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The Impact of Common Market, Up Market, and Down Market on the Herding Behavior of Top 10 Capitalization Cryptocurrencies

Brian Prasetyo Halim¹, Dwi Fitrizal Salim², Farida Titik Kristanti³

Abstract

Cryptocurrencies have become increasingly popular among investors and literature around the world. In recent years, there have been a series of events that caused high volatility due to market corrections of more than 10% to nearly 40% such as COVID-19 and FTX bankruptcy. This research seeks to determine the existence of herding behavior during this timeframe across three distinct market conditions. The approach utilized is the Cross-Sectional Absolute Deviation (CSAD) method, which is known for its popularity and reliability. The analysis will be performed on 10 cryptocurrencies spanning from 2018 to 2024. The selected cryptocurrencies include Bitcoin (BTC), Bitcoin Cash (BCH), Cardano (ADA), Ethereum (ETH), Tether (USDT), BNB (BNB), Tron (TRX), Litecoin (LTC), Monero (XMR), and XRP (XRP). The findings reveal that there is a form of anti-herding behavior present in both the overall market and the rising market, which contradicts numerous earlier studies. The declining market also demonstrates a tendency toward anti-herding behavior, although the significance of this finding is minimal.

Keywords: General Market, Behavior, Cryptocurrency, Herding, Rising Market

Introduction

Since its emergence in the 1990s, the Internet has evolved at a rapid pace. As the technology grew, it expanded into the financial sector. This is how cryptocurrency was born. Inspired by the economic crash of 2008, Japanese programmer Satoshi Nakamoto decided to develop the first cryptocurrency in 2009. He created Bitcoin in the hope of preserving the value of his capital against the impending rise of inflation and the uncertain state of the world (Nakamoto, 2008). Since then, the cryptocurrency has multiplied in number and created its own market whose movement is only affected by the supply and demand of each crypto coin.

Cryptocurrencies are designed to be a means of storing money digitally and to be able to be used for digital payments (Waspada et al., 2023). Cryptocurrencies began as a way to store money digitally and were used as online payments in everyday transactions. This eliminates the need for people to carry large amounts of cash wherever they go, or to take the time to prepare large amounts of cash for large transactions. Initially, cryptocurrencies have little to no value because hardly anyone interested or invested in them. However, cryptocurrency offers several appealing characteristics. To begin with, the fees for transactions are significantly lower compared to those

¹ School of Economics and Business, Telkom University, Indonesia,
Email: brianprasetyohalim@student.telkomuniversity.ac.id

² School of Economics and Business, Telkom University, Indonesia,
Email: dwifitrizalslm@telkomuniversity.ac.id

³ School of Economics and Business, Telkom University, Indonesia,
Email: faridatk@telkomuniversity.ac.id



linked to credit and debit cards. Additionally, cryptocurrency transactions can be conducted anonymously, which is particularly appealing for individuals looking to preserve their privacy (Wahyuni et al., 2024). Lastly, it is important to note that the security measures employed by cryptocurrencies are so sophisticated that they have even been discreetly utilized by criminal syndicates (Bachaeu & Abdulazizova, 2020). As a result, cryptocurrency started to attract more attention.

Today, cryptocurrency is not an uncommon choice as an investment instrument. Its popularity has exploded to the point that no matter the age or capital of the investor, cryptocurrency would be an attractive investment choice. Media coverage also accelerates market growth by bringing cryptocurrencies to the forefront of investors' minds. The interest in cryptocurrencies is significantly influenced by social media, as discussions about their development and usage increase on these platforms, more individuals will become interested in utilizing cryptocurrencies (Waspada et al., 2023).

In contrast to conventional investment instruments, cryptocurrencies are decentralized. They are not managed by central banks and are not influenced by government policies. Transactions between users are conducted directly, without the involvement of third parties (Kurnaman & Rizal, 2023). Furthermore, they are operational at all times of the day and are accessible from any location at any time. This characteristic is the reason why the cryptocurrency market is exponentially volatile, as price fluctuations can occur at any time (Urquhart, 2016). Cryptocurrencies are frequently viewed as speculative investments because of their significant price fluctuations and minimal correlation with traditional assets, regardless of market stability. Baur et al. (2018) back this assertion, as their findings indicate that bitcoins are predominantly utilized as a speculative investment rather than functioning as an alternative currency or means of exchange. Compared to conventional financial assets, cryptocurrencies do not possess robust fundamentals. With their notoriously high volatility and risk, cryptocurrencies are attractive assets for investors with a high-risk tolerance (Deighton Chrisostomides, 2022).

Cryptocurrencies possess a total supply, maximum supply, and circulating supply (Lee et al., 2018). This means that their demand is solely influenced by market dynamics. Unlike traditional investments, which typically have a benchmark price that investors can rely on to evaluate the investment's quality, the price fluctuations of cryptocurrencies are affected by the interplay between investor behavior and the dissemination of information. Research conducted by Gurdgiev & O'Loughlin (2020) shows that investor sentiment can forecast the trends in cryptocurrency prices, indicating a significant influence of herding behavior bias.

Recent research has shown an increasing interest in herding behavior specifically within cryptocurrency markets. The existing literature presents a somewhat unclear depiction of herding behavior, with evidence often dependent on current market conditions and the specific traits of the assets involved. A number of studies have indicated that cryptocurrencies with relatively modest market capitalizations and periods of heightened volatility appear to be more susceptible to herding behavior. This tendency can be attributed to investors relying on the collective action in circumstances characterized by uncertainty (Mnif, 2023).

The examination of herding behavior within the cryptocurrency market is a fairly new area of research, yet it is evolving quickly. Herding behavior refers to a situation where people's individual decisions align with a shared agreement in the market. The decision to follow the market consensus means that investors ignore their own research and information, even if they disagree with the decision (Choi et al., 2022). Investors' decision-making process is largely

influenced by existing market conditions, suggesting that investors' strategies are influenced by their perceptions of market stability and potential risk (Almansour et al., 2023). Some research indicates that herding may occur under specific conditions such as information disparities and market inefficiencies. Herding behavior can significantly influence market dynamics, leading to heightened volatility and the formation of bubbles. The effects of herding tend to intensify during times of market instability or uncertainty. Although multiple factors can instigate it, herding behavior undoubtedly plays a role in escalating volatility and stress in the market (Gusni et al., 2023). Once bitcoin reached a price of \$20,000, it gained immense popularity, and researchers began to apply traditional herding detection methods to the crypto markets. The cryptocurrency market is highly susceptible to herding behavior due to its characteristics.

Christie & Huang (1995) pioneered to identify herding behavior by using Cross-Sectional Standard Deviation (CSSD). Their analysis of the connection between CSSD and market returns allowed them to assess the rationality of market behavior. A lower CSSD value signifies that individual stock returns are more closely grouped around the overall market return, suggesting that investors disregard their own information in favor of following the majority. The study found that CSSD values tend to decrease during times of market stress, supporting the theory that herding behavior is more likely to occur in such periods. Furthermore, asymmetric herding was identified, indicating that divergent market conditions may incite herding behavior during specific periods.

The research by Chang et al. (2000) is recognized as a pivotal study in the empirical examination of herding behavior within financial markets. It aimed to enhance the Cross-Sectional Standard Deviation (CSSD) metric introduced by Christie & Huang (1995) by presenting the Cross-Sectional Absolute Deviation (CSAD). The authors argued that CSAD serves as a more reliable gauge of return dispersion and is more effective for identifying herding behavior, especially in less extreme market environments. The findings indicated that emerging markets displayed a greater tendency towards herding behavior, while this phenomenon was less pronounced in developed markets. Additionally, there are signs of asymmetric herding behavior, which underscores the influence of fear and panic in fostering a herding mindset. Regarding the reliability of CSAD for identifying herding behavior, studies have utilized CSAD to observe such behavior in the cryptocurrency market. It has been shown that CSAD is a more efficient approach for detecting herding tendencies in the crypto market (Vidal-Tomás et al., 2019).

Bouri et al. (2019) suggest that herding behavior is present in cryptocurrency markets, although its strength varies over time. Their findings show a lack of evidence for herding, while the test results indicate that increased uncertainty leads to greater herding tendencies. Philippas et al. (2020) state that external information signals play an important role in shaping investor behavior. Their research shows that these signals can either increase or decrease investors' herding tendencies, depending on how they are interpreted in the decision-making process. Ballis & Drakos (2020) utilized CSSD and CSAD to detect the existence of herding behavior in the cryptocurrency market, while also performing Newey-West and GARCH estimations. The results indicate that herding behavior is present in a rising market, a conclusion that is consistent with the findings of Kallinterakis & Wang (2019) and Kyriazis (2020).

Nonetheless, some research suggests that herding behavior is more evident in declining markets. Vidal-Tomás et al. (2019) observed a notable presence of herding behavior during market downturns. This is further corroborated by the results of Stavroyiannis & Babalos (2019) and, unexpectedly, Kallinterakis & Wang (2019), who also identify significant herding behavior under

falling market conditions. It is indeed possible to find findings like those of Kallinterakis & Wang (2019) that reveal herding behavior occurring in both rising and declining markets at the same time.

The explanations for herding behavior differ from one study to another. Wang et al. (2023) revealed that herding behavior is absent in the cryptocurrency market. However, they identified certain scenarios, such as high volatility and small market cap, where herding is more probable. Tanos & Meharzi (2024) examined herding in cryptocurrency markets during volatile conditions like the COVID-19 pandemic and discovered that delays in price changes during upward trends led to a rise in herding behavior among investors. Gemayel & Preda (2024) indicated that herding behavior is a result of information cascades in low-liquidity cryptocurrencies and found that market conditions, particularly volatility, significantly influence herding behavior. Bogdan et al. (2023) mentioned in their findings that low liquidity promotes the development of herding behavior, and they also observed that positive sentiment tends to foster herding across various sizes of cryptocurrencies. Le et al. (2024) pointed out that herding behavior was not present in cryptocurrencies during the conflict period between Russia and Ukraine, noting that investors tended to act cautiously and rationally in uncertain market environments.

The reasoning also varies for different market conditions such as general market, rising market, and falling market. According to Chiang & Zheng (2010), under stable market conditions herding behavior can occur if there is uncertainty. Rising markets can lead to high market euphoria, which often results in excessive asset appreciation (Shiller, 2005). Rising markets can also lead to the formation of market bubbles, a phenomenon where asset prices exceed their true value. In this market condition, herding behavior tends to increase as investors want to participate in the upward price trend (Corbet et al., 2018). In a falling market, investors typically shift their portfolios into safer assets such as government bonds and gold. This phenomenon is known as the "flight to safety" (Baur & Lucey, 2010). Prolonged declines in prices can cause a wave of panic selling in an attempt to prevent losses, which can further intensify the decrease and potentially lead to exaggerated reactions. The presence of herding behavior in the cryptocurrency market should alert investors to be wary of the fair value of specific coins and the overall market, as the absence of a fundamental value reference complicates the detection of overvaluation and unwarranted optimism in the market (Kaiser & Stöckl, 2020).

Considering insights from earlier research, multiple factors play a role in examining the presence of herding behavior within the cryptocurrency market. This analysis primarily targets asymmetric herding, which has been identified in numerous prior studies. Based on the groundwork of earlier research, the hypotheses for this study are outlined as follows.

H1: There is a significant impact of general market cryptocurrency on herding behavior for the period 2018 - 2024.

H2: There is a significant impact of rising market cryptocurrency on herding behavior for the period 2018 - 2024.

H3: There is a significant impact of falling market cryptocurrency on herding behavior for the period 2018 - 2024.

Data and Methodology

This study uses data from 10 cryptocurrencies sourced from investing.com. The 10 cryptocurrencies are Bitcoin (BTC), Litecoin (LTC), Bitcoin Cash (BCH), Monero (XMR),

Cardano (ADA), Ethereum (ETH), Tether (USDT), BNB (BNB), Tron (TRX), and XRP (XRP). The period covered is from 31 December 2017 to 31 October 2024. The six-year dataset (2018–2024), extends the time frame and updates the analysis period implemented by Ballis & Drakos (2020), with the objective of capturing long-term trends, including periods of market adaptation. This extended dataset includes intervals of significant and relatively normal uncertainty, following the methodology of Wang et al. (2023), though it has been lengthened to evaluate the effects of varying market conditions. The price data for each cryptocurrency will be transformed into profit figures as outlined below.

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

In this context, $P_{i,t}$ represents the current price of the cryptocurrency at day t , $P_{i,t-1}$ refers to its price from the previous day of t , and $R_{i,t}$ indicates the daily return for each cryptocurrency. Additionally, in line with the methodologies established by Chang et al. (2000), Chiang & Zheng (2010), and Vidal-Tomás et al. (2019), this research will utilize an equally weighted market portfolio to determine market returns.

$$R_{m,t} = \frac{\sum_{i=1}^N R_{i,t}}{N} \quad (2)$$

In this context, N represents the total count of cryptocurrencies, $R_{i,t}$ refers to the daily return of each cryptocurrency, while $R_{m,t}$ signifies the daily return of the market. The daily returns of the market are subsequently transformed into monthly returns and computed using the CSAD method.

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (3)$$

Wang et al. (2023) conducted an empirical study on herding, utilizing the subsequent regression model.

$$CSAD_t = \beta_0 + \beta_1 |R_{mt}| + \beta_2 R_{mt}^2 + \varepsilon_t \quad (4)$$

Whereas $|R_{mt}|$ represents the absolute equally-weighted market return, R_{mt}^2 denotes the squared market return. According to Chang et al. (2000), a statistically significant negative coefficient β_2 suggests the existence of herding behavior. When an event occurs that is likely to heighten the correlation between individual asset returns, the variation among asset returns will either diminish or increase at a declining rate. During times of high volatility, if investors tend to exhibit herding behavior, there should be a reduction in the CSAD value. Conversely, if herding is absent, the dispersion grows in a linear fashion as the market return increases (Ballis & Drakos, 2020).

Since asymmetric herding may exist, it is important to test this hypothesis, which will be tested using two different models, similar to those used by Rizal & Damayanti (2019) and Chaffai & Medhioub (2018).

$$CSAD_t^{up} = \beta_0 + \beta_1 |R_{mt}^{up}| + \beta_2 (R_{mt}^{up})^2 + \varepsilon_t \text{ if } R_{mt} > 0 \quad (5)$$

For rising market condition, $|R_{mt}^{Up}|$ represents the absolute equally-weighted market return when it's greater than zero and $(R_{mt}^{Up})^2$ is the squared market return when it is positive.

$$CSAD_t^{Down} = \beta_0 + \beta_1 |R_{mt}^{Down}| + \beta_2 (R_{mt}^{Down})^2 + \varepsilon_t \text{ if } R_{mt} \leq 0 \quad (6)$$

For falling market condition, $|R_{mt}^{Down}|$ signifies the absolute equally-weighted market return when it's less than zero, and $(R_{mt}^{Down})^2$ refers to the squared market return when it's negative.

Results

This study conducted tests using sample consisting of 10 cryptocurrencies. The selected daily data used is from January 2018 - October 2024. The 10 cryptocurrencies are Bitcoin (BTC), Litecoin (LTC), Bitcoin Cash (BCH), Monero (XMR), Cardano (ADA), Ethereum (ETH), Tether (USDT), BNB (BNB), Tron (TRX), and XRP (XRP).

	General Market	Rising Market	Falling Market
N	82	45	37
Mean	0,000119	0,005074	-0,004837
Median	-0,0000162	0,003678	-0,004086
Maximum	0,015429	0,015429	-0,0000425
Minimum	-0,015918	0,0000129	-0,015918
Std. Dev.	0,006437	0,004358	0,003818
Skewness	0,150682	0,843497	-0,975697
Kurtosis	3,009001	2,775729	3,594820
Data represents monthly percentage returns. Data is sourced from https://investing.com			

Table 1: Descriptive statistics of market conditions

Table 1 presents the descriptive statistics for the analyzed sample. To begin with, the daily price data for each cryptocurrency are transformed into daily returns, as specified in equation (1). Applying equation (2) to the daily returns allowed us to compute the equally weighted portfolio of the 10 cryptocurrencies, which serves as a benchmark for market returns. Additionally, the daily data is aggregated into monthly data and categorized into three groups: the general market, which encompasses the entire data set; the rising market, characterized by positive market returns; and the falling market, identified by negative market returns.

The number of observations recorded is 82 for the general market, 45 for the rising market, and 37 for the falling market. The highest standard deviation is found in the general market, recorded as 0.006437, while the rising market comes next with 0.004358, and the falling market shows the lowest standard deviation at 0.003818. This finding suggests that the general market exhibits the greatest volatility among the three market conditions.

In the general market over the period, the lowest return was (-1.5918%) and the highest return was 1.5429%. The average return for the general market stands at 0.0119%. The median return is (-0.00162%), and the standard deviation is 0.006437. The kurtosis value for the general market is 3.009001, indicating that the data possesses moderate tails, as this value is neither too far from nor similar to 3. The Skewness of the general market has a value of 0.150682, which indicates that the data in the general market has a stronger tail to the right.

In the rising market throughout the observation period, the lowest return recorded is 0.00129%, while the highest remains at 1.5429%. The average return during this market condition is 0.5074%. The median return is (-0.3678%), with the standard deviation at 0.004358. The kurtosis is 2.775729, suggesting that the data displays lighter tails since this value is below 3. The skewness for the rising market is 0.843497, indicating that the data here also has a stronger tail to the right.

During the falling market period of the observation period, the lowest return was (-1.5918%) and the highest return was (-0.00425%). The median return stands at (-0.4086%), and the standard deviation is 0.003818. The kurtosis observed in the falling market is 3.594820, implying that the data exhibits heavy tails given that the value exceeds 3. The skewness of the falling market is (-0.975697), indicating that the data in the falling market has a stronger tail to the left.

$CSAD_t = \beta_0 + \beta_1 R_{mt} + \beta_2R_{mt}^2 + \varepsilon_t$			
Variable	Coefficients	Standard Error	p-value
β_0	0,264599	0.024021	0,0000***
β_1	-0,414930	0.321541	0,2007
β_2	2,237926	1.020634	0,0313**
Observations: 82 (***), (**), (*) denotes significance level at (1%), (5%), and (10%).			

Table 2: Regression analysis of general market using CSAD

Table 2 presents the findings from the regression analysis conducted on overall market data. β_1 has a coefficient of (-0.414930), with a probability of 0.2007. This suggests a negative linear association between market return and the dispersion of individual returns. However, this relationship is not statistically significant, as the probability value (0.2007) is higher than the significance threshold (0.05). Meanwhile, β_2 has a coefficient of 2.237926 and a probability of 0.0313. This points to a positive non-linear correlation between market return and individual return dispersion. The relationship is statistically significant since the probability value (0.0313) is below (0.05).

$CSAD_t^{Up} = \beta_0 + \beta_1 R_{mt}^{Up} + \beta_2(R_{mt}^{Up})^2 + \varepsilon_t \text{ if } R_{mt} > 0$			
Variable	Coefficients	Standard Error	p-value

β_0	0,297760	0.044209	0,0000***
β_1	-0,830661	0.555324	0,1422
β_2	3,469362	1.639330	0,0403**
Observations: 45 (***), (**), (*) denotes significance level at (1%), (5%), and (10%).			

Table 3: Regression analysis of rising market using CSAD

Table 3 displays the outcomes of the regression analysis conducted on the rising market data. The coefficient for β_1 is (-0.830661) with a probability of 0.1422. This suggests a negative linear correlation between market return and the dispersion of individual returns. However, this relationship is not statistically significant since the probability value (0.1422) is greater than the significance threshold (0.05). In contrast, β_2 shows a coefficient of 3.469362 with a probability of (0.0403). This reveals a positive non-linear correlation between market return and individual return dispersion. The significance of this relationship is confirmed as the probability value (0.0403) is below (0.05).

$CSAD_t^{Down} = \beta_0 + \beta_1 R_{mt}^{Down} + \beta_2 (R_{mt}^{Down})^2 + \varepsilon_t \text{ if } R_{mt} \leq 0$			
Variable	Coefficients	Standard Error	p-value
β_0	0,239276	0.030509	0,0000***
β_1	-0,006402	0.460170	0,9890
β_2	0,718362	1.642958	0,6647
Observations: 37 (***), (**), (*) denotes significance level at (1%), (5%), and (10%).			

Table 4: Regression analysis of falling market using CSAD

Table 4 presents the findings from the regression analysis conducted on the rising market data. The coefficient for β_1 is (-0.006402) with a probability of 0.9890, suggesting a negative linear association between market return and the dispersion of individual returns. Nevertheless, this relationship is not significant since the probability value (0.9890) is higher than the significance level (0.05). For β_2 , the coefficient is 0.718362 with a probability of (0.6647), indicating a positive non-linear association between market return and individual return dispersion. However, this relationship is also not significant, as the probability value (0.6647) exceeds the significance threshold (0.05).

Discussion

From the tests conducted, there are some notable results. For there to be evidence of herding behavior, the coefficient β_2 must be significantly negative (probability less than 0.05). Referring to Table 2, for the overall market, the value of the coefficient β_2 is 2.237926, which is a positive figure. The probability corresponding to the β_2 coefficient is 0.0313, suggesting that the β_2

coefficient holds significant value. This indicates a lack of evidence for herding behavior, while instead pointing to the presence of anti-herding behavior, as the β_2 coefficient is both positive and significant.

It is the same case for the rising market as the result of the β_2 coefficient is 3.469362, which is a positive value. The p-value of the β_2 coefficient being 0.0403 suggests that the coefficient holds significance. This provides evidence of noteworthy anti-herding behavior in an increasing market movement. The falling market, however, is a different story. The result of the β_2 coefficient is 0.718362, which is a positive value. The probability of the β_2 coefficient being 0.6647 indicates that the coefficient is not significant. This means that there is not enough evidence to support herding behavior, but rather leaning towards insignificant anti-herding behavior as the β_2 coefficient is positive.

The coefficient β_1 being negative is a very unusual result. The negative coefficient can be explained by several things. First, it is possible that there is a dependency between the cryptocurrencies used in this study. As Bitcoin and Ethereum have large market caps, price movements of cryptocurrencies with smaller market caps are likely to be influenced by price movements of cryptocurrencies with larger market caps. Second, investors may be reluctant to make decisions due to the uncertainty of market movements. Normal market conditions may obscure indications or signals to investors to buy or sell, leading them to imitate the choices of other investors. As she shows a negative β_1 coefficient for all three market conditions, this could mean that investors are also hesitant due to market stress. Finally, there is the potential for herding. A decrease in the CSAD value means an increase in the likelihood of herding. Given that absolute market return reflects either upward or downward market fluctuations, this implies that during periods of high volatility, the variation in individual returns tends to align with market returns, indicating herding tendencies.

In this study, the β_2 coefficient during the rising market has the highest positive value and is significant, indicating that the most pronounced anti-herding behavior occurs in a rising market. Positive and significant β_2 coefficient in the rising market can be explained by several things. First, the long-term rising price trend of cryptocurrencies. Over time, the prices of cryptocurrencies generally increase. This trend is reflected in the long-term price patterns of major cryptocurrencies like Bitcoin and Ethereum. As such, investors do not feel the urgency or pressure caused by short-term price increases. Second, the cryptocurrency market is dominated by rational investors. A rational investor will make decisions based on their knowledge and research. As these decisions are different and do not follow the decisions of other investors, there will be a diversity of returns, increasing the dispersion of individual returns. Finally, market adaptation. As the cryptocurrency market has been highly volatile since its inception, investors who are experienced with cryptocurrency assets will adapt to its high volatility. Therefore, these experienced investors will behave more rationally and not follow the decisions of other investors as volatility increases.

When analyzing the outcomes in relation to earlier research, there isn't a study that presents identical results. However, for each market condition there are some that match. For the general market, the results are in line with Kyriazis (2020), Bouri et al. (2019), and Deighton Chrisostomides (2022). Research by Bouri et al. (2019) reveals that the coefficient β_2 for the general cryptocurrency market is both positive and statistically significant, suggesting notable anti-herding behavior. The distinction between this study and prior ones is based on the time frames examined. Their research spans data from 2013 to 2018, while this research looks at data

from 2018 to 2024. The overarching conclusion derived from the studies is that herding behavior in the cryptocurrency market is absent from 2013 to 2024. The results of the studies conducted by Deighton Chrisostomides (2022) and Kyriazis (2020) indicate that there is inadequate evidence to substantiate the presence of herding behavior in the broader cryptocurrency market. Both studies utilized Bitcoin and the S&P500 respectively as benchmarks for market returns, whereas this study employs the average portfolio return as its benchmark. Apart from the difference, the results are still the same.

For rising market condition, the results are in line with Vidal-Tomás et al. (2019) and Stavroyiannis & Babalos (2019). The findings from Vidal-Tomás et al. (2019) indicate that their analysis does not provide adequate evidence to back the existence of herding behavior within the ascending cryptocurrency market condition. Their research also suggests that investors make more independent decisions in rising markets, rather than following other investors. This is because they found no herding behavior in the data they used, even though cryptocurrency performance was highly positive. Stavroyiannis & Babalos (2019) indicated through their analysis that there is a notable presence of anti-herding behavior in the increasing market. Furthermore, the study highlighted that speculative behavior among investors is a prevalent issue in the cryptocurrency market. Regardless of this assertion, the test results from their research did not reveal any herding behavior.

Finally, for falling market conditions. The findings align with the research conducted by Kallinterakis & Wang (2019). The evidence indicates insufficient support for the presence of herding behavior in the declining cryptocurrency market condition. However, the testing utilized the return of the value-weighted portfolio as the benchmark for market return, rather than employing the equally-weighted portfolio. This may suggest that smaller market capitalization cryptocurrencies could have intensified the herding effect in the sample if calculated using an equally-weighted approach. Therefore, it is possible that the smaller cap cryptocurrencies may be able to mitigate the effect of herding if they were in equal standing to the larger ones.

Conclusion

This study examines herding behavior within the cryptocurrency market from 2018 to 2024. The Cross-Sectional Absolute Deviation (CSAD) technique is employed to evaluate the hypothesis. The findings indicate that in both general and positive market scenarios, there is considerable evidence of anti-herding behavior, implying that investors often opt for independent decision-making rather than following the crowd. Meaning that H1 and H2 are accepted, but the behavior is lessened rather than strengthened. This could be attributed to the highly speculative and information-driven nature of the crypto market, where participants often rely on different sources of information and strategies. Interestingly, anti-herding behavior is also observed during falling market conditions, although it is not statistically significant. This implies that even in downturns, investors may not entirely give in to herd behavior, possibly due to the decentralized and unpredictable nature of cryptocurrencies, which promotes a more prudent and individualized approach to decision-making.

The findings challenge the traditional notion that financial markets, including cryptocurrencies, are dominated by herd behavior, especially during periods of uncertainty. Instead, the crypto market appears to foster a more independent and analytical mindset among investors, especially in rising or stable conditions. This has significant implications for market regulators, investors, and policymakers, as it underscores the importance of ongoing education and transparency to minimize irrational behavior and support informed decision-making. As the crypto market

matures, understanding these behavioral patterns will be critical to its integration into the broader financial ecosystem.

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