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Herding Behavior in Cryptocurrency Market

Analyzing the Influence of Portfolio Composition and Bitcoin

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ABSTRACT :

This thesis explores the phenomenon of herding behavior in the cryptocurrency market, where investors often mimic their peers instead of making independent decisions. The study focuses on the impact of herding during significant market fluctuations, particularly during the recent bull market in cryptocurrencies. It also examines how different market portfolio compositions, including the role of Bitcoin, influence this behavior. Despite the growing interest in cryptocurrencies, there remains a notable gap in the literature regarding the complexities of herding behavior within this volatile asset class.

The study employs the Cross-Sectional Standard Deviation (CSSD) by Christie and Huang (1995) and Cross-Sectional Absolute Deviation (CSAD) by Chang et al. (2000) to quantify herding behavior across various cryptocurrencies, employing a quantitative approach. The sample period consists of two subperiods: a stable market from June 20, 2022, to October 15, 2023, and a significant bull market from October 16, 2023, to November 11, 2024. The hypotheses are grounded in psychological insights, which suggest that herding behavior is exacerbated during periods of high volatility.

The results suggest that the herding behavior differed between the two subperiods. In the initial subperiod, "rational" investor behavior was observed in both the CSSD and CSAD methods, indicating a lack of herding. Conversely, the second subperiod observed a substantial negative coefficient in the CSSD model for the market cap-weighted portfolio that excluded Bitcoin. This coefficient suggested that herding behavior became apparent, particularly among altcoins, as market sentiment improved. The analysis demonstrated that the herding measurements were significantly influenced by the compositions of the market portfolios and Bitcoin's impact.

The discussion underscores the inconclusive nature of the findings, and the unique features of the cryptocurrency markets examined. It also addresses the limitations of the methodology and data, such as the absence of investor sentiment factors. This analysis supports the acknowledgment of the complexities of herding behavior and emphasizes the necessity of future research to further investigate these dynamics, particularly the influence of investor sentiment on herding behavior and the evolving nature of investor actions in the cryptocurrency landscape.¹

KEYWORDS: Herding behavior, Behavioral finance, Cross-sectional standard deviation, Cross-sectional absolute deviation, Cryptocurrency market, Bitcoin

¹ In this thesis, artificial intelligence tools were used in a consulting role. ChatGPT was employed to assist with research, while Grammarly was used to enhance writing quality.

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Abbreviations

CAPM	Capital Asset Pricing Model
CSAD	Cross-Sectional Absolute Deviation
CSSD	Cross-Sectional Standard Deviation
EMH	Efficient Market Hypothesis
SML	Security Market Line

1 Introduction

The financial markets have been significantly transformed, and the rapid increase in the popularity of cryptocurrencies has captivated a diverse array of market participants. The cryptocurrency market's value increased by over threefold between 2022 and 2024, rendering it more susceptible to behavioral biases, particularly herding. Herding is a phenomenon in which investors replicate the behaviors of their peers, thereby having a substantial effect on the overall market and prices. Even though herding has been observed in traditional markets, there has been limited research on the subject in the rapidly evolving domain of cryptocurrencies, particularly considering the substantial price fluctuations. In anticipation of the bull market that commenced in 2023, this study examines herding behavior from 2022 to 2024, thus fulfilling the cap.

Herding is a psychological phenomenon that is widely observed in financial markets. In this phenomenon, individuals imitate the actions of others and base their decisions on the actions of others (Spyrou, 2013). This behavior can lead to a higher risk of market collapses, more market fluctuations, and increased volatility in a bull market (Scharfstein & Stein, 1990). It is essential to understand the actions of individuals in the cryptocurrency market, as prices fluctuate rapidly, and traders frequently exhibit emotional responses.

There is a scarcity of research on the ways in which herding changes during bull markets across a variety of cryptocurrencies, particularly in studies that consider the influence of Bitcoin and alternative market portfolios, despite the numerous studies that have investigated herding behavior in cryptocurrency markets (Ballis & Drakos, 2020; Bouri et al., 2019; Calderón, 2018; Vidal-Tomás et al., 2019). By employing historical data, this study will investigate the presence of herding in the cryptocurrency market.

The Cross-Sectional Standard Deviation (CSSD) method, which was developed by Christie and Huang in 1995, and the Cross-Sectional Absolute Deviation (CSAD) method, which was further investigated by Chang et al. (2000), will be employed in this study to assess

the behavior of individuals when they purchase and sell a diverse array of cryptocurrencies. These methods will enable us to conduct a meaningful analysis of investor behavior by allowing us to examine herding behavior in a variety of market environments.

Our objective in this thesis is to improve our comprehension of crypto markets by focusing on herding behavior from 2022 to 2024, with a particular emphasis on the significant bull market that began in late 2023. The goal is to investigate herding behavior in the context of evolving market conditions and a variety of portfolio structures. With the integration of cryptocurrencies into traditional financial systems being facilitated by ETFs and relaxed regulations, this investigation becomes even more interesting.

1.1 Purpose and motivation of the study

The cryptocurrency market has garnered the attention of investors, analysts, and other authorities in recent years due to its substantial growth and evolution. It is becoming increasingly crucial to understand the ways in which investors' decisions are influenced by behavior as this market continues to develop. The primary goal of this paper is to investigate herding behavior in the cryptocurrency market, with a particular focus on the bull market of 2023.

The tendency of herding behavior to increase in response to bullish market conditions is one of the primary motivations for this study. Investors occasionally follow the crowd in traditional financial markets rather than conducting their own research when prices are rapidly increasing. This conduct is known as "herding." However, most of the research on herding in the cryptocurrency market has employed equally weighted portfolios. The purpose of this investigation is to further explore the influence of the market proxy's construction on herding behavior, with a particular emphasis on the utilization of both market capitalization-weighted and equally weighted techniques.

An additional critical motivation for this work is to investigate the influence of Bitcoin's substantial market capitalization on herding measurements. The study will examine the effect of Bitcoin's removal from the market proxy on herding behavior, as it currently holds over half of the total market capitalization. The goal is to discover whether the presence or absence of Bitcoin has a substantial impact on herding behavior measurements when the market attitude is optimistic.

1.2 Structure of the study

The thesis is organized as follows. The first chapter serves as an introduction to the study, outlining the research objectives and anticipated contributions to the field. The second chapter establishes the theoretical framework by emphasizing significant concepts from both traditional and behavioral finance. The third chapter provides a comprehensive summary of the current body of research on cryptocurrencies and herding behaviour in that field. Although the sixth chapter emphasizes descriptive statistics, the fourth and fifth chapters describes the methodology and data used in the empirical analysis. The empirical findings are the subject of the seventh chapter. The research's limitation is the subject of the eight chapter. The results are finally compiled, their relevance is evaluated, and recommendations for future research paths are provided in the final chapter.

1.3 Research hypotheses

Herding behavior has been extensively investigated in a variety of financial environments, and the cryptocurrency market is attracting an increasing amount of attention. The price of cryptocurrencies is more frequently influenced by market sentiment and investor emotions, in contrast to conventional assets, where price fluctuations are typically determined by fundamental factors (Cheah & Fry, 2015; da Gama Silva et al., 2019). This

implies that deviations in return distributions from normalcy may be the result of herding tendencies, as price movements may reflect collective mood rather than fundamental analysis.

Furthermore, the trading of cryptocurrencies is significantly influenced by the general investor mood and social media responses (Jia et al., 2022). Investors are significantly more likely to imitate one another during periods of high volatility, which leads to unusual fluctuations in price patterns. This implies that the returns may not follow a standard distribution and supports the hypothesis that herding behavior is a significant factor in the explanation of the anomalies in cryptocurrency returns. Therefore, considering these facts, we can develop the following null hypothesis for this study:

H0: Cryptocurrency returns follows a normal distribution during the sample period from June 26, 2022, to November 11, 2024.

The subsequent step is to determine whether herding behavior is prevalent in the cryptocurrency market. In this market, herding behavior has been observed in numerous studies, particularly during periods of significant volatility (Vidal-Tomás et al., 2019; Jalal et al., 2020). For instance, Kallinterakis and Wang (2019) demonstrate that herding is more apparent on days when the market is rising, suggesting that investors are more inclined to imitate the trends established by others in appropriate situations. This conclusion is further substantiated by Cheah and Fry (2015), who conduct an investigation into speculative bubbles in Bitcoin markets and conclude that investor behavior can lead to herding during price fluctuations. The results suggest that investors collaborated during significant market events. As a result, these realizations prompt the development of the initial hypothesis:

H1: There is evidence of herding behavior in the cryptocurrency market throughout the sample period from June 26, 2022, to November 11, 2024.

The second hypothesis investigates whether herding behavior is more apparent in bull markets than in stable markets. Several studies have demonstrated that herding is most evident when the crypto market is experiencing upward trends (Gurdgiev & O'Loughlin, 2020; Jalal et al., 2020). For instance, Gurdgiev and O'Loughlin (2020) found that the general optimism of crypto investors is directly correlated with herding behavior in the crypto market, thereby emphasizing their influence. This is also correlated with increasing prices. In the same vein, Jalal et al. (2020) discovered that herding behavior is significantly more pronounced in bullish market conditions, as their research suggests that herding is primarily driven by favorable investment trends. Investors are compelled to adhere to the crowd rather than make independent decisions due to the increased market turbulence that is associated with this herd-like inclination (Jalal et al., 2020). These findings prompt the question of whether herding is also more prevalent in the most recent bull market. Consequently, these observations assist in the development of the second hypothesis in the following manner:

H2: Herding is more intense during the bull market compared to stable market conditions.

The subsequent hypothesis to be examined is whether the composition of the market portfolio affects the analysis of herding behavior. Research has demonstrated that the herding results can be significantly impacted by the asset allocation in a market portfolio. For instance, Vidal-Tomás et al. (2019) demonstrate that herding behavior is evident in down markets when an equally weighted portfolio is implemented. Conversely, when employing a market capitalization-weighted portfolio, the outcomes exhibit distinct herding effects. This disparity suggests that the presence of herding behavior in the market could be concealed or altered by the influence of more dominant, highly weighted assets. If this hypothesis is confirmed by the data, it would underscore the critical importance of asset weighting and portfolio composition in the analysis of the herding phenomenon. Due to this, the third hypothesis is articulated as follows:

H3: Market portfolio composition significantly affects herding results.

The final hypothesis to be tested is whether Bitcoin's dominant market position influences herding behavior in the cryptocurrency market. Vidal-Tomás et al. (2019) have conducted research that indicates the growing popularity of Bitcoin may result in herding behavior among investors, who are more inclined to adhere to the trends associated with the most widely accepted cryptocurrency. Nevertheless, Kallinterakis and Wang (2019) observes that cryptocurrency herding is not exclusively Bitcoin-bound, even though herding is present and even more pronounced when Bitcoin is excluded. This realization emphasizes the necessity of evaluating Bitcoin's impact on herding behavior, particularly in the context of its declining dominance in the broader cryptocurrency market. As Vidal-Tomás et al. (2019) notes, "regardless of being the largest digital currency in terms of market cap, Bitcoin has lost its influence in the cryptocurrency market in favour of other virtual currencies, i.e. traders are not basing their investment decisions solely on the behaviour of Bitcoin." The market portfolio's weighting, whether it is market capitalization-weighted or equally weighted, will be used to further evaluate the impact of Bitcoin's dominance. The effects may be more pronounced in a cap-weighted portfolio due to the substantial presence of Bitcoin, which can dominate overall market dynamics. This emphasizes the significance of portfolio composition, as herding behavior shows substantial variations between cap-weighted and equally weighted portfolios (Vidal-Tomás et al., 2019). The fourth hypothesis can be formulated in the following manner using this comprehensive perspective:

H4: The herding behavior in the cryptocurrency market is significantly influenced by Bitcoin's dominant market position.

2 Theoretical background

This section examines fundamental financial concepts by integrating traditional financial theory with behavioral finance, thereby underscoring their primary distinctions. It commences with an examination of the fundamental financial concepts that elucidate the causes of price fluctuations and market behavior. Traditional finance, which emerged in the mid-20th century, is predicated on the notion that markets function efficiently and that investors are rational, defined here as making decisions based on complete information and logical reasoning, as outlined in classical economic theories. Throughout this thesis, the terms 'rationality' and 'irrationality' refer specifically to these theoretical definitions, acknowledging that actual investor behavior may differ from these constructs. Behavioral finance challenges these presumptions by employing psychological data to elucidate the reasons why individuals consistently make irrational decisions because of cognitive biases and emotional influences. This field, which initially gained popularity in the late 20th century, investigates the psychological and emotional factors that influence investment decisions. It acknowledges that markets do not always operate as they should. The subsequent section addresses herding behavior, which is one of the central concepts of this work.

2.1.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is a fundamental concept in financial economics that posits that asset values reflect all available information. This suggests that it is unlikely to consistently outperform the market through strategic timing or stock selection. Investors cannot achieve this due to the swift and accurate integration of all available information into financial markets (Malkiel, 2003). Even though Eugene Fama was not the first to propose the idea of market efficiency, he is often credited with synthesizing earlier concepts and empirical work into a comprehensive theory and testing it extensively. Since its formalization by Fama in 1970, the Efficient Market Hypothesis (EMH) has significantly influenced both theoretical research and real investment policies.

The theory of a random walk is closely related to the EMH, as it posits that price changes are arbitrary and unaffected by past patterns. This theory posits that information is continuously incorporated into prices, resulting in a “random” pattern of price fluctuations (Malkiel, 2003). However, the practical application of "fully reflecting" knowledge in efficient markets is challenging due to its broad and abstract nature (Malkiel, 2003; Fama, 1970). However, the internet bubble of the late 1990s demonstrates that markets can function effectively even in the presence of “random” mispricing.

Three primary forms of the EMH are derived from Fama's (1970) varying degrees of market efficiency. The current value of an asset is believed to reflect all past trading data in the weak form, which implies that technical analysis is incapable of predicting future price movements. Fundamental analysis is rendered unproductive by the rapid response of prices to new publicly available information, as prices already incorporate all past data, according to the semi-strong form. This form emphasizes the importance of publicly accessible data in price adjustments, as it monitors for evidence that prices do, in fact, respond to news about annual earnings, stock splits, and other significant events (Fama, 1970). The strong form goes further, asserting that current prices reflect all information, public and private, implying that no investor, including insiders, can consistently generate exceptional returns. Each form contributes to the ongoing discussion regarding the efficiency of markets by generating new ideas and inquiries.

The Efficient Market Hypothesis can be better comprehended by visualizing the various forms as concentric circles, each of which represents a progressively greater degree of market efficiency.

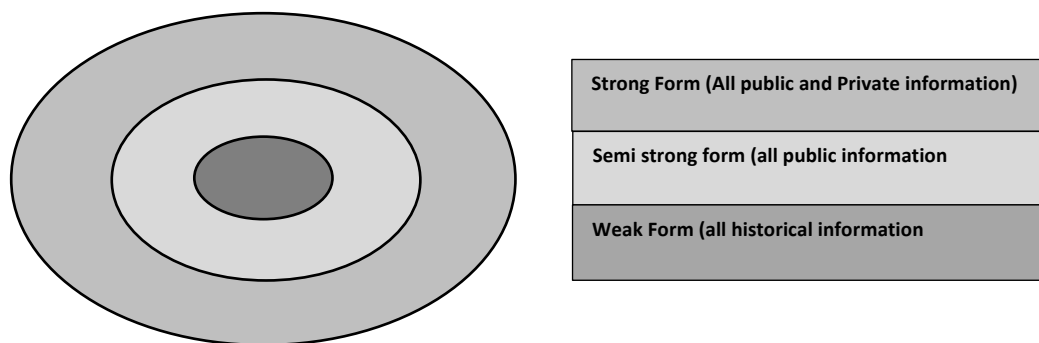


Figure 1. Levels of market efficiency

The weak form, which encompasses all historical price and volume data, is located at the center. It is surrounded by the semi-strong form, in which prices respond rapidly to all publicly available information. The strongest form is represented by the largest circle, which reflects current prices even when private insider information is present.

While the efficient markets model is generally endorsed, it faces criticism, particularly regarding its robust form, with some arguing that market efficiency is influenced by insider knowledge. However, determining whether professional investment managers possess private information is complicated by the nature of new information itself (Fama, 1970). Additionally, Fama describes the robust form of the EMH as a "Simple Statement," highlighting the difficulties associated with empirical testing. It is an oversimplification to assume that information costs are always negligible, as there are genuine expenses related to data collection and processing. Fama also notes the joint-hypothesis problem, which complicates the evaluation of market efficiency by intertwining asset-pricing models with market behavior. This suggests that while efficient markets offer a valuable theoretical framework, their practical application is complex and may be influenced by biases rooted in the foundational assumptions of the analytical models used.

Numerous studies challenge the EMH as well. Shiller (2003) points to the impact of investor sentiment and speculative bubbles on asset values, contradicting the EMH's assumption of rational behavior. Additionally, DeBondt and Thaler (1985) demonstrate

that the market tends to overreact, revealing predictable patterns in stock returns following news releases, which undermines the EMH's claim of immediate price adjustments. Barberis et al. (2005) further illustrate that asset prices often move together in response to investor sentiment, a phenomenon not fully explained by fundamental analysis alone, thereby questioning the core assumptions of the EMH. Despite these challenges, the Efficient Market Hypothesis remains a critical tool for understanding market behavior, serving as a reminder of its limitations in the face of real-world complexities.

2.1.2 The Capital Asset Pricing Model and The Security Market Line

The relationship between risk and anticipated return in financial markets is elucidated by the Capital Asset Pricing Model (CAPM). Developed in the early 1960s by William Sharpe, John Lintner, and Jan Mossin, the CAPM is predicated on the assumption that investors are rational and risk-averse, and it aims to optimize their anticipated returns in relation to a specified level of risk (Bodie et al., 2024). It was proposed as a replacement for the EMH in response to concerns regarding its inadequacy in clarifying investor behavior and asset pricing. CAPM is based on two primary presumptions: the first is that all investors have equal access to information and investment opportunities, and the second is that they are rational and risk averse. Investors employ portfolio diversification to mitigate unsystematic risk, thereby optimizing their anticipated returns and managing risk (Bodie et al., 2024).

The CAPM is particularly beneficial for distinguishing between systematic and unsystematic risks (Sharpe, 1964). It operates based on efficient markets that are unrestricted by trading restrictions and incorporates a pertinent risk-free rate that is applicable to both borrowing and lending. An asset's risk premium is directly proportional to its exposure to systematic risk, which is commonly referred to as market risk, according to a fundamental principle of CAPM (Bodie et al., 2024). This implies that investors are not compensated for the unsystematic risk they assume; consequently, diversification may mitigate this issue to a certain extent. Rather, they are compensated for the systematic risk

they assume; diversification is insufficient to mitigate this. The CAPM asserts that the expected return on an investment is directly proportional to its level of systematic risk. Sharpe (1964) recognizes that the fundamental CAPM model provides a valuable foundation; however, he underscores the importance of a more complex comprehension of risk and return. He argues that the fundamental concept of CAPM continues to be relevant, as the relationship between an asset's risk premium and its exposure to systematic risk is required for the application of CAPM in a broader context.

Sharpe (1964) differentiates between systematic and unsystematic risk, arguing that systematic risk is the primary factor influencing expected returns. This risk is inherent to all securities and cannot be mitigated through diversification. Although unsystematic risk is significant, it is believed to have a less significant impact on expected returns and can be mitigated through the implementation of effective portfolio diversification. Sharpe introduced the concept of beta (β_i) to quantify the sensitivity of an asset to market fluctuations. A beta of one indicates that the asset's price typically moves in tandem with the market. Assets with a beta greater than one exhibit greater volatility than the market, while those with a beta of less than one exhibit lower volatility. Beta is a critical instrument for investors, as it quantifies the volatility of an asset in relation to the broader market. This aids in comprehending the risk profile of investments in response to market fluctuations.

The most often used form of the CAPM is captured in the equation following:

$$E(r_i) = r_f + \beta_i [r_m - r_f] \quad (1)$$

Where: $E(r_i)$ is expected return of an asset; r_f is the risk-free rate; β_i is the beta of asset i ; r_m is the expected market return, $[r_m - r_f]$ is the market risk premium.

Despite its popularity, the CAPM has notable limitations. Its foundational assumptions, such as perfect market efficiency and homogeneous investor expectations, may not accurately reflect real-world conditions. Additionally, the CAPM's focus on systematic risk can lead to an oversimplification of other important factors influencing returns, including company size, value, and momentum. While Sharpe acknowledged the strength of these assumptions in his 1964 paper, he also warned that they may not always hold true. He pointed out that the CAPM is important for understanding how market risk is priced. This shows that investors are often okay with getting lower expected returns on assets that have less risk.

To illustrate the concepts of the CAPM, the Security Market Line (SML) graphically depicts the correlation between an asset's beta and its expected return. A market portfolio's beta can be seen by examining the SML, which is a straight line that crosses the y-axis at the risk-free rate. This line demonstrates the increase in required returns as risk increases, enabling investors to evaluate whether an asset offers an appropriate return in relation to its level of risk (Bodie et al., 2024).

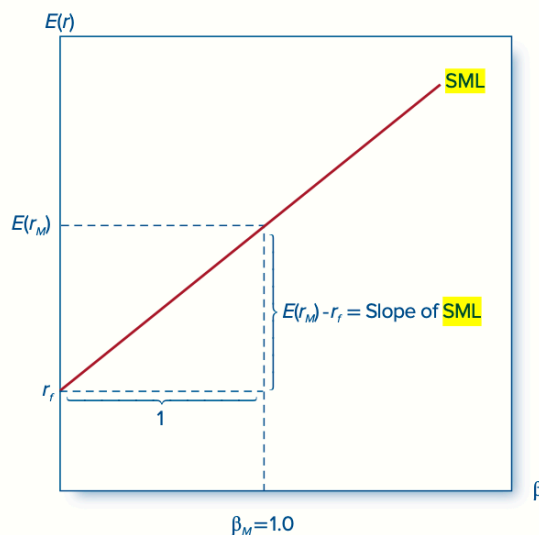


Figure 2. Security market line (Bodie et al., 2024, p. 292)

2.1.3 Multifactor models

Fama and French introduced a novel methodology in 1992 that was intended to address the constraints of the CAPM. Their Three-Factor Model improves upon the CAPM by incorporating two additional elements: size (SMB – Small Minus Big) and value (HML – High Minus Low). Stocks with a high book-to-market ratio (BE/ME) are expected to generate greater returns than those with a low BE/ME, as indicated by the value factor. In the interim, the size factor is indicative of the empirical finding that smaller companies generate superior returns than their larger counterparts.

The next equation reflects the Fama-French Three-Factor Model:

$$E(r)_a = r_f + \beta_a(r_m - r_f) + \beta_b(SMB) + B_c(HML) + e_i \quad (2)$$

Where in addition to equation (1): β_b is sensitivity of an asset to SMB; (SMB) Small minus Big factor; B_c is sensitivity of an asset to HML; (HML) High Minus Low factor; e_i is zero-mean residual.

The Fama-French Five-Factor Model, which was introduced in 2015, represents an expansion of the Three-Factor Model. Its objective is to more effectively address asset pricing anomalies that were not adequately addressed in the previous paradigm. Fama and French concurred that anticipated returns are influenced by factors beyond market risk, size, and value. Consequently, they incorporated profitability (RMW) and conservative moderate aggressive (CMA) into their model investment. The RMW factor captures the enhanced performance of companies with high profitability, while the CMA factor distinguishes the return differences between companies that pursue aggressive investment strategies (characterized by high capital expenditures relative to profitability) and those that adopt conservative investment strategies (characterized by low capital expenditures relative to profitability). The model resolves a variety of asset pricing anomalies, such as the value premium puzzle, profitability, and investment premiums, by incorporating these new elements.

The Fama-French Five-Factor Model is expressed by the subsequent equation:

$$E(r)_a = r_f + \beta_a(r_m + r_f) + \beta_b(SMB) + \beta_c(HML) + \beta_d(RMW) + \beta_e(CMA) + e_i \quad (3)$$

Where in addition to equations (1) and (2): β_d is sensitivity of asset to RMW; (RMW) is Robust Minus Weak factor; β_e is sensitivity of asset to CMA; (CMA) is Conservative Minus Aggressive.

2.2 Behavioral finance

Based on the EMH, the traditional financial theory contends that investors act logically in a market that quickly combines all the available data (Fama, 1998). But especially considering major events like the dot-com bubble and the global financial crisis, this conventional model has failed to explain several market anomalies and investor behavior. Behavioral finance thus developed, realizing that market dynamics and financial decisions are greatly shaped by human emotions and cognitive biases. Emphasizing the need of human emotions and cognitive biases in forming financial decisions and market dynamics, Barberis and Thaler (2002) assert that "behavioral finance is a new approach to financial markets that has emerged, at least in part, in response to the difficulties faced by the traditional paradigm".

The evolution of behavioral finance was significantly influenced by the concepts of cognitive psychology, which investigates thought processes and decision-making. This field has exposed systematic errors and biases that influence human judgment. During the 1980s and 1990s, an increasing number of studies emerged that integrated cognitive psychology, market anomalies, and arbitrage constraints into a comprehensive framework for comprehending financial markets (Barberis & Thaler, 2002; Shleifer, 2000). This formally established behavioral finance, which sought to incorporate the influence

of human psychology and prejudices into models of investor behavior and market dynamics.

A fundamental concept in behavioral finance is the "limits to arbitrage," which posits that even logical investors may encounter challenges in fully exploiting market inefficiencies (Barberis & Thaler, 2002). Arbitrage is a strategy that employs price fluctuations between multiple markets, even though it typically involves substantial risks and necessitates substantial financial resources. The EMH has been the subject of research by behavioral finance academics, who assert that rational investors would promptly rectify market inefficiencies (Barberis & Thaler, 2002). They comprehend that the pursuit of these price variances can be costly, time-consuming, and hazardous. Additionally, arbitrageurs are hindered from effectively correcting market inefficiencies by the restriction of short-selling and the existence of informational asymmetries, which result in certain investors having access to more accurate information (Hirshleifer, 2015).

Cognitive biases, such as overconfidence and hindsight, as well as emotional factors such as fear and exuberance, are emphasized in behavioral finance. These factors may cause regular investors to make decisions that differ from logical investment strategies (Statman, 2014). For instance, investors who are overconfident may believe that they can consistently outperform the market by leveraging their past performance. This, in turn, would result in frequent trading and the assumption that there is an excessive amount of risk. Fear during periods of market volatility can exacerbate this overconfidence, leading investors to sell their assets at a loss and succumb to panic rather than adhering to a long-term investment strategy. Prospect theory, which was constructed by Kahneman and Tversky (1979), provides an indispensable viewpoint for comprehending these behaviors. It emphasizes the fact that individuals find losses to be more unpleasant than they do gains. During market downturns, investors may be compelled to sell their assets quickly due to fear. Conversely, in bullish markets, the temptation of potential returns may result in excessive risk-taking, which is driven by greed. This avoidance of loss can exacerbate emotional responses. Thus, prospect theory

explains the psychological foundations of these emotional responses and demonstrates how they may result in investment decisions that deviate from conventional financial theories.

In general, behavioral finance offers a critical perspective on the complex nature of market dynamics and investor behavior. It is possible to observe the frequency with which financial market trends reflect the psychological processes at play by comprehending the influence of cognitive and emotional biases (Barberis & Thaler, 2003; Shiller, 2003). The January effect, which asserts that stock returns are typically higher in January (Beaver, 1986), the momentum effect, which posits that stocks tend to continue to move in the same direction as previous trends (Jegadeesh & Titman, 1993), and the value premium, which asserts that value stocks frequently outperform growth stocks (Fama, 1998) are among the fascinating instances of these anomalies that researchers have discovered. These deviations from the EMH underscore the significant impact of behavioral factors on investment decisions and suggest that market prices are not solely determined by logical behavior. In this framework, herding behavior is a phenomenon that challenges the foundations of efficient market theory, in addition to the previously mentioned elements. The subsequent sections will investigate the additional impacts of this phenomenon.

2.2.1 Theoretical foundations of herding behaviour

Human behavior exhibits a distinct propensity for conformity, as evidenced by numerous aspects of life, such as consumer behavior and social movements. Social dynamics are significantly influenced by the "herd instinct," which frequently results in group actions that appear to be mass demonstrations, fads, and cultural trends. Herding is characterized by "the alignment of thoughts or behaviors of individuals in a group (herd) through local interactions rather than centralized coordination." Raafat et al. (2009). Herding's multifaceted qualities are evident in its various manifestations, including mass hysteria, the bandwagon effect, and fashion. These forms collectively demonstrate that herding

encompasses a range of interconnected behaviors that are influenced by social interactions (Raafat et al. 2009). Kameda and Hastie (2015) argue that these herding patterns were advantageous for survival in ancestral environments, despite the potential negative repercussions of their behavior in specific contexts. They underscore the evolutionary origins of this behavior. Fundamentally, authors emphasize that humans possess inherent neural, psychological, and behavioral mechanisms that enhance their ability to be socially receptive, thereby allowing them to learn from and be influenced by others. This helps to the understanding of herding behaviors in social environments.

Herding is a multifaceted phenomenon in the financial environment, in addition to its social implications. Several definitions of herding have been proposed by researchers, who have defined it as the inclination of individuals to imitate the actions of others, typically due to cognitive biases and the timing of information acquisition (Hirshleifer et al., 1994). This behavior could be described as the act of independent individuals replicating actions without regard for fundamental values (Hwang & Salmon, 2004). In addition, herding is characterized by managers' propensity to imitate their peers' investment decisions, which is motivated by the desire to preserve a positive reputation and reduce personal risk, particularly in situations where external employment opportunities are scarce and compensation is determined by absolute performance criteria (Scharfstein & Stein, 1990). Kameda and Hastie (2015) also define herding as group behavior in which individuals align their ideas or actions with those of others rather than relying on autonomous evaluations. It is also identified as the propensity of individuals to exhibit correlated behavior, which can lead to group decisions that are methodically inferior to the most optimal ones (Devenow & Welch, 1996). To conclude, herding behavior is characterized by a multifaceted combination of cognitive distortions and social factors that influence financial decision-making.

Herding behavior is crucial in financial markets, as it encourages investors to imitate their peers. This can result in the development of trends or market bubbles, as well as price

distortions. This phenomenon is frequently associated with factors such as market hysteria and wildly optimistic expectations (Devenow & Welch, 1996). This group decision-making could lead to increased volatility, as individuals typically prioritize conformity over rational analysis, thereby disrupting prices and prompting financial crises (Bikhchandani & Sharma, 2000). Some studies suggest that herding may not have a substantial impact on stock prices, particularly among institutional investors whose transactions frequently counterbalance one another. However, evidence of herding and positive-feedback trading in smaller stocks indicates that it can still result in asset mispricing and increase market volatility (Lakonishok et al, 1992). Herding behavior among investment managers can lead to feedback loops that exacerbate market volatility and undermine general market efficiency, as they frequently imitate the actions of their peers rather than relying on their own private information (Scharfstein & Stein, 1990).

However, the separation of rational from irrational behavior among market players is particularly challenging when it comes to quantifying and modeling herding. The interaction of these elements is frequently disregarded by existing theoretical models, resulting in conflicting empirical data regarding the frequency and impact of herding in financial markets (Spyrou, 2013). Spyrou observes that the distinction between genuine herding and group reactions to publicly available data remains a challenge, even though statistical models can identify relationships in investor behavior. The empirical data on herding is contradictory due to these methodological limitations; various studies yield varying conclusions (Spyrou, 2013). In 2004, Hwang and Salmon conducted a study that identified numerous challenges associated with estimating herding behavior in financial markets. The interpretation of observed market activities is affected by the absence of controls for fundamental movements, which makes it difficult to distinguish between herding and independent changes to basic knowledge. This underscores the necessity of understanding the context in which herding may be advantageous or harmful.

2.2.2 Types of herding behavior

The discussion of herding behavior in financial markets reveals its dual nature, which encompasses both rational and irrational aspects. Bikhchandani and Sharma (2000) categorize herding as either intentional or spurious. Spurious herding is the outcome of investors making similar decisions in response to common knowledge or basic considerations, rather than out of a desire to imitate others. This type of herding is occasionally perceived as a rational response to common market signals, in which investors rely on clear financial conditions and comparable information to make decisions. For instance, coordinated market movements may result from numerous investors acting simultaneously in response to a significant economic announcement. This type of behavior has the potential to enhance market efficiency by demonstrating a logical response to new data, thus allowing the efficient allocation of resources based on group insights.

Intentional herding is the act of investors intentionally choosing to imitate the actions of others, frequently due to perceived information advantages, reputation concerns, or a lack of confidence in their own assessments (Bikhchandani & Sharma, 2000). This type of herding can result in increased volatility and market inefficiencies due to the substantial shift in asset values from their natural values. Conversely, unintentional herding arises when individuals independently arrive at the same conclusion and behave in the same way, without regard for the actions of others. This reflects the behavior of an efficient market whereby new information results in parallel decision-making among investors. However intentional herding can be rational as well. Rational herding is shown by stock analysts matching their recommendations with the consensus since they believe that the combined opinion of their peers reflects the best available information, so lowering their individual risk. Similarly, a poorly performing hedge fund manager might improve their performance by copying successful peers, so suggesting that herding can be a rational approach.

Spurious herding can enhance market stability by ensuring that investor behavior aligns with fundamental knowledge, as previously mentioned. However, intentional herding may result in an increase in volatility and an increased risk of experiencing additional market bubbles or collapses whether it was rational or irrational behavior. For example, investors' quick asset sales during market stress can exacerbate declines; conversely, spurious herding may indicate a cautious approach that is driven by generally available data. However, Bikhchandani and Sharma (2000) underscore that it is frequently challenging, if not impossible, to empirically distinguish "intentional herding" from "spurious herding," due to the numerous factors that influence investment decisions.

2.2.3 Root causes of herding

Herding is a multifaceted phenomenon that has been the subject of numerous definitions and interpretations, as previously mentioned. In response to various circumstances, individuals may exhibit herding behavior. This is particularly accurate in the context of the financial markets. Herding is also motivated by a complex set of factors. Investors' behaviour is determined by numerous variables. Four distinct dimensions can be employed to generally categorize the factors that influence investor herding behavior. The initial dimension is informational, which relates to the availability and interpretation of data and knowledge that investors employ to support their decisions. The second dimension is psychological, which encompasses the cognitive distortions and emotional reactions that may influence investors' opinions on risk and opportunity. The third dimension is social, which underscores the impact of social networks and peer behavior on individual investment decisions. At last, the fourth element relates to the concerns about the reputation of institutional investors and the potential risks associated with compensation systems. The combination of these elements has a substantial impact on investment strategies and behavior. This complex combination of variables underscores the fact that herding is not a simple phenomenon.

Investors frequently depend on limited information, available signals, and assumptions rather than conducting extensive research, as they rarely possess comprehensive market knowledge. This can result in traders behaving in a manner like the initial group of investors, under the mistaken assumption that this group possesses superior information (Bikhchandani & Sharma, 2000). This phenomenon is illustrated by information cascades, which occur when the actions of early investors produce a public signal that influences the decisions of later investors, occasionally leading to their disregard of their own information. As a result, the market may experience substantial fluctuations dependent on the initial decisions of a limited number of individuals, which may not accurately represent the actual worth of the involved assets. This behavior can contribute to increased volatility and potential mispricing in financial markets, as later investors follow the herd without a comprehensive understanding of the underlying fundamentals (Bikhchandani et al., 1992). This dependence on readily available information underscores the degree to which informational constraints influence herding behavior, particularly in sectors that are less well-known or during periods of market volatility. This phenomenon is particularly evident in emerging markets, such as cryptocurrency markets, where the absence of precise data exacerbates the dependence on observed investor behavior.

As mentioned, individuals tend to favor group behavior; they frequently prioritize conformity over independent thought and logical analysis. Psychological elements are frequently regarded as the most significant drivers of herding behavior in financial markets due to their impact on investors' perceptions and responses to market information. Herding behavior is significantly influenced by her fear of missing out (FOMO), which compels individuals to pursue potentially lucrative opportunities by following to the crowd. Additionally, herding behavior is influenced by cognitive dissonance, which is the discomfort experienced by investors whose opinions differ from the prevailing market sentiment. Even if it directly contradicts their initial analyses, they could adopt the majority viewpoint to alleviate this psychological conflict (Bikhchandani & Sharma, 2000). Additionally, the concept of social proof has a substantial influence on investor behavior,

as individuals frequently refer to the actions of others as a guide for their own decisions, particularly in uncertain or ambiguous situations.

Professional investors are significantly influenced by career opportunities and reputation pressure, in addition to psychological factors and incomplete knowledge. Financial managers and analysts are frequently subjected to significant pressure to stick to current market trends, particularly during periods of uncertainty. This is because they are often under continuous review. According to Scharfstein and Stein (1990), professional managers frequently follow the investment decisions of their peers under certain circumstances, thereby disregarding their own personal knowledge. Although this conduct is socially ineffective, it may appear rational to managers who are concerned about their reputation in the workplace. They underscore that managers may be hesitant to act on their independent judgments due to their fear of being considered inadequate which would result in them adhering to the prevailing opinion rather than making counterintuitive decisions. Afraid of appearing inadequate, their independent judgment may be overridden. The main-agent issue introduces an additional layer of complexity, as managers' actions may be influenced by their internal motivations to either avoid accountability or demonstrate their expertise (Devenow & Welch, 1996). The evaluation of money managers similarly leads to agency problems, as they are typically assessed against their peers, which encourages them to employ techniques that are similar to prevent underperformance (Lakonishok et al., 1992). Scharfstein and Stein (1990) also emphasize the concept of "sharing the blame," which posits that managers receive more favorable evaluations when their poor investment decisions are in line with those of other market participants. In uncertain market conditions, this inclination is particularly conducive to herding behavior. In support of this assertion, Hirshleifer et al. (1994) demonstrate that even experienced managers opt to imitate the actions of their peers to demonstrate their superior ability to gather information. They also demonstrate that money managers may engage in herding behavior as part of a pooling equilibrium.

In addition to reputational concerns, institutional investors experience additional challenges. Scharfstein and Stein (1990) underscore the critical impact of compensation systems on the herding behavior of management. Managers may be motivated to imitate their colleagues' investment decisions to maintain their employment security when their compensation is contingent upon absolute performance metrics. This fosters an environment in which group decision-making is dictated by the fear of underperformance in comparison to others, rather than autonomous analysis based on personal knowledge. In contrast, managers may be motivated to differentiate their activities to distinguish themselves from their colleagues if their compensation is contingent upon relative performance. This could potentially mitigate the herd-oriented tendency.

3 Literature review

The objective of this chapter is to present a literature review that establishes the foundation for the investigation of herding behavior during the current market bull run in the cryptocurrency market. We begin by examining the primary characteristics of cryptocurrencies as an asset class, such as their technological foundation and the factors that influence their price fluctuations. This prepares one for the examination of herding behavioral. The subsequent section will summarize the early findings in the crypto market, as the objective of this thesis is to examine herding behavior in the crypto market.

3.1 Cryptocurrencies

Cryptocurrencies have significantly changed the financial environment since Satoshi Nakamoto's original proposal of Bitcoin in 2008. Cryptocurrencies are decentralized digital currencies that utilize cryptographic methods to ensure secure transactions function by utilizing blockchain technology, which provides a transparent and immutable ledger of all transactions. This invention addresses the deficiencies of traditional trust-based payment systems by allowing peer-to-peer transactions that are not dependent on intermediaries (Nakamoto, 2008). Cryptocurrencies were first created to offer a safe and decentralized alternative to traditional banking systems. Nowadays, they are also being developed for a variety of applications beyond transactions, including smart contracts (as seen with Ethereum), decentralized finance (DeFi) platforms like Uniswap, non-fungible tokens (NFTs) and just for memes. A lot of cryptocurrencies are mined using proof of work, a method in which very fast computers solve hard math problems to verify transactions and add new blocks to the blockchain. But unlike traditional currencies, cryptocurrencies don't have intrinsic value and their value is mostly based on market demand and sentiment. The rapid development of cryptocurrencies has not only given rise to Bitcoin but also fostered the emergence of hundreds of alternative coins (altcoins), which has promoted a diverse and active ecosystem of digital assets.

As of November 2024, CoinMarketCap maintains a database of over 10,000 cryptocurrencies. Although some of these coins are lesser-known and have low market value and trading activity, others are well-known cryptocurrencies with significant market capitalization and trading volume. Also, it is challenging to determine the total number of cryptocurrencies, as some may cease to exist while others are introduced daily (CoinMarketCap, 2023). Bitcoin, Ethereum, Tether, Solana, and BNB comprise the top five cryptocurrencies in terms of market capitalization. Bitcoin remains the largest cryptocurrency, with a market capitalization of nearly \$1.71 trillion. It accounts for a substantial portion of the total market capitalization of approximately \$2.90 trillion. Bitcoin's dominance in the market is evident in its nearly 58% share of the total market capitalization. Ethereum is the second most valuable cryptocurrency, with a market capitalization of nearly \$400 billion. Additionally, the diverse array of cryptocurrencies is bolstered by the significant market caps of Tether, Solana, and BNB.

Three primary types of digital assets exist, which are typically referred to as coins (Grobys & Sapkota, 2020). The initial type is cryptocurrencies, including Bitcoin, which are used to save money and make purchases. The second type of investment is regular investments, which are security tokens that are tracked on a blockchain to facilitate transactions and prove ownership. The third type is utility tokens, which enable consumers to access specific goods or services.

3.1.1 Cryptocurrency market volatility

The cryptocurrency market's structure is notable for its volatility and significant price fluctuations. Research indicates that these attributes create an environment that is conducive to herding behavior, in which investors frequently imitate their peers rather than making independent decisions based on fundamental analysis (Fry, 2018). Within a market as volatile and unpredictable as cryptocurrencies, the tendency for imitating others can be particularly evident.

Investor behavior and market dynamics are substantially affected by the volatility of the cryptocurrency market, according to the literature. This volatility is primarily caused by internal market factors, particularly the actions of buyers and sellers, which suggests that the market is highly speculative (Baek & Elbeck, 2015). The authors found that from July 2010 to February 2014, the standard deviation of Bitcoin's detrended price ratios is 26 times greater than that of the S&P 500 Index. This volatility is demonstrated by its significantly higher return and standard deviation in comparison to a variety of other asset classes, suggesting that Bitcoin is primarily driven by speculative trading rather than stable investment behavior (Baur et al., 2018). Results support the notion that the cryptocurrency market's instability is exacerbated by the significant price volatility and relatively young age of the market, as discussed by Liu and Serletis (2019). Consequently, cryptocurrencies like Bitcoin are increasingly perceived as investment vehicles rather than merely a means of transaction. Rather than employing these assets for daily expenses, numerous investors elect to retain them in anticipation of substantial price appreciation (Bullmann et al., 2019). This shift in perspective underscores the speculative nature of the market, in which the practical value of cryptocurrencies is occasionally overshadowed by the allure of impressive returns. However, this volatility does present significant opportunities for high returns; however, it also entails substantial risks, which exacerbates the uncertainty associated with risk management and forecasting (Lee et al., 2018).

The evidence of Bitcoin volatility is substantiated by empirical research. For example, the substantial price fluctuations of Bitcoin, which are characterized by high standard deviations and consistent extreme returns, are underscored by the data from Baur et al. (2015). These findings suggest that conventional risk assessment strategies may not adequately capture the unique hazards that cryptocurrencies introduce. In contrast, Lee et al. (2018) have found that cryptocurrencies typically exhibit superior average daily returns when contrasted with traditional asset classes. However, the significant volatility of these digital currencies complicates diversification initiatives for investors and makes it difficult to achieve the optimal balance between risk and return. Additionally, authors

have observed that cryptocurrencies and crypto tokens are still considered experimental, even though they were introduced several years ago. This position thus emphasizes the need of more research on their complexity and related hazards before they can be acknowledged as a major asset class for institutional investors.

Consumer acceptance is as significantly influenced by volatility as investment strategies. Bullmann et al. (2019) contend that the perception of cryptocurrency as dependable mediums of exchange is distorted by substantial price fluctuations, which discourage retail use. In such an environment, herding behavior may become more intense as individuals are more inclined following to trends rather than rely on objective analysis. The existence of this phenomenon raises significant concerns regarding the sustainability of the cryptocurrency market and the potential for market bubbles to be driven by group investor behavior.

Stablecoins are one of the innovative concepts that are being proposed to address volatility concerns and enhance general acceptance. Stablecoins attempt to provide a more stable alternative by tying their value to traditional assets, thereby reducing the tendency to follow the herd during volatile market conditions. This development has the potential to create a more stable cryptocurrency ecosystem, in which investors are less compelled to conform to the crowd and more confident in their decisions.

3.1.2 Information asymmetry in cryptocurrency market

The cryptocurrency market is substantially affected by information asymmetry, particularly in the context of investor herd behavior. Uninformed investors' trading activities can increase volatility, particularly in response to positive market shocks (Baur & Dimpfl, 2018). The serial correlation of returns, as indicated by Avramov et al. (2006) research, suggests the existence of uninformed traders. The volatility generated by these traders is frequently greater than that of informed investors, as they frequently cause price fluc-

tuations that are subsequently reversed. This phenomenon is frequently linked to psychological factors, such as the fear of missing out (FOMO), which leads uninformed traders to purchase assets during periods of market growth. This conduct not only exacerbates volatility but also contributes to upward price movements (Baur & Dimpfl, 2018).

Herd behavior is a critical element of this dynamic, as it results in price fluctuations that may not accurately reflect the assets' intrinsic value, as ignorant investors adhere to market trends. Although informed investors are more active following negative shocks, the asymmetric volatility effect observed in cryptocurrencies—in which positive shocks increase volatility more than negative shocks—indicates that noise trading activity is the dominant behavior following positive shocks (Baur & Dimpfl, 2018).

Kang et al. (2022) further emphasize this phenomenon of information asymmetry: the semi-strong form criteria are met by only 2.69% of cryptocurrencies, while the weak-form EMH criteria are met by only 6.04%. These low percentages demonstrate that most cryptocurrencies do not accurately reflect the data at hand in their prices, thereby exacerbating the effects of uninformed trading. The study suggests that the speculative nature of the cryptocurrency market is indicative of a market in which information is not consistently available or interpreted, particularly for assets developed after November 2017. This inefficiency allows irrational traders to have a disproportionate impact on price movements, particularly during periods of positive market sentiment, thereby increasing volatility.

Additionally, it is impossible to disregard the role that social media and information dissemination play in this context. Twitter/X and Reddit for example have become indispensable components of the Bitcoin ecosystem due to their rapid dissemination of news and ideas. Numerous young, inexperienced investors depend on social media for research, rendering them particularly susceptible to influence that could exacerbate market inefficiencies and perpetuate speculative bubbles. Herd behavior can be the result of unin-

formed investors imitating the decisions of those with more knowledge, thereby exacerbating the impacts of this environment. For instance, tweets from influential individuals can initiate a buying or selling tsunami during significant market fluctuations, thereby exacerbating volatility. The rapid dissemination of both accurate and false information creates an environment that is conducive to speculation, in which uninformed traders may base their decisions on hype rather than thorough analysis.

Additionally, the legal framework of cryptocurrencies influences the frequency of information asymmetry. In contrast to traditional financial markets, which are subject to stringent regulations intended to ensure transparency and protect investors, the cryptocurrency market remains largely unregulated. This lack of control can lead to significant discrepancies in information access, which enables dishonest players to exploit naive traders using bogus plans or pump-and-dump operations. Consequently, investors who are not adequately informed may experience losses as they are unable to effectively navigate the intricacies of the market.

3.1.3 Speculative nature in cryptocurrency market

The cryptocurrency market's high volatility is primarily the result of speculative trading activities that are closely associated with herding events. Investors frequently make decisions based on short-term price fluctuations rather than long-term fundamentals, which exacerbates market fluctuations. This is supported by Bouri et al. (2019), who observe that practitioners' varying perspectives on the value of cryptocurrencies are the result of a lack of consensus on their legitimacy; some regard Bitcoin as fraudulent, while others regard it as the future of money. This continuous argument not only discourages financial analysts from suggesting or rating cryptocurrencies, but it also forms a market that is primarily reliant on socially produced perspectives. In addition, a significant number of cryptocurrency market participants are individual investors, who are typically young and inexperienced. These investors rely on social media and online forums for

information, rendering them particularly susceptible to external influences (Bouri et al. 2019).

Haykir and Yagli's (2022) research further emphasizes the role of investor psychology and market dynamics in the cryptocurrency environment by expanding upon this understanding of speculative behavior. Their research demonstrates that the environment is conducive to speculative trading due to the absence of inherent value in cryptocurrencies, as well as the influence of social media and community sentiment. FOMO can result in an increase in the number of investors who enter the market as prices rise, thereby inflating the market and generating speculative bubbles. Conversely, panic selling can result in cascading effects, which exacerbate market declines and illustrate the herding behavior that is so prevalent in the cryptocurrency market. The writers argue that price bubbles are created by both rational and irrational herding behaviors, which are driven by the fear of missing out on potential gains. This is because investors frequently emulate the actions of others in the market. This herding effect is particularly apparent during periods of elevated uncertainty, as investors are more inclined to adhere to trends than conduct thorough investigations.

Additionally, the allure of rapid profits attracts a diverse array of investors, many of whom lack the necessary knowledge or experience to navigate the intricacies of the market. This influx of inexperienced traders can exacerbate speculative activity, as they frequently rely on trends and the actions of others rather than conducting extensive research. Consequently, the cryptocurrency market's speculative nature not only causes significant price fluctuations but also perpetuates a cycle of volatility that may be detrimental to uninformed investors. The cryptocurrency landscape is characterized by volatility, which is exacerbated by the potential for substantial financial gain and the rapid price swings that create a high-stakes environment in which speculation reigns supreme.

3.1.4 Investor sentiment in cryptocurrency market

Investor mood, which is closely associated with speculative trading, is frequently observed to affect prices. Positive news is rapidly disseminated and may induce purchasing behavior, while negative news may induce panic selling. This phenomenon is particularly evident in the cryptocurrency market, where the rapid dissemination of information through social media platforms magnifies the impact of sentiment. Naeem et al. (2021) assert that the Twitter Happiness sentiment index significantly predicts the returns of significant cryptocurrencies, such as Bitcoin, during extreme market conditions. The research underscores that a positive attitude is associated with higher returns, thereby corroborating the theory that investor behavior is significantly influenced by emotional responses to news and market trends.

Even more, Milka (2020) emphasizes the significant impact of social media on the market dynamics in the cryptocurrency industry. His research indicates that the sentiment conveyed in tweets has the potential to induce substantial price fluctuations, particularly when the messages are issued by prominent investors or influential figures. For instance, the volatility of the cryptocurrency market can be underscored by a single tweet from a prominent individual, which can trigger a speculative buying or selling frenzy. This phenomenon is closely associated with herding behavior.

Anamika et al. (2023) provide a convincing illustration of how Bitcoin sentiment specifically influences the price movements of other cryptocurrencies, in addition to its own, by building on this knowledge of investor mood and its significant influence on cryptocurrency prices. The research indicates that a positive attitude toward Bitcoin can lead to increased buying activity, thereby affecting the entire cryptocurrency market. Bitcoin's price fluctuations typically dictate the market's overall trajectory, as it is the most frequently employed cryptocurrency. Investors who exhibit a favorable attitude toward Bitcoin are more inclined to invest in altcoins such as Ethereum and Litecoin, as they are under the impression that these assets would also benefit from the positive sentiment

toward Bitcoin. Investors' confidence in other cryptocurrencies is bolstered by the increasing Bitcoin attitude, which results in a collective movement to acquire these assets, according to the research. As a result, the interaction between Bitcoin sentiment and investor behavior not only underscores the volatility of the cryptocurrency market but also demonstrates how emotional reactions can influence market dynamics, thereby enhancing the connectivity of Bitcoin prices and the cryptocurrency's influence as a market leader.

Sentiment's influence is apparent in the increasing correlations between trading volumes and price movements among investors in either a positive or negative mood, within the context of herding. Herding behavior may manifest as a surge in purchasing activity as positive news is disseminated, resulting in rapid price increases. Conversely, panic selling may result from negative sentiment, which causes investors to withdraw from the market in unison, thereby exacerbating price declines.

3.1.5 Cryptocurrency market interconnectedness

The connectivity of cryptocurrencies, particularly in relation to herding behavior among investors, has been the primary focus of recent research. This interconnection underscores the intricate interactions among numerous digital assets and their combined impact on market dynamics, particularly during periods of volatility. According to research, the price fluctuations of other cryptocurrencies are significantly influenced by the network of returns, which is primarily composed of Bitcoin and Litecoin (Ji et al., 2019). This central role, particularly in Bitcoin, can significantly influence herding policies, as its price fluctuations frequently serve as benchmarks for other cryptocurrencies. The trading patterns of smaller cryptocurrencies may exhibit a greater degree of correlation because of significant price fluctuations in these leading cryptocurrencies, which may indicate a collective reaction among investors. Higher trading volumes and coordinated price movements over the market are indicative of herding behavior. This interdependence underscores the importance of Bitcoin as not only individual assets but also as the primary

drivers of market attitude and behavior, thereby affecting the dynamics of herding in the cryptocurrency landscape.

Continuing this theme of interconnectedness, Koutmos (2018) emphasizes that Bitcoin is the primary contributor to return and volatility spillovers in an 18-major cryptocurrency sample. This outcome corroborates the notion that the price fluctuations of Bitcoin have a substantial impact on the broader cryptocurrency market, potentially inducing a ripple effect that could exacerbate investors' herding behavior. The research indicates that the interdependence among cryptocurrencies is becoming increasingly apparent, as return and volatility spillovers have been steadily increasing over time.

The cryptocurrency market is more interconnected than the traditional stock market for a variety of significant reasons. The influence of significant assets such as Bitcoin and Ethereum, which significantly influence the price movements of lesser altcoins, results in high degrees of correlation among cryptocurrencies, particularly during periods of volatility. This results in synchronized trading patterns. This connectivity might lead to herding behavior among investors, in which individuals respond to market trends rather than acting independently. The 24/7 nature of Bitcoin trading facilitates immediate responses to news and events, thereby further enhancing the connectivity of digital assets. In contrast, the stock market operates within predetermined trading hours. Additionally, the cryptocurrency market's dynamic and youthful nature allows for rapid fluctuations in investor sentiment, which results in more robust spillover effects than those observed in the stock market, where individual stocks are typically influenced by company-specific news. These characteristics typically suggest that the cryptocurrency market is more connected than the traditional stock market, which would also account for a higher degree of herding.

3.2 Herding behavior in cryptocurrency markets

The stock market has been the primary focus of early research on herd behavior. For instance, Chang et al. (2000) investigated herding behavior in international equity markets and discovered that, while developed markets such as the United States and Hong Kong exhibit minimal herding tendencies, emerging markets such as South Korea and Taiwan exhibit significant herding. Lakonishok et al. (1992) investigated the impact of institutional investors' behavior on stock prices by concentrating on herding and feedback trading across various stock sizes. They found minimal evidence of herding among institutional managers, particularly in higher stocks, based on a 769-equity fund sample analysis. The cross-sectional standard deviation of returns (CSSD) was employed to quantify herding behavior in some of the first empirical studies, including those conducted on traditional markets by Christie and Huang (1995). They discovered that investors who aligned with the general market consensus exhibited a decrease in CSSD during significant market fluctuations, which implies a propensity to follow the herd.

Most of the early research focused on traditional asset markets; however, as cryptocurrencies gained more recognition, studies on herding behavior began to emerge. In the cryptocurrency markets, herding has particularly potent effects, as irrational crowd-following behavior can result in excessive price fluctuations. For instance, Youssef (2020) discovered that herding decreases as trading volume increases and intensifies during periods of market volatility. According to Vidal-Tomás et al. (2019), herding is more prevalent in down markets, indicating that investors tend to follow the herd in adverse circumstances. Moreover, Da Gama Silva et al. (2019) emphasized that herding is evident during periods of high risk, suggesting that investor group behavior is driven by fear. Conversely, Ballis and Drakos (2020) documented significant herding in market movements that were on the rise, thereby demonstrating that positive trends may motivate increased imitation. Additionally, Gurdgiev and O'Loughlin (2020) have demonstrated the substantial influence of behavioral prejudices on price increases; investor mood has also been identified as a significant factor. Cary (2024) examined the sentiment patterns of cryptocurrency enthusiasts during market downturns, which revealed a distinct herding behavior

in comparison to that of conventional investors. Bouri et al. (2019) also observed that herding behavior is subject to change over time and has a significant impact on price volatility. This was further substantiated by Jalal et al. (2020), who discovered that herding is particularly apparent in bullish and high-volatility conditions. Several studies have demonstrated that herding behavior in crypto markets is characterized by illogical crowd-following, particularly during periods of market volatility and unfavorable conditions. Herding in the crypto market is also significantly influenced by investor sentiment; distinct behaviors are observed during both market collapses and increasing trends.

Moreover, herding behavior in cryptocurrency markets during bearish and bullish periods has garnered significant research interest due to its emphasis on the tendency of investors to imitate one another's actions in response to fear and uncertainty, as well as the influence of greed and overexcitement on similar behavior during up-market cycles. Herding behavior in cryptocurrency markets has been the subject of research, which indicates that it can manifest in both bullish and bearish periods, albeit in varying forms and intensities. Numerous studies demonstrate that herding behavior is prevalent during periods of optimism. For instance, research conducted by Jalal et al. (2020) indicates that herding is particularly effective in the presence of positive trends and high volatility. In the same vein, Shrotryia and Kalra (2022) found that herding is significantly more prevalent during bullish phases, thereby corroborating the hypothesis that favorable market movements motivate traders to engage in coordinated behavior. During bearish periods, herding behavior is also evident; however, it manifests in a distinct manner. According to research conducted by Kyriazis (2020) and Coskun et al. (2020), herding can be more consistently observed during market downturns. For example, Kyriazis (2020) found that herding was more apparent during bearish conditions and was not statistically significant during bullish times, thereby refuting the conventional wisdom that herding only increases during market stress. However, research conducted by Coskun et al. (2020) indicates that anti-herding tendencies may emerge in bearish conditions, leading investors to prioritize their own strategies over adhering to the herd. This reveals a substantial disparity in the results. In general, the findings of numerous studies indicate that herding

behavior is a multifaceted phenomenon that can manifest in both bullish and bearish periods. In bullish markets, herding is driven by optimism and the desire to capitalize on rising trends, while in bearish markets, it is a more reactive and frightened response to declining prices.

The CSSD method by Christie and Huang (1995) or the CSAD method by Chang et al. (2000), or both, are the methods that are most frequently employed in herding studies in financial markets, including those that are focused on cryptocurrencies. The CSSD method reduces the standard deviation by computing the standard deviation of individual asset returns relative to the market return, assuming herding results in a convergence of returns toward the market. For instance, Vidal-Tomás et al. (2019) found that the CSAD method revealed significant herding behavior during down markets, despite the CSSD approach indicating that rational asset pricing models could explain extreme price movements. This suggests that collective investor behavior was influencing the movements. The CSSD approach is enhanced by the CSAD method, which captures the non-linear relationship between market returns and the dispersion of individual returns by applying the absolute deviation of individual asset returns. Subsequently, both methodologies will be examined with greater precision. For example, Da Gama Silva et al. (2019) discovered that the CSAD exhibited a smaller herd effect than the CSSD during recessionary periods, suggesting that absolute deviations provide an alternative perspective on investor behavior. The CSSD approach was also found to have significant herding effects in up-markets by Kallinterakis and Wang (2019). Their CSAD study demonstrated that herding was more apparent during periods of low volatility and high trading volume. This work will employ both the CSSD and CSAD methodologies to achieve comparable outcomes and a comprehensive understanding of herding behavior in the cryptocurrency market.

4 Data

In this paper, we investigate the daily pricing of eight key cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), XRP, Dogecoin (DOGE), USDC, and Cardano (ADA). The selection of these cryptocurrencies was based on their significant market presence; collectively, they comprise over 80% of the total market capitalization of the cryptocurrency sector. Solana, the fourth-largest cryptocurrency, was excluded because of data-related issues. Consequently, this investigation comprises eight of the top ten cryptocurrencies in the crypto market in terms of market capitalization. However, it is important to note that this limited selection may introduce statistical limitations, as it does not account for the diverse behaviors and dynamics of other cryptocurrencies that could also influence market trends.

The data covers the period from June 20, 2022, to November 11, 2024, offering a comprehensive analysis of the market's dynamics during this period. The starting point was chosen on June 20, 2022, since the bear market was nearing its conclusion at that time, as the total cryptocurrency market capitalization had decreased from nearly \$3 trillion to below \$1 trillion. The examination is conducted over two distinct time frames. The first period, which lasted from June 20, 2022, to October 15, 2023, was distinguished by a stable environment in which the crypto market steadily raised its market capitalization from approximately 901 billion to 1.06 trillion. This period is distinguished by a period of relative market stability and consolidation. The market capitalization can be visualized in the table 1 below.

Table 1. Global cryptocurrency market cap (CoinGecko, 2025)



Conversely, the second period, which spanned from October 16, 2023, to November 11, 2024, can be classified as a bull run. During this period, the market capitalization increased from \$1.06 trillion to an astonishing \$2.72 trillion. This significant increase is indicative of increased investor interest and optimism, which results in more pronounced price movements and more noticeable herding behavior among market players. We will be able to more accurately illustrate the distinct dynamics of herding behavior in both stable and optimistic market conditions by conducting a separate analysis of these two periods. The daily price data and market capitalizations for each cryptocurrency was obtained from CoinMetrics.

The impact of different market portfolio compositions on herding measurements can be used to evaluate her herding behavior. In accordance with Kallinterakis and Wang (2019) and Vidal-Tomás et al. (2020), both equal-weighted and value-weighted market portfolios will be implemented. In addition, research excludes Bitcoin from computations which will enable the differentiation of herding dynamics among smaller cryptocurrencies.

We use the following formula to compute the daily returns for the equal-weighted market portfolio so facilitating our study:

$$r_{m,t} = \frac{\sum_{i=1}^N r_{i,t}}{N} \quad (4)$$

Where: $r_{m,t}$ represents the market return at time t ; N is the total number of cryptocurrencies included in the market portfolio. $r_{i,t}$ denotes the daily return of each individual cryptocurrency i at time t .

To continue our analysis, we determine the daily returns for the market capitalization-weighted portfolio using the following equation:

$$r_{m,t} = \sum_{i=1}^N w_{i,t} \cdot r_{i,t} \quad (5)$$

Where in addition to equation (4): $w_{i,t}$ represents the percentage of market capitalization on each day t .

5 Methodology

At first, we employ the CSSD method by Christie and Huang's (1995) to investigate herding behavior in the cryptocurrency market, a technique that is widely recognized in the herding literature. This method enables us to evaluate the degree of return dispersion among cryptocurrencies, thereby revealing whether investors are acting independently or in response to market behavior. In this context, dispersion is the term used to describe the degree of variation in returns among various cryptocurrencies within the market. A high degree of dispersion suggests that the price movements of individual cryptocurrencies are diverse, which implies that investors are making independent decisions based on their own analyses or market signals. In contrast, a low level of dispersion suggests that returns are clustering around the average, which may suggest that investors are collectively reacting to market trends or sentiments, thereby exhibiting herding behavior.

The CSSD method serves as a robust foundation for identifying herding by measuring the dispersion of returns across a set of assets. It calculates the standard deviation of returns for a group of cryptocurrencies over a specified period. The CSSD is mathematically defined as follows:

$$CSSD_{m,t} = \sqrt{\frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{N - 1}} \quad (6)$$

Where: $R_{i,t}$ is the observed return of cryptocurrency i at time t , and $R_{m,t}$ is the cross-sectional average return of the N cryptocurrencies in the market portfolio at time t .

A significant reduction in this dispersion during periods of significant market fluctuations would indicate herding behavior, as investors frequently imitate the actions of others rather than relying on their own knowledge and convictions (Christie & Huang, 1995). To quantitatively evaluate this phenomenon, we will implement a regression model that

encapsulates a relationship between market returns and the CSSD. The regression model can be expressed as follows:

$$CSSD_{m,t} = \alpha + \beta^U D_t^U + \beta^L D_t^L + u_t \quad (7)$$

In this context, D_t^U equals 1 if the market return on day t falls within the extreme lower tail of the distribution, and it is 0 in all other cases. Similarly, D_t^L equals 1 if the market return on day t is in the extreme upper tail of the distribution, and it is 0 otherwise. Additionally, u_t represents the error term at time t .

We continue to investigate herding behavior in the cryptocurrency market by employing the Cross-Sectional Absolute Deviation (CSAD) technique, which is suggested as a complementary approach to the CSSD method. Developed by Chang et al. (2000), the CSAD approach provides a more robust analysis of herding behavior by utilizing a measure that is less sensitive to outliers. Consequently, it effectively addresses some of the limitations associated with the CSSD method.

The CSAD is defined mathematically as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (8)$$

Where: $R_{i,t}$ represents the observed return of cryptocurrency i at time t , and $R_{m,t}$ is the absolute value of the cross-sectional average return of the N cryptocurrencies in the market portfolio at time t .

This formula allows us to assess the extent to which individual asset sets deviate from the market consensus by capturing the average absolute deviation of individual cryptocurrency returns from the market return. Similarly, a decrease in the CSAD during these periods would indicate herding behavior, reflecting a movement of investors

toward a shared market attitude. Conversely, an increase in the CSAD would suggest that investors are acting independently, thereby reflecting their own views and knowledge.

To empirically evaluate this relationship, we will regress the CSAD against the market return to determine the degree to which return dispersion is correlated with market fluctuations. We will examine the following regression model:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + u_t \quad (9)$$

Where, $R_{m,t}$ represents the return of the market index at time t , while $|R_{m,t}|$ indicates the absolute value of that return. Additionally, $R_{m,t}^2$ refers to the squared market return, and u_t signifies the error term at time t .

A statistically significant positive coefficient for γ_3 would indicate that the dispersion of returns increases in tandem with the rise in market return. This suggests that investors are differing in their perspectives and reactions to market fluctuations. Conversely, a statistically significant negative coefficient for γ_3 would imply that herding behavior—where investors align their actions with the market consensus—leads to a reduction in dispersion during periods of significant market movements (Chang et al., 2000).

6 Descriptive statistics

Table 1 displays descriptive statistics (CSSD, CSAD, and R_m) for equally weighted and market-cap weighted cryptocurrency portfolios, both with and without Bitcoin. The results indicate that the selected weighting approach and the inclusion of Bitcoin have resulted in substantial variations in portfolio performance qualities. The significantly higher standard deviations across all three measures (CSSD, CSAD, R_m) in Bitcoin-inclusive portfolios indicate a significantly higher level of volatility, necessitating additional research into the unique risk profile of Bitcoin.

However, Bitcoin's substantial impact on distribution kurtosis serves as a compelling argument against the null hypothesis of normally distributed returns. The kurtosis values of portfolios that contain Bitcoin are significantly higher than the expected value of three for a normal distribution. It is evident that these extremely high values indicate distributions with significantly heavier tails and sharper peaks than a normal distribution. This implies that the probability of encountering both positive and negative extreme returns is significantly greater than that of a normal distribution. The kurtosis is rather high, which firmly refutes the null hypothesis of normally distributed returns.

Table 2. Descriptive statistics of cross-sectional standard deviations and cross-sectional absolute deviations

Market portfolio	Equally weighted			Market cap weighted		
	CSSD	CSAD	Rm	CSSD	CSAD	Rm
Mean	0,022	0,015	0,002	0,022	0,015	0,002
Median	0,018	0,013	0,000	0,019	0,013	0,000
Maximum	0,273	0,131	0,124	0,273	0,132	0,123
Minimum	0,002	0,001	-0,152	0,002	0,001	-0,15
Std. Dev	0,017	0,011	0,026	0,017	0,011	0,026
Skewness	5,131	3,008	0,292	5,089	3,000	0,327
Kurtosis	57,267	19,052	4,076	56,542	18,828	4,053
N	874	874	874	874	874	874
	Equally weighted without BTC			Market cap weighted without BTC		
	CSSD	CSAD	Rm	CSSD	CSAD	Rm
Mean	0,025	0,016	0,002	0,024	0,017	0,002
Median	0,020	0,013	0,001	0,020	0,013	0,000
Maximum	0,311	0,129	0,179	0,307	0,129	0,187
Minimum	0,003	0,001	-0,181	0,002	0,000	-0,180
Std. Dev	0,021	0,012	0,031	0,021	0,013	0,033
Skewness	4,667	2,927	0,343	4,931	2,966	0,423
Kurtosis	45,411	15,381	5,302	48,328	15,343	5,422
N	874	874	874	874	874	874

This table lists the descriptive statistics of daily cross-sectional standard deviations (CSSD), cross-sectional absolute deviations (CSAD) and daily market returns (Rm) for the whole sample period with equally weighted - and market cap weighted market portfolios with and without bitcoin.

Figure 3 illustrates the price fluctuations of market-cap weighted and equally weighted cryptocurrency portfolios from June 20, 2022, to November 11, 2024, both with and without Bitcoin. While all four portfolios exhibit a general upward trend over the long term, their performance varies significantly across sub-periods and portfolio compositions. The data is divided into two sub-periods, which have already been discussed, along a vertical line.

Portfolios that incorporate Bitcoin exhibit rather more pronounced price volatility in comparison to portfolios that exclude Bitcoin. The inclusion of Bitcoin leads to a more pronounced price swing and a more drastic increase in both market-cap weighted and equally weighted portfolios. This discovery is consistent throughout the duration. The portfolios that include Bitcoin exhibit a greater number of price fluctuations, including significant increases and decreases, even though all portfolios demonstrated growth. Portfolios that do not contain Bitcoin exhibit a more consistent trajectory. In addition, the volatility of market-cap weighted portfolios is generally lower than that of their equally weighted counterparts, a trend that is consistent regardless of the inclusion of Bitcoin.



Figure 3. The price developments of different portfolio compositions 20.6.2022-11.11.2024

Figures 4 and 5 visually investigate potential herding behavior in equally weighted and market-cap weighted portfolios, with and without Bitcoin, by examining the relationship between market returns and cross-sectional dispersion (CSSD and CSAD). In these scatter plots, a linear relationship would suggest that herding is not present, thereby reflecting independent investor behavior by demonstrating that individual asset returns move

in proportion to the total market. In contrast, deviations from linearity, particularly increased dispersion at specific market return levels (e.g., during sharp market declines or rallies), indicate herding, in which investors respond similarly to market stimuli. Although some indirect inferences can be drawn, the data do not directly reveal herding behavior in either set of scatter plots. This suggests that equally weighted portfolios may experience less herding and make less synchronized investment decisions than market-cap weighted portfolios, as evidenced by the increased number of dispersed data points in both datasets. The distributions of the market-cap weighted portfolios, particularly those that include Bitcoin, are slightly tighter, which suggests the possibility of some herding. The disproportionate influence of a few large-cap assets is the cause of the non-linear relationship observed in market-cap weighted portfolios. As a result, the portfolio's overall return is significantly influenced by the non-linear movements of the large-cap assets, even if the overall market exhibits a linear trend. This results in a less predictable and less linear relationship between the portfolio return and the overall market return. Consequently, the analysis offers a glimpse into the potential for herding behavior; however, any conclusions drawn about these dispersions are speculative, as the data does not definitively confirm the presence or absence of herding in the cryptocurrency market.

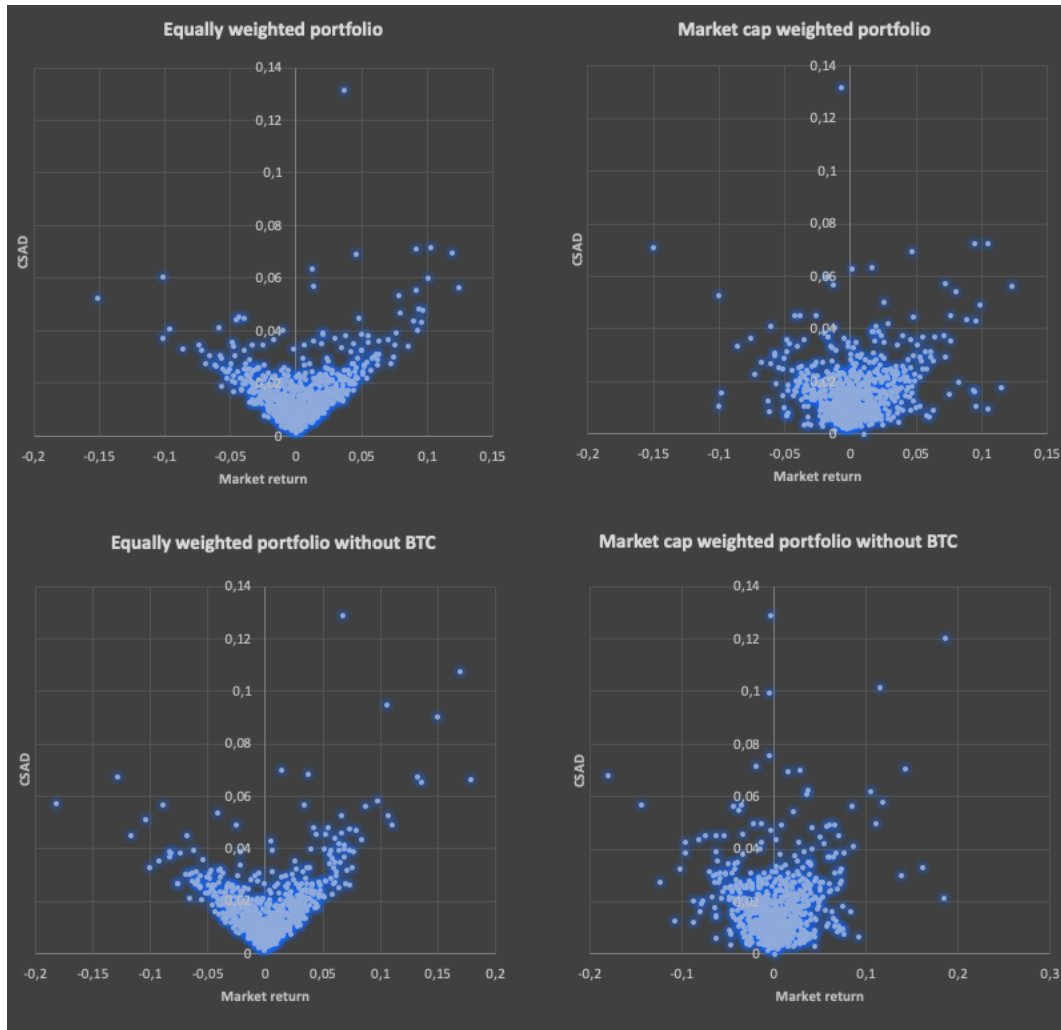


Figure 4. Relationship between CSAD and market return 20.6.2022-11.11.2024

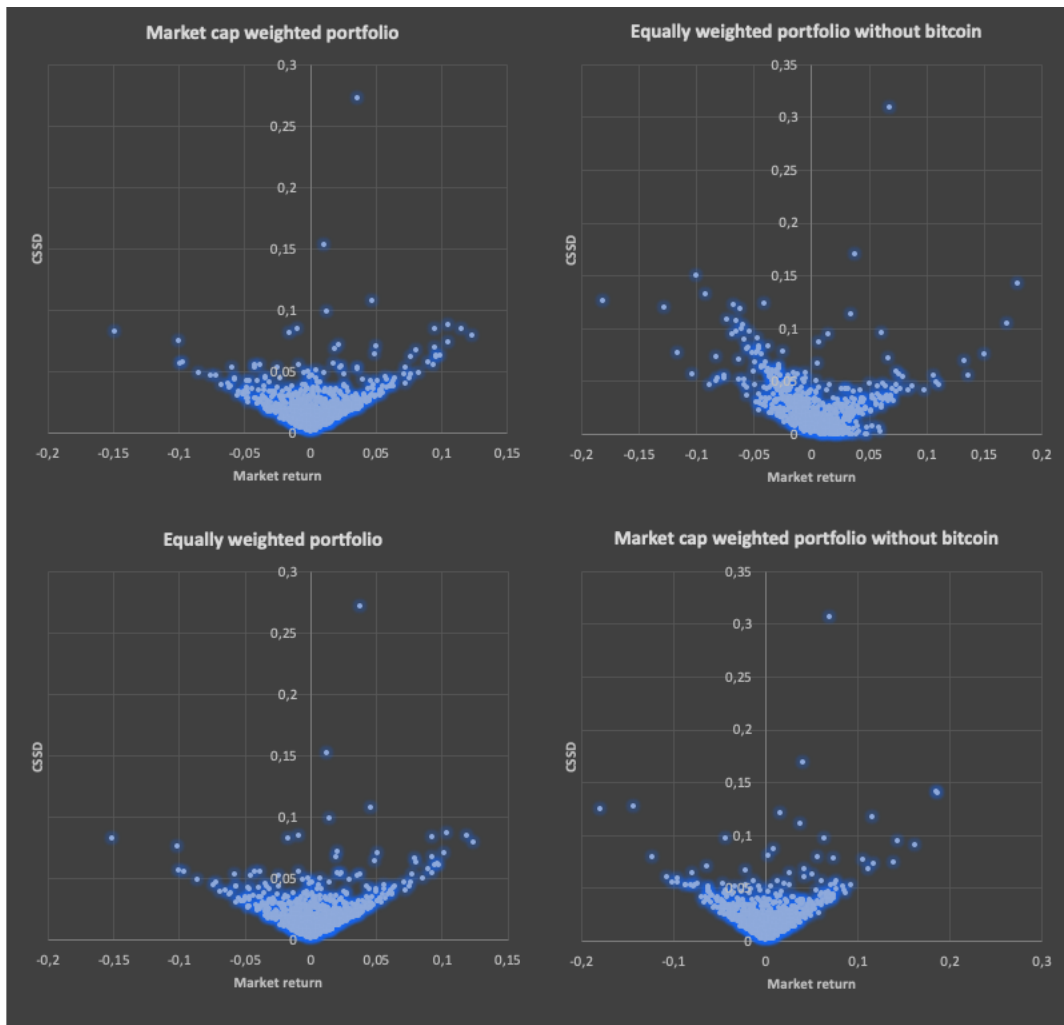


Figure 5. Relationship between CSSD and market return 20.6.2022-11.11.2024

7 Results

The results of our investigation into herding behavior in the cryptocurrency market from June 26, 2022, to November 11, 2024, are summarized in this section. A variety of hypotheses regarding the normal distribution of returns, the impact of portfolio composition—particularly in relation to Bitcoin's predominance—and the changes in herding that occur in bullish versus neutral market conditions are examined. Furthermore, we make use of the previous CSSD and CSAD studies to compare our findings with those of previous studies. This allows us to contextualize our findings within the broader body of knowledge regarding cryptocurrency markets.

7.1 Herding during the entire sample period

Tables 1 and 2 display the regression results for two models that tested herding behavior in the cryptocurrency market from June 26, 2022, to November 11, 2024, using a variety of portfolio compositions. Table 2 employs the CSAD measure, while Table 1 employs the CSSD. The values in parentheses represent t-statistics, with significant coefficients ($p < 0.10$) indicated by *, **, or *** for 10%, 5%, and 1% significance levels, respectively.

The coefficients for α , β^U , and β^L in Table 1 (CSSD) are consistently positive and highly significant across all portfolio types, including market cap weighted, equally weighted, and variations that exclude Bitcoin. This strongly suggests that there was no herding behavior during the investigated period, indicating a tendency towards anti-herding. The results showed minimal variation regardless of the composition of the portfolio or the inclusion of Bitcoin.

Table 2 (CSAD) emphasizes the squared market return coefficient (y_3) in a distinct manner. The study does not demonstrate any statistical evidence of herding, as the coefficients are either positive or, in one instance, negative, but they are not statistically

significant at conventional levels across all portfolio scenarios. This implies that herding behavior was not present in the cryptocurrency market during the specified timeframe.

Table 2. Estimates of herd behavior with the CSSD measure for entire period

Portfolio	α	β^U	β^L
Equally weighted	0,0193 *** (35,363)	0,0305 *** (12,710)	0,0206 *** (8,583)
Market cap weighted	0,0195 *** (35,536)	0,0312 *** (12,924)	0,0204 *** (8,475)
Equally weighted without BTC	0,0213 *** (33,397)	0,0397 *** (14,169)	0,0332 *** (11,870)
Market cap weighted without BTC	0,0214 *** (33,149)	0,0401 *** (14,114)	0,0329 *** (11,573)

This table reports the estimated coefficients for the model in equation (6).

The numbers in the parentheses are t-statistics.

*** significance at the 1% level

** significance at the 5% level

* significance at the 10% level

Table 3. Estimates of herd behavior with the CSAD measure for entire period

Portfolio	α	γ_1	γ_2	γ_3
Equally weighted	0,0078 *** (18,538)	0,0334 *** (3,471)	0,4027 *** (13,515)	-0,0368 (-0,110)
Market cap weighted	0,008 *** (18,768)	0,0328 *** (3,357)	0,393 *** (12,933)	0,1032 (0,303)
Equally weighted without BTC	0,0144 *** (20,920)	-0,0295 ** (-2,212)	0,0736 ** (1,930)	0,3738 (1,132)
Market cap weighted without BTC	0,0147 *** (20,322)	-0,0307 ** (-2,266)	0,0776 ** (2,013)	0,338 (0,8156)

This table reports the estimated coefficients for the model in equation (8).

The numbers in the parentheses are t-statistics

*** significnace at the 1% level

** significance at the 5% level

* significance at the 10% level

In conclusion, the findings of this study demonstrate that the absence of herding behavior during the sample period is consistent with previous field research. Youssef (2022) identified substantial anti-herding activity in the cryptocurrency market by employing the CSAD model and market capitalization. In the same vein, Vidal-Tomás et al. (2019) conducted an analysis of 65 digital currencies using both equally-weighted and market capitalization-weighted methods. Their findings indicate that extreme price swings are not attributed to herding behavior, as evidenced by the notably positive coefficients in CSSD and CSAD research. Additionally, Bouri et al. (2019) focused on 14 of the most prominent cryptocurrencies and employed market capitalization weighting to illustrate that the CSAD of cryptocurrency returns increases in tandem with market returns. This analysis provides evidence of anti-herding behavior through a significant coefficient on squared market returns.

Based on the regression results presented in Tables 1 and 2, we reject the hypothesis (H1) that there is evidence of herding behavior in the cryptocurrency market during the sample period from June 26, 2022, to November 11, 2024. Both the CSSD and CSAD measures consistently demonstrate a lack of herding behavior, as evidenced by the positive and statistically significant coefficients in the CSSD model and the absence of significant negative coefficients in the CSAD model. These results suggest that market players acted logically and without herding influence across a variety of portfolio compositions. As a result, the data does not substantiate the existence of herding behavior in the cryptocurrency market during the designated period, leading to the conclusion that H1 is not supported by the relevant evidence.

7.2 Herding during different subperiods

The cryptocurrency market exhibits intriguing dynamics as a result of herding behavior during multiple subperiods. The CSSD measure for the period from June 20, 2022, to October 15, 2023, as illustrated in Table 3, demonstrates findings that are consistent with those of the entire study period. The coefficients for α , β^U , and β^L are consistently positive and highly significant across all portfolio types. This strongly implies a consistent absence of herding behavior during this period, indicating a tendency towards anti-herding, where investors acted independently rather than following the crowd.

However, the subsequent subperiod, which took place from October 16, 2023, to November 11, 2024, demonstrated a discernible shift in the results. Although the CSSD measure yields comparable results for the majority of coefficients, the market cap-weighted portfolio, which excludes Bitcoin, exhibits a highly significant and negative coefficient, as illustrated in Table 4. This alteration suggests that herding behavior may be present, particularly within this portfolio composition, during the latter half of the study's duration.

The potential shift in investor attention from Bitcoin to altcoins is indicated by the negative coefficient in the market cap-weighted portfolio that excludes Bitcoin. This suggests that investors are reacting to changes in altcoins and diversifying their portfolios, thereby influencing market dynamics, perhaps more so than they are with Bitcoin. This portfolio composition may also suggest that altcoin volatility and speculative trading are on the rise, as evidenced by herding behavior.

Table 4. Estimates of herd behavior with the CSSD measure 20.6.2022-15.10.2023

Portfolio	α	β^U	β^L
Equally weighted	0,0179 *** (21,440)	0,0284 *** (7,818)	0,0218 *** (5,993)
Market cap weighted	0,0179 *** (21,545)	0,0293 *** (8,043)	0,0218 *** (5,998)
Equally weighted without BTC	0,0194 *** (20,971)	0,0451 *** (11,195)	0,0357 *** (8,855)
Market cap weighted without BTC	0,0194 *** (21,127)	0,0477 *** (11,924)	0,0362 *** (9,052)

This table reports the estimated coefficients for the model in equation (6).

The numbers in the parentheses are t-statistics.

*** significance at the 1% level

** significance at the 5% level

* significance at the 10% level

Table 5. Estimates of herd behavior with the CSSD measure 16.10.2023-11.11.2024

Portfolio	α	β^U	β^L
Equally weighted	0,0212 *** (32,136)	0,0326 *** (11,188)	0,018 *** (6,149)
Market cap weighted	0,0213 *** (32,341)	0,033 *** (11,308)	0,018 *** (6,268)
Equally weighted without BTC	0,0236 *** (28,015)	0,0334 *** (8,948)	0,029 *** (7,845)
Market cap weighted without BTC	0,0428 *** (13,050)	0,0413 *** (12,273)	-0,021 *** (-6,105)

This table reports the estimated coefficients for the model in equation (6).

The numbers in the parentheses are t-statistics.

*** significance at the 1% level

** significance at the 5% level

* significance at the 10% level

The analysis of herding behavior using the CSAD measure across two subperiods is detailed in Table 5 and Table 6. This reveals that there are no negative coefficients indicating herding behavior in either period. In the initial subperiod from June 20, 2022, to October 15, 2023, both the market capitalization weighted and equally weighted portfolios exhibit negative coefficients, as illustrated in Table 5. However, these coefficients are not statistically significant. The equally weighted and market cap weighted portfolios exhibit positive coefficients, which are also not statistically significant, with the exception of Bitcoin.

The equally weighted and market capital weighted portfolios exhibit positive but non-significant coefficients in the second subperiod from October 16, 2023, to November 11, 2024, as illustrated in Table 6. Nevertheless, the market cap-weighted and equally weighted portfolios, which exclude Bitcoin, exhibit significant and favorable coefficients. The absence of negative coefficients over both periods suggests that the cryptocurrency market does not exhibit clear herding behavior.

Table 6. Estimates of herd behavior with the CSAD measure 20.6.2022-15.10.2023

Portfolio	α	y_1	y_2	y_3
Equally weighted	0,0070 *** (12,078)	0,0319 ** (2,253)	0,4172 *** (9,943)	-0,211 (-0,474)
Market cap weighted	0,0072 *** (12,230)	0,0324 *** (2,243)	0,4083 *** (9,455)	-0,079 (-0,1715)
Equally weighted without BTC	0,0128 *** (14,245)	-0,033 * (-1,8713)	0,0977 *** (1,9580)	0,3466 (0,8444)
Market cap weighted without BTC	0,0132 *** (13,800)	-0,0342 * (-1,913)	0,1024 ** (2,002)	0,331 (0,8156)

This table reports the estimated coefficients for the model in equation (8).
The numbers in the parentheses are t-statistics
*** significnace at the 1% level
** significance at the 5% level
* significance at the 10% level

Table 7. Estimates of herd behavior with the CSAD measure 16.10.2023-11.11.2024

Portfolio	α	y_1	y_2	y_3
Equally weighted	0,009 *** (14,968)	0,028 ** (2,095)	0,348 *** (7,883)	0,625 (1,143)
Market cap weighted	0,010 *** (15,212)	0,026 * (1,937)	0,337 *** (7,605)	0,781 (1,431)
Equally weighted without BTC	0,009 *** (14,090)	0,051 *** (3,8919)	0,341 *** (9,052)	0,794 ** (2,175)
Market cap weighted without BTC	0,009 *** (14,358)	0,048 *** (3,790)	0,340 *** (9,762)	0,888 *** (2,842)

This table reports the estimated coefficients for the model in equation (8).
The numbers in the parentheses are t-statistics
*** significnace at the 1% level
** significance at the 5% level
* significance at the 10% level

In contrast to the findings of Papadamou et al. (2021) and Shrotryia and Kalra (2022), which observed significant herding behavior among cryptocurrencies during bullish periods and extreme economic conditions, this study found herding behavior only within

one specific portfolio composition. While both studies highlighted the tendency of digital assets to exhibit similar price movements in favorable market conditions, my results suggest that this convergence was not universally present, indicating a variation in investor behavior during the analysis period. Although, these differences could be attributed to variations in the data period and the specific cryptocurrencies selected for analysis.

The results indicate a complex acceptance of the hypothesis H2: "Herding is more intense during the bull market compared to neutral market conditions." The initial subperiod, which spanned from June 20, 2022, to October 15, 2023, exhibited a relatively stable market environment in which herding behavior across various portfolio compositions was evidently absent. This stability suggests that investor actions were not influenced by collective behavior, thereby refuting the notion that herding is prevalent in neutral or stable conditions.

In contrast, the second subperiod, which spans from October 16, 2023, to November 11, 2024, is characterized by a more optimistic market environment. During this period, the market cap-weighted portfolio, which excludes Bitcoin, exhibited a negative and highly significant coefficient with CSSD measure. This demonstrates herding behavior, which indicates that investors began to exhibit group behavior as the market became more optimistic, particularly in relation to altcoins. Consequently, the fact that herding was developed in the later subperiod suggests that it can be observed in specific settings, particularly in favorable market conditions, even if the hypothesis is not entirely supported under all circumstances. As a result, the hypothesis 2 is partially accepted.

7.3 Impact of market composition and Bitcoin's dominance on herding

The examination of the cryptocurrency market provides an insightful examination of the impact of the market's composition and the dominant position of Bitcoin on investor behavior. The results indicate that the composition of the market portfolio has a

significant impact on the observed results. For the whole study period the equally-weighted portfolio exhibited a negative coefficient (γ_3), while the market-cap weighted portfolio exhibited a positive coefficient, as indicated by the CSAD measure in table 2. However, it is important to note that neither coefficient exhibited any statistical significance.

When comparing the equally-weighted portfolio without Bitcoin to the market-cap weighted portfolio without Bitcoin in the second subperiod in table 4, the CSSD demonstrated a significant change in weighting. The equally-weighted portfolio exhibited a positive and significant coefficient, in contrast to the market-cap weighted portfolio, which exhibited a negative and significant coefficient. Other results were intriguing in that they did not exhibit any differences between market portfolio weightings, suggesting that the impact of portfolio composition may not be consistent across all measures and periods assessed.

Portfolios that did not include Bitcoin throughout the study period with both methods exhibited more greater coefficients with both weighting techniques than those that did. This trend suggests that the absence of Bitcoin has enabled other cryptocurrencies to perform more favorably. Similarly, stable times demonstrated a trend in which both measures exhibited more positive coefficients in portfolios that did not include Bitcoin. Despite the fact that herding was evident in this scenario, the market-cap weighted portfolio without Bitcoin exhibited a negative coefficient in the second subperiod, in contrast to the market-cap portfolio consisting of Bitcoin.

Additionally, the CSAD measure underscored the impact of Bitcoin during stable periods in table 5, as the coefficients (γ_3) for portfolios that included Bitcoin were negative and those for portfolios that excluded Bitcoin were positive, as determined by both weighting techniques. Additionally, in table 6 the CSAD measures that did not include Bitcoin had significant coefficients in the second subperiod, while those that did included

Bitcoin had non-significant coefficients. This further emphasizes the potential impact of Bitcoin on the portfolio's overall performance.

The results provide partial support for H3, which asserts that the composition of market portfolio significantly influences herding results. Although the significance of these effects is contingent upon the measure and period, the coefficient differences between the equally-weighted and market-cap weighted portfolios indicate that composition does contribute to herding behavior results. The research results support the hypothesis that Bitcoin has a substantial impact on herding results. Portfolios that did not include Bitcoin consistently exhibited higher coefficients across both weighting techniques, indicating that the absence of Bitcoin facilitated the performance of other cryptocurrencies. In stable market conditions, portfolios that did not contain Bitcoin also exhibited higher positive coefficients. Furthermore, the CSAD measures demonstrated that portfolios that included Bitcoin had negative coefficients, whereas those that excluded it exhibited significant positive coefficients, particularly in the second subperiod. Bitcoin's substantial impact on herding behavior and overall portfolio performance is underscored by these findings.

To gain insights from this study, Investors in the cryptocurrency market should exercise caution and maintain a keen understanding of market dynamics in light of the discussions in this study. Although the methods employed in this study could not clearly capture herding behavior, it is evident that such behavior exists in the market. Given the interconnectedness of major cryptocurrencies and the speculative nature of the market, it is essential to conduct comprehensive research and refrain from making impulsive decisions based solely on market trends or the actions of others. Diversifying investments across a wider variety of financial assets, rather than focusing on a limited number of cryptocurrencies, can help reduce the risks associated with high volatility. Furthermore, staying informed about market developments and understanding the distinctive characteristics of various cryptocurrencies will enable investors to make more informed decisions.

8 Limitations

Several methodological limitations must be recognized when employing the CSSD and CSAD measurements to detect herding in the cryptocurrency market. Initially, both CSSD and CSAD concentrate on the capture of herding behavior in relation to market consensus, potentially omitting other forms of herding that may occur in different contexts or under varying market conditions. As Spyrou (1995) notes, the reliance on these measures may result in inconclusive evidence regarding herding, as they fail to consider the subtleties of investor behavior, such as "silent" or "passive" herding, in which investors refrain from making trades based on the observed actions of others. Furthermore, the CSAD model's assumption that herding is a linear function of market returns may not be valid in the volatile cryptocurrency market, where non-linear relationships may emerge during periods of extreme price movements, as emphasized by Hachicha et al. (2007). Furthermore, the potential for spurious results is present if the measures fail to adequately account for the underlying market fundamentals, which can make it difficult to differentiate between herding behavior and independent adjustments to market conditions. Hwang and Salmon (2000) emphasize that investors are reacting to fundamental changes rather than following each other, which may result in the appearance of herding if a cryptocurrency's price decreases in response to regulatory news.

The influence of investor sentiment on herding behavior is another critical factor that this study failed to adequately capture. In the cryptocurrency market, where assets often have no fundamental value, market sentiment is a critical factor in influencing investor decisions. The methodologies used in this study do not consider these sentiment-driven dynamics, which are especially evident in the volatile crypto environment. Although this study did not find widespread herding among the measurements during the study period, it is important to recognize that herding behavior may still be present. The persistent nature of this phenomenon is highlighted by the assertion that "no market will ever be completely free of herding," as noted by Hwang and Salmon (2000).

Additionally, this investigation must recognize numerous data-related constraints, in addition to its methodological constraints. The findings can be significantly influenced by the selection of cryptocurrencies that are analyzed, as the market is characterized by a diverse array of digital assets, each with unique properties and investor bases. The scope of this investigation is restricted to eight cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), XRP, Dogecoin (DOGE), USDC, and Cardano (ADA). This limited selection may not offer a comprehensive understanding of herding behavior throughout the entire cryptocurrency market, as it disregards an extensive number of other cryptocurrencies that may exhibit distinct trading dynamics and investor behaviors. For example, Bitcoin and Ethereum, which are among the most prominent cryptocurrencies, might show unique herding patterns in contrast to smaller, less liquid altcoins.

Lastly, the selected study period, which extended from June 20, 2022, to November 11, 2024, was another substantial limitation of this investigation. The precise onset of a bull market was particularly difficult to determine, as it was difficult to differentiate it from a stable period. Consequently, this investigation may have failed to adequately document the initial phases of the bull run, which could have resulted in a restricted comprehension of herding behavior during this critical period. Furthermore, the analysis may have overlooked future market dynamics and investor behaviors that could have emerged as the market evolved, as the bull run had not concluded by the end of the study period. This limitation indicated that the results may not have accurately represented the full range of herding behavior throughout the entire bull market, which could have resulted in different conclusions if a more extensive observation period had been incorporated.

9 Conclusions

This study examined the phenomenon of herding behavior in the cryptocurrency market, with a particular emphasis on two distinct time periods: June 26, 2022, to October 15, 2023, and October 16, 2023, to November 11, 2024. The research attempted to find out whether herding occurs in the cryptocurrency market and whether there were any noticeable shifts in herding behavior between these periods by employing the CSSD and CSAD models. Furthermore, the study investigated the influence of portfolio composition, with a particular emphasis on Bitcoin's dominance, on investor behavior. The results indicate that while the observed herding behavior was influenced by variations in portfolio structure, the impact was not as pronounced as anticipated. Additionally, Bitcoin did influence the herding behavior results.

The empirical results suggest that the cryptocurrency market did not exhibit herding behavior during the initial period, which was characterized by a relatively stable market environment. The CSSD and CSAD results consistently illustrated that market participants acted rationally, without any significant influence from collective behavior. In contrast, the second period, which was characterized by a more optimistic market environment, observed a minimal emergence of herding behavior. The CSSD model only showed significant negative coefficients in the market cap weighted portfolio when Bitcoin was excluded. This suggests that as market sentiment became more positive, particularly among altcoins, investors began to exhibit group behavior.

This study provides inconclusive evidence regarding herding behavior in the cryptocurrency market, which is influenced by specific data samples and varying market conditions, as outlined in the limitations section. The restricted selection of cryptocurrencies and the selected study period indicate that herding may not be universal, but rather dependent on specific contexts. Although Papadamou et al. (2021) and Shrotryia and Kalra (2022) conducted significant research on herding during bullish periods, this study only discovered evidence of herding within a single portfolio composition. Contrary to Vidal-Tomás et al. (2019), who contended that herding is more

apparent in down markets than in up markets, this underscores the ongoing debate regarding the circumstances in which herding occurs. Overall, these results emphasize the necessity of additional research to comprehend the complexity of herding behavior in the cryptocurrency market.

Future research on herding behavior in the cryptocurrency market should prioritize the role of investor sentiment, as it is likely the most significant factor influencing market dynamics in an environment where cryptocurrencies frequently lack fundamental value. It is essential to comprehend the impact of investors' varying levels of optimism or pessimism on herding behavior, as price movements in the crypto market are frequently driven by emotional responses rather than intrinsic worth. Furthermore, future research should consistently examine herding behavior to capture the evolving landscape of the cryptocurrency market, which is characterized by the loosening of regulations and the introduction of a variety of ETFs. This changing context may introduce new dynamics and influences on investor sentiment, which could further impact herding patterns.

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