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Research Article

Dynamics of Herding Behavior in Cryptocurrency Markets Amid Market Crashes

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ABSTRACT

Herding behavior is expected to intensify with increasing uncertainty in financial markets, especially after jarring structural changes such as the pandemic. For this reason, in this study we examined herding behavior in the cryptocurrency market amid market crashes. Using daily cryptocurrency price data in 02.01.2018 - 22.03.2023 of the 9 most traded cryptocurrencies, the presence of herding behavior was investigated using the cross-sectional absolute deviation (CSAD) method. The dynamics of herding behavior was explored in 3 sub-periods: the Pre-Covid Period, the Covid-19 Period and the Post Market Crash Period after Tesla's Announcement. We also tested if the largest cryptocurrencies were driving small cryptocurrencies in the 3 sub-periods as well as the whole period. The findings of the study reveal that there is no herding in the market in significant market fluctuations. Moreover, there seems to be no asymmetric herding behavior as we distinguish between up and down markets. Hence, our findings imply rational investment decision-making. Yet, the results indicate that the largest cryptocurrencies are wielding a substantial influence over the rest of the market across the overall period and in the Post Covid Period (Period 2) in both up and down markets. However, in Period 1 and Period 3, the herding of small cryptocurrencies varies depending on whether the market returns are positive or negative. Our findings imply that the dynamics of the herding behavior between large and small cryptocurrencies has shifted with significant market crashes (outbreak of Covid-19, Tesla's announcement).

Keywords: Herding Behavior, Cryptocurrency Markets, Market Crashes, Covid-19

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1. Introduction

Behavioral finance has been popular among investors, financial asset managers, and academic researchers. At its core, the field of behavioral finance seeks to understand and explain market inefficiencies and mispricing by examining behavioral biases and cognitive limitations. Several critical approaches, such as Prospect Theory and Herd Psychology, have been developed within behavioral finance to grasp how individual behavior impacts financial decision-making. Households and inexperienced investors are particularly susceptible to herding behavior, as they often rely on the knowledge and opinions of more experienced individuals when making investment decisions. Herding behavior can be defined as a form of behavior that is based on information and reputation. This behavior can be observed in various group settings, including large-scale demonstrations, riots and strikes, religious gatherings, and sporting events. Herding behavior is believed to be driven by various factors such as peer pressure, a desire to save time by not conducting extensive research, and a fear of guilt (Tversky The popularity of cryptocurrencies has increased in recent years due to their decentralized nature, transparency, and security, which is based on cryptography. Cryptocurrencies offer a decentralized form of exchange that utilizes cryptographic functions to execute financial transactions and leverages blockchain technology to achieve decentralization, transparency, and immutability. Furthermore, the security of cryptocurrencies is primarily based on cryptography, as evidenced by the use of Elliptic Curve Cryptography in Bitcoin transactions. This type of public-key cryptography uses mathematical algorithms to guarantee the security of financial transactions (Stancel, 2015); (Antonopoulos, 2017). & Kahneman, 1989).

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The cryptocurrency market has experienced rapid and uneven growth since its inception, with the launch of the first cryptocurrency, Bitcoin, in January 2009. Today, cryptocurrencies have gained widespread acceptance and have seen substantial development, and thus more than 8,000 cryptocurrencies are being traded in the market (Arias-Oliva, de Andrés-Sánchez, & Pelegrín-Borondo, 2021). Many hedge funds and asset managers have incorporated cryptocurrency-related assets into their investment portfolios and trading strategies in response to this growth. In addition, the proliferation of financial technologies and the emergence of new financial assets have led to the recognition of cryptocurrencies as an emerging asset class. With a global market capitalization of around $400 billion, the cryptocurrency market is rapidly approaching the size of a medium-sized stock market or some of the largest US companies, highlighting the significant growth and development of the cryptocurrency market in its short lifespan (Goforth, 2019).

One of the crucial characteristics of cryptocurrencies is the absence of financial intermediaries in the transaction process, resulting in reduced transaction costs for investors. Additionally, cryptocurrencies are not controlled by any central authority due to their decentralized nature within the blockchain framework, making them theoretically resistant to government control and interference. The lack of intermediaries and decentralization of cryptocurrencies have made them attractive to investors.

The outbreak of the highly contagious coronavirus (COVID-19) pandemic, declared as a large-scale emergency by the World Health Organization, has led to drastic decreases in sales and production of many companies in the global economy as well as significant changes in consumer purchasing habits. The impact of COVID-19 is widely recognized as an unprecedented global catastrophe, with a far-reaching impact on public health and the economy. As a result, the pandemic has seriously affected many assets in the global financial markets, particularly in the foreign exchange (Feng, Yang, Gong, & Chang, 2021); (Fasanya, Oyewole, Adekoya, & Odei-Mensah, 2021) and cryptocurrency markets (Demir, Bilgin, Karabulut, & Doker, 2020); (Iqbal, Fareed, Wan, & Shahzad, 2021). In this context, investor asset allocation, portfolio management decisions, as well the handling of financial instruments have garnered significant attention from academic and investment communities.

Herding behavior, especially during times of crisis when investors may experience similar fears and become more vulnerable to widespread financial unrest, is a topic of interest in the literature. Herding behavior occurs when investors, faced with uncertain information, tend to follow the investment decisions and actions of others, or rely too heavily on publicly available information at the expense of their knowledge (Bikhchandani & Sharma, 2000); (Chiang & Zheng, 2010); (Galariotis, Rong, & Spyrou, 2015). The COVID-19 pandemic has generated a "black swan effect" on cryptocurrencies leading to behavioral anomalies such as herding behavior. Thus, herding remains influenced by market trends, but its strength did not increase during the COVID-19 pandemic (Yarovaya, Matkovskyy, & Jalan, 2021).The uncertainty and instability brought on by pandemics such as COVID-19 can increase investor fears about investing in cryptocurrency markets, leading to the imitation of other investors' behavior and herding behavior.

Therefore, examining the behavior of cryptocurrencies in the face of the pandemic is necessary to comprehend the effects of the pandemic on this emerging asset class. Since herding behavior is expected to intensify with increasing uncertainty in financial markets, especially after jarring structural changes and market crashes such as the pandemic, herding behavior was explored in 3 sub-periods: the Pre-Covid Period, the Covid-19 Period and the Post Market Crash Period after Tesla's Announcement. Moreover, we tested if the largest cryptocurrencies were driving small cryptocurrencies in the 3 sub-periods as well as the whole period. Daily cryptocurrency price data from 02.01.2018 until 22.03.2023 of the 9 most traded cryptocurrencies were utilized. In the post-Covid-19 period, the cross-sectional absolute deviation (CSAD) was used to explore herding behavior in the cryptocurrency markets. This provides a fresh comparison of investor behavior in unprecedented situations, which has not been explored extensively in the existing literature.

The findings of the study reveal that there is no herding in the market in significant market fluctuations. Moreover, there seems to be no asymmetric herding behavior as we distinguish between up and down markets. These results imply rational investment decision-making. Yet, the results indicate that the largest cryptocurrencies are wielding a substantial influence over the rest of the market Moreover, we explore if the largest cryptocurrencies are driving small cryptocurrencies in the 3 sub-periods as well as the whole period analyzed. To the best of our knowledge, this is one of the first studies to investigate if the dominance of large cryptocurrencies varies in different market conditions. The findings of this study may offer valuable insights to investors, asset managers, and policymakers by shedding light on the impacts of the pandemic and market crashes on the herding behavior and dominance of large cryptocurrencies in the cryptocurrency markets. These insights can help them make more informed decisions regarding investment strategies, risk management, and regulatory frameworks.

2. Theoretical Framework

Herding behavior in financial markets refers to investors' tendency to imitate other investors' behavior, leading to excessive volatility and short-term trends (Banerjee, 1992); (Kabir & Shakur, 2018). This behavioral bias can result from unintentional factors, such as events that cause investors to sell and buy the same asset simultaneously (Lakonishok, Shleifer, & Vishny, 1992), and deliberate factors, such as knowledge ladders and reputational concerns (Forbes & Rigobon, 2002). Previous research has attempted to measure market-wide herding behavior through the relationship between cross-sectional distribution and stock returns (Christie & Huang, 1995); (Hwang & Salmon, 2004) and has found that herding behavior is driven by emotional and psychological factors rather than macroeconomic factors (Lakshman, Basu, & Vaidyanathan, 2013); (Chen, Jang, & Kim, 2007).

Studies on herding behavior have primarily focused on stock markets (Chiang & Zheng, 2010) and commodity markets (Demirer, Lee, & Lien, 2015), with mixed and inconclusive evidence for their existence (Galariotis et al., 2015). However, it is essential to distinguish between actual herding behavior, where market participants act in unison, and "fake herding" behavior, where market participants make similar decisions based on similar information.

The evidence for herding behavior in cryptocurrency markets is limited, with a few studies suggesting its existence (Bouri, Gupta, & Roubaud, 2019); (Kaiser & Stöckl, 2020); (Kallinterakis & Wang, 2019). While the Efficient Market Theory suggests that fundamental factors drive market price formation, it cannot explain the volatility observed in speculative markets (Javaira & Hassan, 2015). Therefore, the extreme volatility in cryptocurrency markets may be driven by behavioral factors, such as herd psychology. The study of herding behavior in cryptocurrency markets has become increasingly crucial as cryptocurrencies have gained widespread attention due to their impressive returns and have attracted many new investors to the financial markets.

The COVID-19 pandemic has provided a unique opportunity to examine herding behavior in cryptocurrency markets during this unprecedented "black swan" event. However, it is essential to note that while the COVID-19 pandemic may be considered a "black swan" event for cryptocurrency markets, it is not entirely unprecedented for traditional financial markets. Previous studies have discussed the impact of pandemics and infectious diseases on the economy (Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018). The literature also provides evidence of the impact of previous pandemics, such as SARS, Ebola, Zika, H1N1, and HIV/AIDS, on economies and markets (Haacker, 2004); (Hoffman & Silverberg, 2018). The evidence for herding behavior in cryptocurrency markets is limited; the COVID-19 pandemic has provided a unique opportunity to examine this phenomenon in this emerging asset class.

The Sectional Standard Deviation (CSSD) and Sectional Absolute Deviation (CSAD) proposed by Christie and Huang (1995) and (Chang, Cheng, & Khorana, 2000) respectively, are commonly used techniques for measuring herding behavior in financial markets. These measures are based on the distribution of returns and are considered static measures. However, many researchers have found that dynamic models are necessary to capture the structural breaks and nonlinearities in the data. For example, Bouri et al. (2019) studied the swarm behavior for 14 cryptocurrencies and found no significant swarm behavior under static models but discovered swarm behavior when using the "rolling window" technique. The study suggested that uncertainty increases the tendency for herding behavior.

Poyser (2018) found that herding behavior is present in positive market returns when examining asymmetric herding for 100 cryptocurrencies. Haryanto, Subroto, and Ulpah (2020) detected herding behavior in up and down markets to distinguish between positive and negative market returns and suggested that herding behavior follows market trends. Vidal-Tomás (2021) observed swarm behavior only in down markets when analyzing asymmetric swarming for 65 cryptocurrencies. Finally, Ballis and Drakos (2020) concluded that there is swarm behavior after examining asymmetric swarming for six leading cryptocurrencies.

The literature provides conflicting results on herding behavior in cryptocurrency markets. Various studies suggest that herding behavior may be present in cryptocurrency markets, but the results vary based on the type of model used and the market conditions. da Gama Silva, Klotzle, Pinto, and Gomes (2019) claimed that herding behavior was mainly observed during bear market days, unlike Kyriazis, Papadamou, and Corbet (2020) who asserts that herding behavior mainly occurs in the cryptocurrency market during bull markets.

3. Data and Methodology

The aim of the current study is to investigate the price reactions of cryptocurrencies and the dynamics of herd behavior in the cryptocurrency market amid market crashes. To examine the herding behavior in cryptocurrencies, 9 cryptocurrencies with the largest market volume were analyzed (a list of the cryptocurrencies included in the study together with the trading volumes are given in Appendix 1). Cryptocurrencies, the market cap of which are above 0.5% were included in the study. Hence, 9 cryptocurrencies were considered, the total market cap of which represents approximately 83.28% of the total market (See Appendix 2). We used a market portfolio with equal weights to calculate market returns, consistent with the approach of previous studies such as (Chang et al., 2000) and (Chiang & Zheng, 2010).

From the Investing.com database, daily price data for the period from 02.01.2018 to 22.03.2023 were obtained for analysis. In addition, periodic analysis was performed alongside a comprehensive global examination. The duration of the study was divided into three distinct intervals to facilitate our analysis. The initial period, which lasted 743 days, ran from 02.01.2018 to 14.01.2020. The second period, which included a total of 492 days, ran from 15.01.2020 to 19.05.2021. Finally, the final period, with a total duration of 671 days, extended from 20.05.2021 to 22.03.2023.

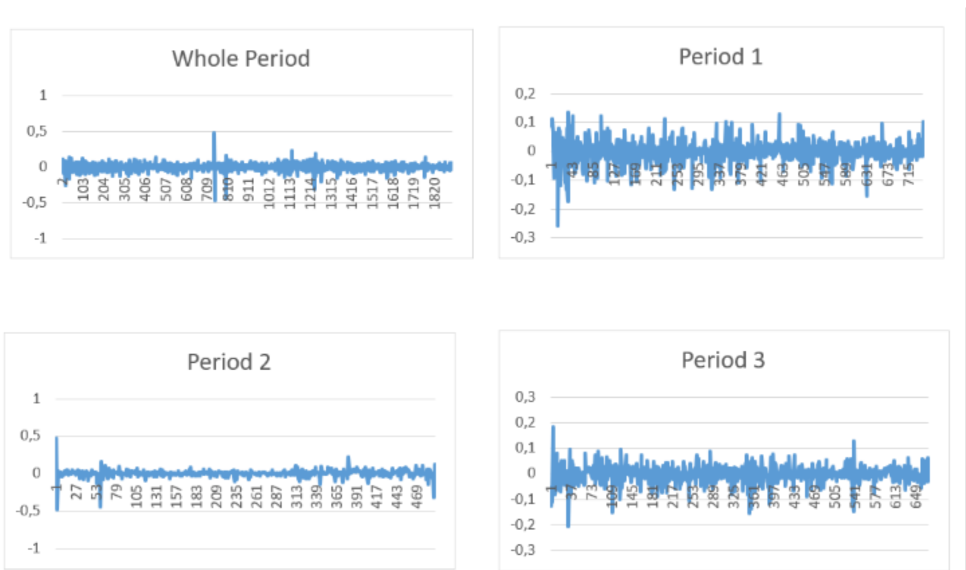

Figure 1: Market Portfolio Returns 02.01.2018 - 22.03.2023.

The first sub-period represents the pre-covid market conditions until the market crashes on the 15th of January 2020 (Day 746) by 47.4% upon the outbreak of the pandemic. The second sub-period represents covid-19 dominant market conditions until the market crash of 31.3% on 19th of May (Day 1235) following Tesla's Announcement regarding the withdrawal of the decision to accept the digital payments over concerns about the adverse impacts of cryptocurrency mining on the environment (Smith, 2023). The third sub-period represents the post market crash period after Tesla's Announcement until 22nd of March 2023.

Methods for identifying herding behavior fall into two broad categories. Lakonishok et al. (1992) and Sias (2004) are among the proponents of the first approach which focuses on a micro perspective and examines instances where certain types of investors exhibit herding behavior. As for the second approach, its advocates are (Christie & Huang, 1995); (Chang et al., 2000). With this second approach, attention is paid to the macro level which examines market activities and the prices of financial products accessible to any investor. The second approach forms the foundation of this study.

Table 1: Descriptive Statistics of Market Returns

	Whole Period (%)	Period 1 (%)	Period 2 (%)	Period 3 (%)
Mean	0.0259	-0.1485	0.4737	-0.1094
Standard Error	0.1008	0.152	0.2517	0.1395
Median	0.231	-0.0397	0.6043	0.1018
Standard Deviation	4.4023	4.143	5.5827	3.6133
Sample Variance	0.1938	0.1716	0.3117	0.1306
Kurtosis	2207.4059	336.505	3069.0204	400.1264
Skewness	-101.2729	-57.9591	-146.826	-61.529
Range	94.6278	39.2654	94.6278	38.5822
Minimum	-47.4485	-25.8811	-47.4485	-20.3958
Maximum	47.1793	13.3843	47.1793	18.1863
Sum	49.3551	-110.3127	233.0658	-73.398
Count	1906	743	492	671

Thanks to the method developed by (Chang et al., 2000) herding behavior can be spotted across the range of market returns. This is achieved by using the cross-sectional absolute deviation (CSAD) of returns, which is expressed by equation (1).

$$CSAD_{m,t} = \frac{\sum_{i=1}^{n} |R_{i,t} - R_m, t|}{N} \tag{1}$$

The variables in equation (1) are defined as follows: Ri,t refers to the return of a specific asset i during a given time period t, Rm,t refers to the average cross-sectional return of the market portfolio at time t , and N represents the total number of assets considered in the analysis. Later, in the regression equation (2) the dispersion of returns in the event of large market fluctuations is used by the method.

$$CSAD_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 |r_{m,t}| + \beta_3 r_{m,t}^2 + u_t \tag{2}$$

In accordance with the Capital Asset Pricing Model (CAPM), Chang et al. (2000) expressed the CSAD method, with evidence that the variation in returns is proportionally related to market returns in a linear fashion. According to

Vidal-Tomás (2021) a significant negative β3 coefficient shows the presence of herding behavior, while a significant positive β3 coefficient indicates rational asset pricing

Following Chiang and Zheng (2010), to identify the asymmetric herding effect, which is based on whether the market is rising (up) or falling (down), we divided the market returns into two categories. The regression equation (3) embodies the generalized form that incorporates all market return distributions.

$$CSAD_{m,t} = \alpha + \beta_1(1-D)r_{m,t} + \beta_2 D r_{m,t} + \beta_3(1-D)r^2_{m,t} + \beta_4 D r^2_{m,t} + u_t \quad (3)$$

The variables (1-D) and D are considered as dummy variables that take the value 1 when $r_{m,t}$ ≥0 and rm,t t<0, respectively.

To better understand the inner workings of this market as a final step, we observed whether smaller cryptocurrencies display herding behavior with larger virtual currencies. We followed the methodology employed by (Chiang & Zheng, 2010) whereby we split our sample into two sub-markets, with the aim of distinguishing between smaller and larger cryptocurrencies. The first sub-market comprises the 4 largest cryptocurrencies in terms of market capitalization, namely Bitcoin, Ethereum, Tether, and BNB, which represents 78.21% of the total market in terms of market cap. The second sub-market comprises 5 small cryptocurrencies namely XRP, Cardano, Dogecoin, TRON and Litecoin, which represents 5.1% of the total market in terms of market cap. (See Appendix 2).

$$CSAD_{s,t} = \alpha + \beta_1(1-D)r_{s,t} + \beta_2 D r_s, t + \beta_3(1-D)r^2_{s,t} + \beta_4 D r^2_{s,t} + \beta_5 CSAD_{l,t} + \beta_6(1-D)r^2 l, t + \beta_7 D r^2 l, t + u_t \quad (4)$$

In equation (6), subscript denoted by ’s’ pertains to a sub-market comprising of small digital cryptocurrencies, whereas ’l’ denotes a sub-market consisting of the largest ones.

4. Findings

4.1. *Is there herding behavior in the market in significant market fluctuations?*

Table II demonstrates the regression results of CSADm,t on market returns for the generalized form. It seems there is no herding in the market in significant market fluctuations as indicated by the absence of a negative coefficient $r^2_{m,t}$. Thus, these positive coefficients align with predictions made by rational asset pricing models.

Table 2: Regression Results of CSADm,t on Market Returns (Whole Period)

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.0135	0.0005	24.42	0.0000***
$r_{m,t}$	0.1609	0.0083	19.286	0.0000***
$\|r_{m,t}\|$	0.1322	0.0177	7.471	0.0000***
$r^2_{m,t}$	2.3336	0.0624	37.372	0.0000***

***significance at the 1% level;
** significance at the 5% level;
* significance at the 10% level

4.2. Is there asymmetric herding behavior?

The results in Table III indicate there is no asymmetric herding behavior as we distinguish between positive and negative market returns. The positive coefficients (1-D)r2m,t and Dr2m,t imply that the behavior of market participants in up and down markets was consistent with rational investment decision-making.

Table 3: Regression Results of $\text{CSAD}_{m,t}$ on Market Returns for Up and Down Markets (Whole Period)

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.0137	0.0005	24.926	0.0000***
(1-D) $r_{m,t}$	0.2337	0.0218	10.733	0.0000***
Drm,t	-0.0156	0.0204	-0.765	0.444
$(1\text{-D})r^2_{m,t}$	2.7641	0.0921	29.997	0.0000***
$Dr^2_{m,t}$	2.0730	0.0744	27.869	0.0000***

***significance at the 1% level;
** significance at the 5% level;
* significance at the 10% level;

4.3. *Are the largest cryptocurrencies driving small cryptocurrencies?*

Table IV furnishes compelling evidence that small cryptocurrencies are herding with the largest cryptocurrencies. Significant negative values of (1-D)r2l,t and Dr2l,t indicate that the largest cryptocurrencies are wielding a substantial influence over the rest of the market across the overall period. In the Pre-Covid Period, the largest cryptocurrencies seem to drive the small ones when market returns are negative, but not when market returns are positive. Since the outbreak of Covid-19 the dynamics of the herding behavior between large and small cryptocurrencies have changed. Small cryptocurrencies seem to herd with the largest ones both in up and down markets. Yet, there seems to be another shift in the herding behavior after the market crash following Tesla's Announcement. Hence, in the last sub-period the dominance of large cryptocurrencies seems to disappear in down market while it continues in up markets.

In short, the results suggest that the performance of the rest of the market was driven by the behavior of the large cryptocurrencies in the whole period and in the Post Covid Period (Period 2) in both up and down markets. The positive and significant values of CSADl,t during the whole period and Period 2 highlight the dominance of Bitcoin, Ethereum, Tether, and BNB in the cryptocurrency market. However, in Period 1 and Period 3, the herding of small cryptocurrencies varies depending on whether the market returns are positive or negative.

5. Conclusion

Using daily cryptocurrency price data in 02.01.2018 - 22.03.2023 of the 9 most traded cryptocurrencies, this study investigated the herding behavior in the cryptocurrency market amid market crashes by employing the cross-sectional absolute deviation (CSAD) method. The data of the study comprise the 4 largest cryptocurrencies in terms of market capitalization, namely Bitcoin, Ethereum, Tether, and BNB, representing 78.21% of the total market in terms of market cap, and 5 small cryptocurrencies namely XRP, Cardano, Dogecoin, TRON and Litecoin, representing 5.1% of the total market in terms of market cap.

Firstly, we explored if there was herding behavior in the market in significant market fluctuations, and we found that there seems to be no herding. Secondly, we distinguished between up and down markets, and similarly, we found no evidence for asymmetric herding behavior. These results imply that there was rational investment decision-making in the cryptocurrency market during the investigated period, which contests the commonly held perception that herding behavior becomes more pronounced under amplified uncertainty. In this respect, our findings are consistent with (Yarovaya et al., 2021). Finally, we examined whether the largest cryptocurrencies were driving small cryptocurrencies.

Regarding the dominance of the largest cryptocurrencies in the market, our results highlight that the largest cryptocurrencies were wielding a substantial influence over the rest of the market across the overall period) in both up and down markets. These findings are consistent with (Vidal-Tomás, 2021). Our study differs from similar studies as

Table 4: Regression Results of CSADm,t on Market Returns for the Small and Largest Cryptocurrencies

	Coefficients	Standard Error	t Stat	P-value
Whole period				
Intercept	0.0113	0.0008	14.767	0.0000***
$(1\text{-}D)r_{s,t}$	0.1906	0.0228	8.374	0.0000***
$Dr_{s,t}$	0.0043	0.0213	0.202	0.834
$(1\text{-}D)r^2_{s,t}$	1.6729	0.0389	43.032	0.0000***
$Dr^2_{s,t}$	1.3472	0.0381	35.396	0.0000***
$CSAD_{l,t}$	0.2631	0.04818	5.462	0.0000***
$(1\text{-}D)r^2_{l,t}$	-3.2998	0.4559	-7.238	0.0000***
$Dr^2_{l,t}$	-1.7141	0.1063	-16.124	0.0000***
Period 1				
Intercept	0.0129	0.0011	11.271	0.0000***
$(1\text{-}D)r_{s,t}$	0.1212	0.0593	2.042	0.0415**
$Dr_{s,t}$	-0.0917	0.0402	-2.281	0.0228**
$(1\text{-}D)r^2_{s,t}$	1.7818	0.4708	3.785	0.0002***
$Dr^2_{s,t}$	0.6888	0.3343	2.060	0.0394**
$CSAD_{l,t}$	0.0908	0.0636	1.427	0.1541
$(1\text{-}D)r^2_{l,t}$	0.1166	0.6341	0.184	0.8541
$Dr^2_{l,t}$	-1.0023	0.5985	-1.675	0.0944
Period 2				
Intercept	0.0095	0.0021	4.422	0.0000***
$(1\text{-}D)r_{s,t}$	0.2595	0.0501	5.178	0.0000***
$Dr_{s,t}$	0.0966	0.0567	1.703	0.0891**
$(1\text{-}D)r^2_{s,t}$	1.5805	0.0721	21.917	0.0000***
$Dr^2_{s,t}$	1.2283	0.0841	14.605	0.0000***
$CSAD_{l,t}$	0.6306	0.1233	5.116	0.0000***
$(1\text{-}D)r^2_{l,t}$	-6.2984	1.1009	-5.721	0.0000***
$Dr^2_{l,t}$	-1.7065	0.1638	-10.418	0.0000***
Period 3				
Intercept	0.0115	0.0008	14.733	0.0000***
$(1\text{-}D)r_{s,t}$	0.2290	0.0485	4.726	0.0000***
$Dr_{s,t}$	-0.0800	0.0345	-2.317	0.0208**
$(1\text{-}D)r^2_{s,t}$	1.6908	0.4903	3.448	0.0006***
$Dr^2_{s,t}$	0.7490	0.2051	3.652	0.0002***
$CSAD_{l,t}$	0.0112	0.0676	0.166	0.8680
$(1\text{-}D)r^2_{l,t}$	-4.7671	0.8804	-5.415	0.0000***
$Dr^2_{l,t}$	-0.6012	0.4775	-1.259	0.2085

we analyze the dynamics of the herding behavior between large and small cryptocurrencies in different sub-periods. According to the findings of the study, although the performance of the rest of the market was driven by the behavior of the large cryptocurrencies in the Post Covid Period (Period 2) in both up and down markets, the herding of small cryptocurrencies varied depending on whether the market returns are positive or negative in Period 1 and Period 3. Hence, our results imply that the dynamics of the herding behavior between large and small cryptocurrencies has shifted with significant market crashes (outbreak of Covid-19, Tesla's announcement).

Our findings are limited by the time and the sample of the study. We focused on only 9 cryptocurrencies. Although these cryptocurrencies represent a significant portion of the market cap, the conclusions drawn may not fully apply to the entire market. Besides, we determined the sub-periods of the study by identifying the market crashes rather than applying structural break tests. Further studies may explore how the dynamics of the herding behavior between large and small cryptocurrencies change with structural break tests.

Ethics Committee Approval: AWe respectfully explain that our study did not involve human subjects or animals and therefore did not require ethical review.

Peer-review: Externally peer-reviewed.

Author Contributions: Conception/Design of Study- P.R.D., B.G., Ö.S.; Data Acquisition- P.R.D., B.G.; Data Analysis/Interpretation- P.R.D., B.G., M.A.C.K.; Drafting Manuscript- P.R.D., B.G., Ö.S., M.A.C.K.; Critical Revision of Manuscript- Ö.S.; Final Approval and Accountability- P.R.D., B.G., Ö.S., M.A.C.K.

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Appendices

Appendix 1: Cryptocurrencies Included in the Study

ID	Cryptocurrency
1	Bitcoin
2	Ethereum
3	Tether
4	BNB
5	XRP
6	Cardano
7	Dogecoin
8	TRON
9	Litecoin

Appendix 2: Market Cap Analysis of Selected Cryptocurrencies

ID	Crypto	Symbol	Market Cap (Million $)	Market Cap (%)	
1	Bitcoin	BTC	545.290	47.6%	
2	Ethereum	ETH	219.440	19.2%	
3	Tether	USDT	79.040	6.9%	
4	BNB	BNB	51.590	4.5%	**78.21%**
5	XRP	XRP	23.020	2.0%	
6	Cardano	ADA	12.990	1.1%	
7	Dogecoin	DOGE	9.990	0.9%	
8	TRON	TRX	6.140	0.5%	
9	Litecoin	LTC	5.870	0.5%	**5.1%**
Total	**Sample**		**953.37**		
Total	**Universe**		**1144.781**		**83.28%**