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Impact of Liquidity and Investors Sentiment on Herd Behavior in Cryptocurrency Market

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Abstract: This research addresses the impact of individual investors on the cryptocurrency market, focusing specifically on the development of herd behavior. Although the phenomenon of herd behavior has been studied extensively in the stock market, it has received limited research in the context of cryptocurrencies. This study aims to fill this research gap by examining the impact of liquidity and sentiment on herd behavior using the CSAD model, considering small, medium, and large cryptocurrencies. The results show different outcomes for cryptocurrencies of different sizes, consistently demonstrating that the herding effect is more pronounced under conditions of lower liquidity, as determined by the turnover volume and liquidity ratio of cryptocurrencies. Proxy measures such as the Twitter Hedonometer and CBOE VIX were used to measure investor sentiment and show the prevalence of herding behavior in optimistic times for all cryptocurrencies, regardless of their market capitalization. Consequently, this study provides valuable insights into the manifestation of herd behavior in the cryptocurrency market and highlights the importance of liquidity and sentiment as influencing factors. These findings improve our understanding of investor behavior and provide guidance to market participants and policymakers on how to effectively manage the risks associated with herd effects.

Keywords: behavioral finance; herd behavior; Twitter Hedonometer; VIX; liquidity ratio

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1. Introduction

Herding behavior is an interesting phenomenon that has serious implications for the market, leading to inefficient asset prices and high volatility during periods of market turmoil (Choi et al. 2022). Bikhchandani and Sharma (2000) argued that herd behavior occurs when investors tend to imitate the decisions of others. In the existing literature, there are two types of views on herd behavior, either rational or irrational. Devenow and Welch (1996) show that investors ignore their prior beliefs and follow others without rational reasons. According to Scharfstein and Stein (1990), managers act rationally by taking the same investment actions as others and completely disregarding their own private information in order to maintain their position within the equally valued peer group. Christie and Huang (1995) argued that herd behavior is more likely during periods of market stress because investment decisions depend on market conditions. Tingyu Zhou and Lai (2009) point out that herding behavior is especially popular for small stocks and during economic downturns, and that investors are more likely to sell in herds than buy stocks. They argue that herding behavior can be short-lived and occurs only in a particular industry, suggesting that herding behavior is not a permanent phenomenon.

While herd behavior has been extensively studied in financial markets (Gavrilakis and Floros 2023; Bougatef and Nejah 2023; Fei and Zhang 2023; Yang and Chuang 2023; Tlili et al. 2023; Bogdan et al. 2022; Bouri et al. 2021), its study in the cryptocurrency market is still limited. Therefore, this article focuses on herd behavior in the crypto market for several reasons. First, cryptocurrencies have experienced a rapid development and have become popular assets in global financial markets (Fang et al. 2021), attracting the attention of investors and policymakers mainly due to their unique characteristics (Stavroyiannis and Babalos 2019; Urquhart 2018; Angerer et al. 2021). Moreover, the cryptocurrency market has distinctive characteristics such as high volatility, large size, and significant heterogeneity. Consequently, the study of herd behavior in the cryptocurrency market is of paramount importance due to the inherent dependence of cryptocurrency values on the beliefs and decisions of individual investors rather than fundamental factors (Kumar 2021). Behavioral patterns observed among crypto investors suggest that they tend to engage in sentiment- and volume-driven trading activities, often focusing on short-lived trends. This behavior, characterized by the use of hourly and daily frequencies for trades with significant sentiment and volume, confirms the prevalence of noisy trading in the cryptocurrency market (Karaa et al. 2021). Third, despite the increasing importance of institutional investors in the cryptocurrency market as the sector gains recognition among the general public (Huang 2022), a significant portion of the market is still occupied by individual investors, who are often less informed and less cautious compared to institutional investors (Ozdamar et al. 2022).

Based on scientific advances, it is postulated that the phenomenon of herd behavior in the cryptocurrency market can be influenced by both liquidity and sentiment. Moreover, the unregulated nature of this market and the prevalence of individual investors with comparatively lower levels of knowledge (Jia et al. 2022) further enhance the above influence. One of the relevant components of market illiquidity is the information asymmetry between "informed" and "uninformed" traders (Glosten and Milgrom 1985; Easley et al. 1996). Since the fundamental values on the cryptocurrency market are not tangible, herding can be driven by informed traders who act based on their private signals, especially when informed traders receive aligned signals which refer on buying or selling. Consequently, sentiment and liquidity intensity are believed to have tangible effects on the cryptocurrency market, necessitating an investigation of their impact on herd behavior within three distinct categories of cryptocurrency characterized by different sizes. Therefore, this research includes two research questions:

RQ1. Identify whether liquidity has an impact on herding effect in the crypto market.
RQ2. Identify whether sentiment has an impact on herding effect in the crypto market.

The existing literature on herd behavior in the cryptocurrency market is limited in terms of studying the relationship between liquidity and herd behavior, as well as investment sentiment and herd behavior. Previous empirical studies have mainly focused on the largest cryptocurrencies and neglected the comprehensive understanding of the phenomenon. In contrast, this study aims to gain insights by examining three categories of cryptocurrencies according to market capitalization size: large, medium, and small. While the popular press and academic research predominantly highlight a few cryptocurrencies such as Bitcoin, Ethereum, and XRP, it is important to acknowledge the extensive presence of numerous cryptocurrencies currently circulating in the market (King and Koutmos 2021). To investigate the presence of herd behavior in the overall market, this study uses a sample of 100 cryptocurrencies. The goal of the study is to analyze the impact of liquidity and sentiment on herd behavior and, most importantly, to identify differences between cryptocurrencies of different sizes.

The subsequent sections of this paper are organized as follows. Section 2 provides a comprehensive review of the relevant literature. Section 3 outlines the data collection and methodology used in this study. Section 4 presents and discusses the empirical results derived from the analysis. Finally, Section 5 summarizes the findings and draws conclusions for future research.

2. Literature Review

In 2021, the total market capitalization of cryptocurrencies exceeded USD 2.6 trillion, highlighting the great social importance of cryptocurrencies (CoinGecko 2021). According to data as of 31 May 2023, the total market capitalization of the cryptocurrency market is

USD 1.18 trillion. Based on data from Statista (March 2023), the above market capitalization would rank 15th among the largest exchange operators in the world. This position is currently slightly higher than that of the Johannesburg Stock Exchange. This positioning underscores the size and relevance of the market on a global scale. Considering the extensive studies on the herd effect in various stock markets around the world, the study of the crypto market is particularly interesting, as the herd effect in stock markets has been intensively studied (Raimundo Junior et al. 2022).

There are numerous reasons for the occurrence of the herd phenomenon in both highly developed and less-developed markets. In line with previous findings, the authors have explored various reasons that influence the herding behavior of investors in the crypto market. For example, some authors believe that the reasons for herding behavior in the crypto market lie in a weak regulatory environment (Nadarajah and Chu 2017). Bouri et al. (2018) investigated the presence of herding behavior in the cryptocurrency market by performing rolling-window analysis and applying logistic regression to the daily closing prices of 14 leading cryptocurrencies from 2013 to 2018, and they found that herding behavior tends to occur when uncertainty increases. Vidal-Tomas and Ibanez (2018) analyzed the presence of herding behavior in the cryptocurrency market using the cross-sectional standard deviation (absolute) of returns. They used 65 digital currencies from 2015 to 2017 and showed that the extreme dispersion of returns can be explained by rational asset pricing models, although it is possible to observe herding behavior in down markets, highlighting the inefficiency and risk of cryptocurrencies. Calderón (2018) analyzed a sample of leading cryptocurrencies and suggested that cryptocurrency investors often deviate from the rational asset pricing model during times of market stress, and follow the crowd instead. Manahov (2021) measured herd behavior by observing the buying and selling behavior of cryptocurrency users trading on 28 different exchanges. They found significant evidence of herd behavior in the Bitcoin, Ethereum, Ripple, Litecoin, Dash, CRIX, and CCI30 markets across the entire data set during up markets. The results of Coskun et al. (2020)'s time-varying Markov switching model for the third subperiod (2/28/2017–1/16/2018) indicate the presence of herding behavior during periods of low volatility, while anti-herding behavior occurred during high volatility, and the effect of uncertainty on anti-herding behavior was significant. Finally, the results suggest that there was no significant asymmetric behavior in upward and downward phases of the market. Yarovaya et al. (2021) used a combination of quantitative methods to estimate hourly prices for the four most traded cryptocurrencies—USD, EUR, JPY, and KRW—for the period from 1 January 2019 to 13 March 2020. Their results suggest that COVID-19 does not reinforce herding behavior in the cryptocurrency market. In all markets studied, herding behavior remains dependent on up or down days in the markets, but did not become stronger during COVID-19. Mandaci and Cagli (2022) investigated whether herding behavior was present before and during the COVID-19 pandemic by analyzing intraday data from Bitcoin and eight altcoins. The authors' results suggest significant herd behavior concentrated during the COVID-19 outbreak. The results of the causality test show that herd behavior has a significant impact on market volatility.

Lakonishok et al. (1992), Liao et al. (2011), Galariotis et al. (2016), Litimi et al. (2016), BenSaïda (2017), and Vo and Phan (2019) have highlighted numerous factors in the stock market that contribute to the occurrence of herd behavior. In particular, these studies highlighted sentiment and liquidity as important variables that have a significant impact on the occurrence of herding behavior. The inclusion of sentiment, which encompasses the prevailing emotions and attitudes of market participants, and liquidity, which refers to the ease of trading and the availability of buyers and sellers, as key determinants underscores their critical role in shaping and controlling the dynamics of herd behavior. However, there is evidence that weakly supports the notion that sentiment influences herd behavior (Vieira and Pereira 2015). In the following section, we briefly review previous research that has examined the relationship between liquidity and herd behavior.

Manahov (2021) obtained millisecond data for the five major cryptocurrencies—Bitcoin, Ethereum, Ripple, Litecoin, and Dash—and two cryptocurrency indices—Crypto Index (CRIX) and CCI30 Crypto Currencies Index—to study the relationship between cryptocurrency liquidity, herd behavior, and profitability during periods of extreme price movements (EPMs). The author found a presence of herding behavior during up markets across the entire dataset. Arsi et al. (2022) point out that herding behavior in ten leading cryptocurrencies from 2016 to 2019 was influenced by the state of market liquidity. Herding asymmetries are not only perceived during bull and bear phases, but also on days with high and low liquidity. They argue that herding behavior is mainly explained by crypto traders' sentiment depending on liquid/illiquid periods. Market activity is believed to be the source of herd behavior in cryptocurrencies, which leads to uptrends in the market when trading volume increases due to aggressive investment by investors (Bikhchandani and Sharma 2000), so the excessive volatility in the cryptocurrency market could be explained by behavioral factors such as herd behavior.

In addition to the aforementioned impact of liquidity on herd behavior, the role of sentiment remains relatively unexplored in the context of the cryptocurrency market. Considering this research gap, Jia et al. (2022) conducted a comprehensive study on the impact of investor sentiment on herding behavior in the cryptocurrency market for the period from 2016 to 2022. Their results provide compelling evidence of the relationship between herd behavior and investor sentiment in the cryptocurrency market. They also found significant herding behavior during euphoria and dysphoria and conclude that investors tend to engage in intense herding behavior during periods of dysphoric sentiment, especially for large cryptocurrencies. Using data from the top 20 cryptocurrencies and the MV Index Solution Crypto Compare Digital Assets for the large-cap index, Amirat and Alwafi (2020) found no evidence of herding behavior using a cross-sectional estimate of absolute standard deviation. However, using a rolling-window analysis, the results show significant herding behavior that varies over time. Finally, the authors found an inverse relationship between herding behavior and the Bloomberg Consumer Comfort Index, implying that traders who feel less confident prefer to ignore their expectations and follow the market trend. Choi and Yoon (2020) investigated whether there is herding behavior in the Korean stock market and whether investor sentiment can be an important factor for the occurrence of herding behavior. It was confirmed that investor sentiment is one of the most important factors that can cause herd behavior in the Korean stock market. They found that herding behavior occurs during downward phases of the market and that negative herding behavior occurs during periods of low trading volume and low volatility. Sentiment is an important driver of leading and highly capitalized cryptocurrency traders' behavior during extreme bear market (Kyriazis and Prassa 2019). Based on previous academic research, this study aims to investigate the impact of liquidity and sentiment on small, medium, and large cryptocurrencies. Various proxy variables are used to capture herd effects within the top and bottom 5%, 10%, and 15% tail levels. By examining these specific market segments, this study aims to provide further insight into the relationship between liquidity, sentiment, and small, medium, and large cryptocurrencies.

3. Data and Methodology

The sample for this study was selected based on data from the cryptocurrency data provider www.coingecko.com. The selection criterion was to choose the one hundred largest cryptocurrencies in terms of market capitalization as of 28 December 2022. These cryptocurrencies were divided into three groups based on their market capitalization: Large-cap cryptocurrencies with a market capitalization of more than USD 10 billion, mid-cap cryptocurrencies with a market capitalization between USD 1 billion and USD 10 billion, and small-cap cryptocurrencies with a market capitalization of less than USD 1 billion. To ensure a comprehensive and robust analysis, the sample period for this study extends from 27 December 2019 to 28 December 2022, a period chosen to cover a large time frame and allow for a thorough examination of the research variables. A strict criterion was applied to ensure consistency and reliability of the data. Only cryptocurrencies for which complete daily data were available throughout the sample period were considered and included in the sample. This selection criterion ensured that the analysis is based on reliable and continuous data, which increases the validity of the results.[1] Based on the closing price data, logarithmic returns for all cryptocurrencies in the study sample were calculated using the following formula:

$$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

$R_{i,t}$ represents the return of stock i on day t, calculated as the natural logarithm (ln) of the closing price P of stock i on day t. The term $t-1$ denotes the previous day. If there was no trading on the previous days, these values were replaced by the values of the last available day. The market return is calculated as the average return of cryptocurrencies on a given day, which can be represented by the following equation:

$$R_{m,t} = \frac{\sum R_{i,t}}{N} \tag{2}$$

$R_{m,t}$ represents the market return as the sum of the returns of cryptocurrencies $R_{i,t}$ on a given day divided by a number of cryptocurrencies N which are included in a certain index. One of the well known approaches to detecting herd behavior was carried out by Christie and Huang (1995). They suggested the use of cross-sectional standard deviations of returns (CSSD) in order to detect herd behavior, which was formulated as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}} \tag{3}$$

where $R_{i,t}$ represents the return on asset i in period t, while $R_{m,t}$ is the average cross-sectional return on the market portfolio in period t. In the numerator of the equation, N represents the number of assets. Since the CSSD model is quite sensitive to outliers, Chang et al. (2000) later proposed another model based on the cross-sectional absolute deviation (CSAD) model in order to measure daily average of the absolute dispersion, which can be expressed as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \tag{4}$$

Chang et al. (2000) argued in a paper that the relationship between cross-sectional deviation and market returns tends to be nonlinear under extreme market conditions. Therefore, they use the square of market returns to detect such a nonlinear relationship and proposed following quadratic equation in order to detect herding:

$$CSAD_t = \alpha_0 + \alpha_1|R_{m,t}| + \alpha_2 R_{m,t}^2 + \varepsilon_t \tag{5}$$

According to model (5), if the variable α_2 is negative and significant, a nonlinear relationship between market returns and CSAD can be inferred, suggesting herd behavior. As cryptocurrencies have become an integral part of the financial system and are increasingly accepted as a means of payment (Brauneis et al. 2021), their liquidity has steadily increased in recent years. According to Crypto.com (2022), the number of cryptocurrency holders is increasing year over year, with a 39% increase in 2022 alone, from 306 million in January to 425 million in December. In addition, trading volume in the cryptocurrency market is increasing, indicating an increase in liquidity (Shahzad et al. 2019; Hasan et al. 2022). Previous research has shown that liquidity indicators can be relevant factors in predicting the herding effect (Galariotis et al. 2016; Vo and Phan 2019; Ferrouhi 2021). Therefore, this paper aims to investigate the influence of two liquidity indicators on the herd effect of cryptocurrencies.

Similar to the study by Vo and Phan (2019), this paper examined the occurrence of herding behavior during periods of high and low trading volume, where the authors used dummy variables D1 and D2 that are equal to 1 when liquidity is in the top 25% tail and the bottom 25% tail, respectively. To determine the impact of the trading volume variable, this study introduced dummy variables for different liquidity thresholds. The dummy variable D_H = 1 when it is above the upper threshold, and the dummy variable D_L = 1 when the trading volume is below the lower threshold of 5%, 10%, and 15%, respectively, whereupon the following equation was established:

$$CSAD_t = \alpha_0 + \alpha_1 |R_{m,d}| + \alpha_2 R_{m,d}^2 + \alpha_3 D_H R_{m,d}^2 + \alpha_4 D_L R_{m,d}^2 + \varepsilon_d \tag{6}$$

In addition to trading volume, the effect of liquidity on herd behavior was tested by using the liquidity ratio (Cooper et al. 1985; Khan and Baker 1993; Amihud et al. 1997; Amihud 2002) LR indicator. This ratio is sometimes called Amivest measure of liquidity. The following equation shows how it is calculated:

$$CLR_{id} = \sum_{i=1}^{N} \frac{Tv_{id}}{|R_{id}|} \tag{7}$$

Equation (7) represents the liquidity ratio for cryptocurrency CLR (crypto liquidity ratio) for a given sample that includes cryptocurrencies within the sample of small-cap, mid-cap, and large-cap cryptocurrencies. Tv represents the sum of trading volume of the cryptocurrencies within the set N divided by the sum $|R_{id}|$ absolute daily returns of the cryptocurrency i on day d. In other words, this indicator shows how much capital needs to be traded for the cryptocurrency to move $+/-$ 1% in price. More capital also means more liquidity. The indicator CRL is used in Equation (6) in the same way as turnover, i.e., the dummy variable D_H = 1 if it is above the upper limit, and the dummy variable D_L = 1 if the CLR is below the lower limit of 5%, 10%, and 15%.

Despite the growing importance of institutional investors in the cryptocurrency market as the sector gains recognition among the general public (Huang et al. 2022), a significant portion of the market is still occupied by individual investors, who are often less informed and less cautious compared to institutional investors (Ozdamar et al. 2022). In their paper, authors Subramaniam and Chakraborty (2020) assume that the crypto market is dominated by retail investors; similar views are held by Almeida and Gonçalves (2023), who additionally note that such investors are often not rational as they make decisions based on market sentiment. In line with the above, two cognitive and emotional traits are used as proxies, namely optimism and pessimism. Following the study of Youssef and Waked (2022) on the impact of media coverage on herd formation, we modified the equation to test the impact of sentiment on the herd formation effect. The resulting equation is as follows:

$$CSAD_t = \alpha_0 + \alpha_1 |R_{m,d}| + \alpha_2 R_{m,d}^2 + \alpha_3 D_o R_{m,d}^2 + \varepsilon_d \tag{8}$$

$$CSAD_t = \alpha_0 + \alpha_1 |R_{m,d}| + \alpha_2 R_{m,d}^2 + \alpha_3 D_p R_{m,d}^2 + \varepsilon_d \tag{9}$$

Dummy variables, denoted as D_o and D_p, were used to capture the extreme ends of the distribution, specifically the 15%, 10%, and 5% upper tail, representing optimism, and the 15%, 10%, and 5% lower tail, signifying pessimism. These variables were assigned a value of 1 if the corresponding variable fell within the range.

One of the proxy measures used to approximate sentiment is the Twitter Hedonometer (2023). This index is created using an extensive compilation of about 10,000 sentiment-related words accessible on the website https://hedonometer.org (accessed on 6 January 2023). A higher Twitter Hedonometer (2023) score means that the content being studied has a higher level of overall satisfaction or positive sentiment. The potential herd effect results that can be derived from the Twitter Hedonometer must be interpreted carefully in an academic context. It is critical to acknowledge and account for the potential bias inherent in the indicator itself, particularly the English language bias described by Sifat et al. (2023). Furthermore, Sifat et al. (2023) study shows a preference for the use of text analysis software tailored to the linguistic characteristics of each region to facilitate the processing of emotions. Since it is not possible to comprehensively capture the myriad of cryptocurrency discussion platforms spread across the globe, the Twitter index is considered a suitable proxy measure of investor sentiment.

In addition to the Twitter index, the VIX (CBOE Volatility Index) is also used as a sentiment indicator. The VIX serves as a widely recognized measure of market volatility and is an important indicator of investor concern in the financial markets. Higher VIX values indicate a greater likelihood of significant price fluctuations, which investors tend to perceive with pessimism and vice versa.

4. Empirical Findings

To determine whether herding behavior is present in the market in general, the entire sample of 100 cryptocurrencies was tested using the CSAD and CSSD models during the period from 27 December 2019 to 28 December 2022, resulting in a total of 1096 daily observations per cryptocurrency. Table 1 contains the descriptive characteristics of the main variables included in the study for small, medium, and large cryptocurrencies.

Table 1. Descriptive statistics.

			Small Cap					
Variable	**CSADsc**	**RMsc**	**ABSRMsc**	**SQRMRsc**	**TN-Small**	**LR-Small**	**VIX [1]**	**Twitter [1]**
Mean	3.2550	0.0883	2.9834	19.9038	7,163,377,900	27,002,771	24.6420	5.9806
St. dev.	1.4454	4.4625	3.3186	95.8859	6,407,312,361	21,692,598	8.6326	0.0757
Kurtosis	11.4197	21.4955	52.7603	556.6127	9.2630	43.4043	9.6592	2.2637
Skewness	2.0748	−2.3855	5.0442	21.3992	2.5183	4.2633	2.4199	−0.9507
Count	1096	1096	1096	1096	1096	1096	1096	1096
			Medium Cap					
Variable	**CSADmc**	**RMmc**	**ABSRMmc**	**SQRRMmc**	**TN-Medium**	**LR-Medium**		
Mean	2.8532	0.0705	3.1571	22.8106	17,365,719,753	206,884,923		
St. dev.	2.2188	4.7777	3.5854	106.4767	13,439,253,454	144,113,720		
Kurtosis	262.1390	20.0161	46.4664	413.8887	11.4054	7.3502		
Skewness	12.5583	−2.4046	4.9208	18.2435	2.5801	1.9743		
Count	1096	1096	1096	1096	1096	1096		
			Large Cap					
Variable	**CSADlc**	**RMlc**	**ABSRMlc**	**SQRRMlc**	**TN-Large**	**LR-Large**		
Mean	2.1310	0.1249	2.1169	9.8129	74,430,060,767	5,097,388,535		
St. dev.	1.9868	3.1315	2.3101	39.5919	49,170,596,348	4,678,041,327		
Kurtosis	41.0179	14.5941	34.8504	427.8930	29.4714	77.0654		
Skewness	4.6249	−1.3357	4.1087	18.1806	3.9981	5.9790		
Count	1096	1096	1096	1096	1096	1096		

Note: [1] The VIX index and Twitter were utilized to predict the occurrence of herding behavior across all three size categories of cryptocurrencies.

From the results in Table 1, the largest mean CSAD value for small-cap cryptocurrencies is 3.255, followed by 2.8532 for medium-cap, and 2.131 for large-cap, indicating that small-cap cryptocurrencies have a higher degree of volatility compared to other cryptocurrencies. The high liquidity prevalent in large-cap cryptocurrencies certainly contributes to this. In terms of standard deviation, it is interesting to note that RM has the highest standard deviation for mid-cap cryptocurrencies, followed by small-cap and large-cap currencies. The explanation for this could be that, according to the number of observed small-cap cryptocurrencies in the sample, they dominate, which is why the average value fluctuates less.

The overall model together with the split sample, i.e., large-cap, mid-cap, and small-cap cryptocurrencies, was tested. The results are presented in Table 2.

Table 2. Baseline herding model results.

Sample	CSSD Model			CSAD Model		
	α_0	D_t^U	D_t^L	α_0	$\lvert R_{m,d} \rvert$	$R_{m,t}^2$
Full sample	4.461945 ***	2.74906 ***	3.86606 ***	2.23017 ***	0.29051 ***	0.00037
(100 cryptocurrencies)	(0.07854)	(0.40606)	(1.40059)	(0.08778)	(0.02397)	(0.00052)
Large cap	2.33906 ***	6.44432 ***	4.25570 ***	0.66870 ***	0.67857 ***	0.00263
(9 cryptocurrencies)	(0.06597)	(0.95390)	(0.53033)	(0.05863)	(0.04385)	(0.00498)
Medium cap	3.84627 ***	3.11814 ***	5.41480 *	1.93350 ***	0.26729 ***	0.00332
(24 cryptocurrencies)	(0.08777)	(0.49505)	(2.92373)	(0.14737)	(0.06611)	(0.00550)
Small cap	4.66528 ***	2.82980 ***	2.35907 ***	2.48276 ***	0.25392 ***	0.00074 **
(67 cryptocurrencies)	(0.08126)	(0.42031)	(0.45393)	(0.09639)	(0.02065)	(0.00043)

Note: This table reports regression results using the CSAD model developed by Chang et al. (2000)—Equation (5)—and the CSSD model developed by Christie and Huang (1995): $CSSD_t = \alpha_0 + \alpha_1 D_t^u + \alpha_2 D_t^l + \varepsilon_t$. CSSD is calculated according to Equation (3). Newey–West standard errors are given in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2 provides estimation results for the overall crypto-market following the CSSD and CSAD models. The method tests whether investors converge to the market consensus in the presence of the herd effect, and thus whether individual returns remain close to market returns. Assuming that investors tend to suppress their beliefs and converge to the market consensus in turbulent times, one should expect the coefficients $\alpha 1$ and $\alpha 2$ to be negative and statistically significant. In the CSAD method, the negative and significant coefficient with respect to squared returns shows that, in these years, the dispersion of returns decreased as market returns increased, contradicting the linear market model and suggesting the presence of a herd effect.

Based on the estimation results obtained from the CSAD model, it is inferred that the $R_{m,t}^2$ is not significantly negative, thereby indicating the absence of herding behavior in the cryptocurrency market. This conclusion is in consonance with prior studies by Arsi et al. (2022), Bouri et al. (2019), and Jia et al. (2022). Since the CSAD model is considered more appropriate for studying the herd effect, it is used in the remainder of this study.

In order to investigate the first research question concerning the impact of liquidity on the herding effect, the following results pertain to the influence of turnover volume on liquidity. Various levels of liquidity were examined, and a dummy variable was assigned a value of 1 if the turnover volume fell within the 5%, 10%, and 15% upper tail, as well as the 5%, 10%, and 15% lower tail.

According to the results from the Table 3 empirical results suggest the presence of herd behavior in mid-market-cap cryptocurrencies, especially when the impact of low turnover volume is studied. The herding effect was observed at the 5%, 10%, and 15% levels, suggesting that investors tend to engage in herding behavior during periods of low turnover in mid-cap cryptocurrencies. In contrast, the results do not indicate a herding effect for low- and high-market-cap cryptocurrencies. This suggests that the impact of turnover volume on herding behavior differs across market capitalization categories, with mid-sized cryptocurrencies more prone to herding behavior in the context of low turnover volume. Yousaf and Yarovaya (2022) came to similar conclusions when studying traditional cryptocurrencies, namely the absence of the herd effect when examining high and low volumes of turnover. Although there are not many papers that examine this research question in the cryptocurrency market, this topic has been well studied in capital markets. According to BenSaïda (2017), the results are slightly different from those for the stock market, as the author concludes that turnover volume does not trigger herding behavior, while Litimi et al. (2016) claim that turnover volume triggers herding behavior during crises or calm times. Choi and Yoon (2020) show that negative herding behavior occurs when trading volume is low in the Korean capital market.

Table 3. Estimated herding during high and low turnover volumes on the crypto market.

Liquidity Tail Bound	Intercept	$D\lvert R_{m,d}\rvert$	$R^2_{m,d}$	$D_H R^2_{m,d}$	$D_L R^2_{m,d}$
Panel A: Small cap					
±5%	2.506 ***	0.234 ***	0.001 **	0.014 ***	0.035 ***
	(0.094)	(0.021)	(0.000)	(0.004)	(0.012)
±10%	2.413 ***	0.301 ***	−0.005 **	0.006 ***	0.005 ***
	(0.096)	(0.030)	(0.002)	(0.002)	(0.002)
±15%	2.416 ***	0.301 ***	−0.006 **	0.007 ***	0.006 ***
	(0.097)	(0.030)	(0.003)	(0.002)	(0.002)
Panel B: Medium cap					
±5%	1.917 ***	0.278 ***	0.004	−0.004	**−0.046 *** **
	(0.155)	(0.071)	(0.006)	(0.006)	**(0.016)**
±10%	2.054 ***	0.228 ***	0.001	0.014	**−0.027 *** **
	(0.088)	(0.042)	(0.002)	(0.012)	**(0.006)**
±15%	2.082 ***	0.209 ***	0.001	0.014	**−0.014 ** **
	(0.104)	(0.055)	(0.003)	(0.011)	**(0.007)**
Panel C: Large cap					
±5%	0.665 ***	0.678 ***	0.003	−0.002	0.031 ***
	(0.058)	(0.043)	(0.006)	(0.005)	(0.012)
±10%	0.667 ***	0.677 ***	0.003	−0.001	0.015
	(0.057)	(0.041)	(0.005)	(0.005)	(0.020)
±15%	0.668 ***	0.679 ***	0.003	−0.0001	0.001
	(0.054)	(0.041)	(0.005)	(0.005)	(0.017)

Note: The table reports the regression results using Equation (6). Newey–West standard errors are given in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

From the review of previous research, it can be concluded that the results are inconsistent regarding the influence of turnover volume on herd behavior. It should also be noted that the complexity of discovering factors that influence herd behavior is largely dependent on context, characteristics, and the observed sample. The influence of turnover volume on herd behavior in mid-market-cap cryptocurrencies can also be attributed to the specific context in which the basis of reduced market activity and lack and asymmetry of information lies. Due to the inherent human tendency to rely on social cues and heuristics, the tendency to mimic the behavior of investors in the market, which in this case is represented by mid-cap cryptocurrencies, is reinforced. The weak market activity, reduced information flow, and limited number of active participants in this particular context encouraged the perception of others as more important compared to their own beliefs.

In addition to evaluating the effect of turnover volume, another liquidity measure, namely the CLR indicator as per Equation (7), was also examined. The corresponding results are presented in Table 4.

The results from Table 4 show the presence of herd behavior in terms of the low CLR indicator observed in small-cap cryptocurrencies and the high CLR indicator observed in large-cap cryptocurrencies, at significance levels of 5% and 10%. This result is consistent with previous research on small-cap stocks in the capital market as conducted by Hsieh et al. (2020) and Hung et al. (2010), where the herd effect was also observed. Since the CLR indicator captures the price impact of trading activity, the identification of herd behavior in small-cap cryptocurrencies supports the existing literature on small-cap stocks.

Table 4. Estimating herding during high and low CLR indicator on the crypto market.

Liquidity Tail Bound	Intercept	$D\|R_{m,d}\|$	$R^2_{m,d}$	$D_H R^2_{m,d}$	$D_L R^2_{m,d}$
			Panel A: Small cap		
±5%	2.508 ***	0.223 ***	0.003 *	0.043 ***	−0.002
	(0.094)	(0.024)	(0.002)	(0.009)	(0.002)
±10%	2.518 ***	0.208 ***	0.007 ***	0.040 ***	**−0.006** ***
	(0.106)	(0.025)	(0.002)	(0.119)	(0.002)
±15%	2.524 ***	0.204 ***	0.008 ***	0.026 ***	**−0.006** ***
	(0.120)	(0.025)	(0.002)	(0.008)	(0.002)
			Panel B: Medium cap		
±5%	1.870 ***	0.309 ***	−0.002	0.080 ***	0.005
	(0.172)	(0.079)	(0.003)	(0.030)	(0.006)
±10%	1.888 ***	0.297 ***	−0.001	0.021 **	0.004
	(0.166)	(0.779)	(0.003)	(0.009)	(0.006)
±15%	1.932 ***	0.261 ***	0.004	0.019 *	−0.0003
	(0.181)	(0.088)	(0.06)	(0.011)	(0.006)
			Panel C: Large cap		
±5%	0.655 ***	0.699 ***	−0.002	**−0.077** **	0.004
	(0.066)	(0.053)	(0.006)	(0.032)	(0.006)
±10%	0.655 ***	0.705 ***	−0.004	**−0.099** **	0.006
	(0.065)	(0.051)	(0.006)	(0.040)	(0.005)
±15%	0.669 ***	0.687 ***	−0.001	−0.060	0.003
	(0.064)	(0.050)	(0.006)	(0.040)	(0.005)

Note: Table reports regression results by using Equation (6). Newey–West standard errors are given in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

With respect to large-cap cryptocurrencies, the results of the study indicate the presence of a herding effect during periods of high CLR indicator (5% and 10% level), suggesting that herding behavior persists during periods of increased liquidity as measured by CLR. It is important to note that the likelihood of herding behavior during periods of high liquidity is significantly lower for large-cap cryptocurrencies. However, the results of this study support this claim and confirm that investors are susceptible to various behavioral biases. These divergent influences arise from investor sentiment, a topic that is discussed in more detail in subsequent sections of this paper.

The obtained results are significant as they show the manifestation of herd behavior across different cryptocurrency sizes (i.e., small, medium, and large-cap cryptocurrencies) during periods of optimistic market sentiment measured with the Twitter Hedonometer. Due to the limited availability of studies examining the impact of sentiment on cryptocurrencies, relevant studies examining the capital market were also used to compare the results. The results from Table 5 are inconsistent with the findings of Ren and Wu (2018), which show an increased propensity of investors to engage in herding behavior during periods of negative emotions in the Chinese stock market. In addition, the findings of Kuhnen and Knutson (2011) suggest that events that evoke positive and stimulating emotions, such as excitement, tend to lead to riskier decisions. However, our results are supported by previous research in capital markets. In particular, Blasco de las Heras et al. (2018) highlight high investor sentiment as a factor contributing to increased herding behavior. In addition, Sheikh et al. (2023) find a positive relationship between optimistic sentiment in the Chinese capital market and the prevalence of herding behavior. Moreover, in their study of the KOSDAQ market, Choi and Yoon (2020) show the occurrence of herding behavior during periods when investors have optimistic views about the future outlook. Moreover, the results contradict the findings of Jia et al. (2022), who find a greater propensity of investors to conform to the beliefs of others during optimistic market periods.

Table 5. Estimating herding during optimism and pessimism by using Twitter Hedonometer.

Sentiment Tail Bound		Intercept	$D\|R_{m,d}\|$	$R^2_{m,d}$	$D_oR^2_{m,d}/D_pR^2_{m,d}$
Panel A: Small cap					
+5%	optimism	2.480 ***	0.257 ***	0.001	−0.006
		(0.096)	(0.021)	(0.000)	(0.282)
−5%	pessimism	2.460 ***	0.268 ***	−0.000	0.001
		(0.096)	(0.026)	(0.001)	(0.001)
+10%	optimism	2.473 ***	0.263 ***	0.001	**−0.001** **
		(0.092)	(0.021)	(0.000)	(0.004)
−10%	pessimism	2.458 ***	0.270 ***	−0.001	0.001
		(0.096)	(0.026)	(0.001)	(0.001)
+15%	optimism	2.460 ***	0.269 ***	0.001	**−0.007** ***
		(0.079)	(0.020)	(0.000)	(0.002)
−15%	pessimism	2.452 ***	0.273 ***	−0.001	0.002
		(0.095)	(0.026)	(0.001)	(0.001)
Panel B: Medium cap					
+5%	optimism	1.928 ***	0.273 ***	0.003	−0.012
		(0.148)	(0.067)	(0.005)	(0.009)
−5%	pessimism	2.261 ***	0.077	0.018	−0.015
		(0.197)	(0.124)	(0.013)	(−0.010)
+10%	optimism	1.914 ***	0.284 ***	0.003	**−0.016** ***
		(0.150)	(0.070)	(0.005)	(0.006)
−10%	pessimism	2.262 ***	0.079	0.018	−0.015
		(0.197)	(0.123)	(0.013)	(0.010)
+15%	optimism	1.894 ***	0.293 ***	0.003	**−0.013** ***
		(0.151)	(0.070)	(0.005)	(0.005)
−15%	pessimism	2.252 ***	0.087	0.017	−0.015
		(0.190)	(0.117)	(0.012)	(0.010)
Panel C: Large cap					
+5%	optimism	0.668 ***	0.680 ***	0.003	−0.006
		(0.059)	(0.044)	(0.005)	(0.016)
−5%	pessimism	0.802 ***	0.555 ***	0.018	−0.015
		(0.106)	(0.093)	(0.013)	(0.010)
+10%	optimism	0.662 ***	0.687 ***	0.002	**−0.014** *
		(0.064)	(0.044)	(0.005)	(0.008)
−10%	pessimism	0.802 ***	0.555 ***	0.018	−0.015
		(0.089)	(0.085)	(0.013)	(0.010)
+15%	optimism	0.658 ***	0.689 ***	0.003	**−0.009** *
		(0.065)	(0.045)	(0.005)	(0.005)
−15%	pessimism	0.792 ***	0.567 ***	0.017	−0.014
		(0.086)	(0.082)	(0.012)	(0.010)

Note: The table reports regression results by using Equation (8) for optimistic behavior and 9 for pessimistic behavior. Newey–West standard errors are given in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

In Table 5 besides the Twitter Hedonometer, presence of herding was tested using the Chicago Board Options Exchange Volatility Index (VIX) in order to test the impact of investor sentiment on herding effect on the cryptocurrency market. Herd behavior was tested using equations 8 and 9, where a high VIX index indicator implies high volatility, which may influence pessimistic investor sentiment. A dummy variable was created to represent VIX values that exceeded the upper thresholds of 5%, 10%, and 15%, and was assigned the value 1. This dummy variable denoted periods of increased volatility that could correspond to pessimistic investor sentiment. Conversely, a separate dummy variable was created for the lowest VIX values of 5%, 10%, and 15%, which was also assigned the value 1. This dummy variable denoted periods of lower volatility, possibly indicating optimistic investor sentiment. Equations (8) and (9) were used in order to research herding effect. When evaluating the results for small-cap, medium-cap, and large-cap cryptocurrencies, a statistically significant result was observed in terms of the impact of the VIX (with a 5% tail limit) on herding behavior exclusively in the large-cap cryptocurrency category. The lowest 5% of the VIX index was replaced by the value of dummy variable 1, which may indicate optimistic behavior. These results confirm the previous conclusions from the Twitter Hedonometer analysis. Detailed results are provided in Table 6.

Table 6. Estimating herding during by using VIX on large-cap cryptocurrencies[2].

Sentiment Tail Bound		Intercept	$D\|R_{m,d}\|$	$R^2_{m,d}$	$D_o R^2_{m,d}$
−5%	optimism	1.928 *** (0.148)	0.273 *** (0.067)	0.003 (0.005)	−0.012 (0.009)

*** represent statistical significance at the 1% level, respectively.

These results in Table 6 are in accordance with Ali (2022), since the author concluded that herding behavior is involved during low-VIX periods in the cryptocurrency market. Similar findings were made by Jia et al. (2022), who claimed that herd behavior is involved during low- and high-VIX periods in the cryptocurrency market. According to Aharon (2021), the VIX has a stronger effect on the smallest and medium-sized firms in size-ranked stock portfolios. The VIX effect on herding intensifies at higher quantiles in the CSAD distribution and during significant VIX fluctuations. Economou et al. (2018) investigated the relationship between the VIX and herding behavior in stocks in the U.S., U.K., and Germany. The authors found empirical results supporting the statistically significant impact of fear on herd estimates. The current literature examining the potential impact of the VIX on the herd phenomenon remains relatively limited, particularly in the context of cryptocurrencies of different-sized market capitalizations.

5. Endogeneity Concerns

The obtained results should be interpreted with caution, as there are many other relevant factors besides liquidity and investor sentiment that can influence herd behavior in the cryptocurrency market. It is important to highlight that the rise in popularity of cryptocurrencies has coincided with significant monetary expansions implemented by central banks in response to several crises, including the subprime mortgage crisis, the Eurozone crisis, and the COVID-19 pandemic (Cortes et al. 2022). It is argued that the implementation of quantitative easing policies by these central banks could potentially lead to an inflationary impact on various assets, which include cryptocurrencies (Cortes et al. 2022; Dedola et al. 2020; Hartley et al. 2021). Consequently, the performance of cryptocurrencies in terms of returns, as well as phenomena such as herd behavior and liquidity in the cryptocurrency markets, could be affected by the actions of monetary authorities at the global level. In addition, government guarantees and the credibility of the fractional reserve banking system have a role in the herd effect in the cryptocurrency market. The relationship between government guarantees, the credibility of the fractional reserve banking system, and herding behavior in cryptocurrencies is complex. Strong government guarantees and a perceived credible fractional reserve banking system can foster a sense of security among investors, leading them to choose traditional financial institutions and avoid the cryptocurrency market, which can lead to a herd effect (Dantas et al. 2023). Conversely, weak government guarantees, a weaker fiscal position, or doubts about the credibility of the fractional reserve banking system may lead investors to seek alternative assets such as cryptocurrencies for diversification or as a hedge against potential financial instability (Acharya et al. 2012; Dantas et al. 2023). In such cases, herding behavior in cryptocurrencies could increase as investors may believe that these digital assets offer more security and potential returns.

6. Conclusions

Herding behavior implies behavioral convergence when investors tend to follow others. This phenomenon can be driven by both rational and irrational factors. Although this phenomenon is well studied on financial markets, studies which deal with its occurrence in the cryptocurrency market are still limited. This research aims to investigate the impact of liquidity and sentiment on herd behavior in three distinct categories of cryptocurrency, i.e., on small, medium, and large-cap cryptocurrencies. This study aimed to investigate two primary research questions: (1) the impact of liquidity on the herd effect in the cryptocurrency market and (2) the impact of sentiment on the herd effect in the cryptocurrency market. In addition, the analysis examined these effects for three different categories of cryptocurrencies based on their market capitalization: small-cap, medium-cap, and large-cap cryptocurrencies. By answering these research questions, this study contributes to the current understanding of herd behavior in the cryptocurrency market and extends the existing literature on this topic by shedding light on the interplay between liquidity, sentiment, and the occurrence of herd behavior in different segments of the cryptocurrency market.

Regarding our first research question, the results suggest that, in terms of liquidity, after testing turnover volume, the effect was not found for low- and high-cap cryptocurrencies, while it was present during periods of low liquidity on low-cap cryptocurrencies. After using another proxy variable for liquidity—CLR (also known as Amivest measure of liquidity)—the results revealed that herd behavior is present during periods of low CLR indicator (5% and 10%) for small-cap cryptocurrencies and at the same levels during periods of high CLR indicator for large-cap cryptocurrencies. The results show that the herd effect in the cryptocurrency market occurs mainly when liquidity is low and trading activity is weak, which can lead to reduced information flow as participants follow the behavior of others in the market. The only exception is that herding is present during periods of high CLR indicator on large-cap cryptocurrencies. It is important to note that herding behavior can occur in any market, regardless of the level of liquidity or the size of the cryptocurrencies involved. While higher liquidity may mitigate the effects of herding behavior to some degree, it does not eliminate the possibility of herding behavior in large-cap cryptocurrencies, even during periods of high liquidity.

In relation to the results of the second research question, there is strong evidence of the presence of herd behavior in the cryptocurrency market, especially on optimistic days. To measure investor sentiment, the Twitter Hedonometer was used as a proxy, since a significant portion of investors are individuals. The study found significant herd behavior occurring in 10% and 15% of all cryptocurrencies, regardless of their market capitalization. Results based on the VIX index also support this findings, since herd behavior is present on large-cap cryptocurrencies during periods of low VIX index on 5% level.

The relationship between turnover volume and herd behavior remains an active area of research, and further empirical investigation is needed to gain a deeper understanding of the dynamics involved. The topic of the influence of liquidity and sentiment on herd behavior in cryptocurrencies is still insufficiently researched to our current knowledge. Most studies in this area focus primarily on capital markets. Research studies dealing with the cryptocurrency market mainly focus on cryptocurrencies with high market capitalization and neglect cryptocurrencies with medium and low market capitalization. This research contributes to filling that gap by investigating the impact of liquidity and sentiment on herding behavior across differently sized cryptocurrencies. Although herding is a short-lived phenomenon, it is very important to explore reasons for its occurrence in order to help policy makers, investors, and other market participants to manage risk in creating an investment portfolio. Overall, understanding herd behavior in the cryptocurrency market is crucial for investors and policymakers, given the unique characteristics and significance of cryptocurrencies in global financial markets.

7. Limitations and Future Recommendations

Although this study has provided insights into the impact of liquidity and sentiment on herd behavior in the cryptocurrency market, it is important to acknowledge some limitations and consider them as a recommendation for future research. Research on the herd effect based on the Twitter Hedonometer must be interpreted with caution due to biases such as a reliance on the English language. The cryptocurrency market is a decentralized market with traders investing from all parts of the world, so it is advisable to include additional proxy measures to achieve higher significance in quantifying investor sentiment. Similarly, the VIX, an index based on the volatility of option prices on the S&P 500, reflects the outlook of investors who invest in assets linked to the aforementioned index. Consequently, results derived from the VIX should also be taken with caution. In addition, it is important to point out a limitation of the present study, namely, the use of a static CSAD model in the empirical analysis. To increase the credibility and reliability of the assessment of the occurrence of the herd effect, future researchers are advised to use a regime-switching model. This analytical approach takes into account the dynamic nature of investor sentiment and its fluctuations over time, allowing for adjustments that reflect changing market conditions. A significant body of capital markets literature, including Balcilar et al. (2013), Mand and Sifat (2021), and Fu and Wu (2021), has already addressed the use of regime switching. Incorporating such a methodology would expand existing knowledge derived from static models and contribute to a more comprehensive understanding of the herd effect. Therefore, it is recommended that future research efforts incorporate regime switching or even advanced methodologies to further improve scientific understanding in this area.

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Notes

[1] Due to space limitation list of the included cryptocurrencies in the study sample is available upon request.

[2] The table has been shortened to show only the significant results; the full table is available on request.

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