 cryptocurrencies	2015-2019	CSAD	The study did not find evidence of herding using CSAD.
Ballis and Drakos (2020)	6 major cryptocurrencies	2015-2018	CSSD & CSAD	Investors in the cryptocurrency market act irrationally and imitate others decisions with no reference to the own beliefs.
Parveen et al. (2021)	5 cryptocurrencies	2015-2020	CSAD	Herding in the cryptocurrency market decreases with an increase in investor attention.
Bouri et al. (2019)	14 leading cryptocurrencies	2013-2018	CSAD	They found no evidence of herding behavior.
Da Gama Silva et al. (2019)	50 cryptocurrencies	2015-2018	CSSD & CSAD	Extreme periods of adverse herd behavior.
Gümüş et al. (2019)	CCI 30 index	2015-2018	CSSD & CSAD	They found no evidence of herding behavior.
Haryanto et al. (2020)	BTC	2011-2013	CSSD & CSAD	Herding in bearish as well as bullish periods using a return dispersion model.
Jalal et al. (2020)	CCI30 index comprising 30 cryptocurrencies	2015-2019	CSSD & CSAD	Herding in cryptocurrency in upper quantiles in bullish and high volatility periods.
Kallinterakis and Wang (2019)	296 cryptocurrencies	2013-2018	CSAD	Herding is significant and strongly asymmetric.
Kumar (2020)	100 cryptocurrencies	2013-2019	CSAD	Anti-herding behavior is found in a bullish market.
Mandaci and Cagli (2021)	Bitcoin and 8 altcoins	during COVID-19	CSAD	Herding behavior during the COVID-19 outbreak.
Omane-Adjepong et al. (2021)	292 digital currencies	2016-2019	CSAD	(1) The study found symmetric crowd and imitation trading which is dependent on time. (2) Asymmetric herd behavior in the cryptocurrency and stock market.
Papadamou et al. (2021)	216 cryptocurrencies	2017	Cross-sectional ratio	The study found powerful herding behavior.

Raimundo Júnior et al. (2022)	80 cryptocurrencies	2015-2018	CSSD	Herding toward the market shows significant movement and persistence regardless of market conditions.
Rubbaniy et al. (2021)	101 cryptocurrencies	2015-2020	CSAD	The results document significant evidence of herding in the cryptocurrency market in both bearish and bullish markets.
Senarathne and Jianguo (2020)	CCI30 data for 30 cryptocurrencies	2015-2019	CSAD	Herding on non-fundamental information is found to be more pronounced during an upward trending period.
Susana et al. (2020)	Top 10 cryptocurrencies	2019-2020	CSSD & CSAD	Herdings were evident among all the 10 cryptocurrencies in normal market conditions but not during market upswings and downswings.
Vidal-Tomás et al. (2019)	65 cryptocurrencies	2015-2017	CSSD & CSAD	The cryptocurrency market is characterized by herding during down markets. The smallest cryptocurrencies are herded with the largest ones.
Yarovaya et al. (2021)	BTC, ETH, LTC, BCH, MONA, XEM, ZAIF, XMR, XRP	2019-2020	CSAD	The COVID-19 pandemic did not amplify herding in cryptocurrency markets.