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Examining herding behavior in the cryptocurrency market

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Abstract

Research background: The research employs the Cross-Sectional Absolute Deviation of returns (CSAD) model, augmented with modifications by Chiang and Zheng (2010) to address asymmetric investor behavior, facilitating the detection of herding behavior. Additionally, the study leverages Quantile Regression (QR), demonstrated by Barnes and Hughes (2002) to effectively capture extreme values in financial data with fat tails or skewed distributions. This approach is particularly relevant in the context of the volatile cryptocurrency market, allowing for the analysis of outliers and the assessment of the magnitude of return impacts using T-stat and Quantile Process Estimates.
Purpose of the article: This study primarily centers its empirical analysis on identifying market-wide herding behavior (Henker *et al.*, 2006) within the cryptocurrency market, spanning from January 1, 2016, to February 1, 2019, juxtaposed with the period from January 1, 2019, to January 7, 2022. The selected time frames were chosen to evaluate potential shifts in herding

dynamics within this market, particularly during its phases of rapid expansion and subsequent stagnation.
Methods: The Cross-Sectional Absolute Deviation (CSAD) methodology, as proposed by Chiang and Zheng (2010), was employed for herding detection, alongside the incorporation of dummy variables to discern the market conditions under which herding occurs. Herding behavior manifests when dispersion diminishes, or its increase is less than proportionate to market returns, indicating an inverse correlation between market returns and dispersion in the presence of herding. Additionally, CSAD estimation was conducted utilizing quantile regression to encompass a broader range of quantiles, facilitating the identification of herding tendencies across various return magnitudes. To delve further into investor behavior, Bitcoin was utilized as an illustrative example, elucidating investor reactions to market bubbles through the application of the Hodrick-Prescott (HP) Filter.
Findings & value added: The findings reveal instances of herding behavior during downward market movements and at higher return levels preceding 2019. However, post-2019, herding is observed during upward market movements and at medium to higher return levels. This study presents compelling evidence of herding phenomena coinciding with the bursting of bubbles, particularly concerning Bitcoin. The findings provide a deeper understanding of how herding manifests differently across distinct market conditions and timeframes, offering actionable insights for investors and policymakers navigating the volatile cryptocurrency landscape. Additionally, by highlighting the correlation between herding behavior and market bubbles, particularly in the context of Bitcoin, this study contributes to the broader discourse on cryptocurrency market dynamics.

Introduction

The emergence of digital currencies represents a convergence of financial market evolution and technological advancements. Bitcoin's introduction in 2008 by Nakamoto, notably during a crisis, captured widespread attention due to its low transaction costs, decentralized payment system, and independence from government control. This innovation sparked significant interest, evident in its growing popularity, soaring prices, expanding academic literature, and competition from alternative digital currencies. However, these alternatives often fall short of fulfilling the functions of traditional money, resembling speculative investments more closely.

The limitations of rational theories in explaining market anomalies have led to the emergence of behavioral finance. Recent research underscores the substantial influence of investor behavior on market prices and values, offering insights into the causes of past financial crises. Understanding this phenomenon is crucial, as it holds the potential to mitigate future crises by informing more nuanced market analyses and regulatory approaches. Recent literature has witnessed a significant expansion in studies focusing on the intersection of cryptocurrencies and behavioral finance. This growing body of research underscores the increasing interest and importance of understanding the dynamics of cryptocurrency markets and the behavioral factors shaping investor decisions. M'bakob (2024) study on cyclical speculative bubbles in Bitcoin (BTC) and Ethereum (ETH), along with Gamayel and Preda (2024) investigation into trading behavior during market downturns, exemplify this trend. Moreover, Wang *et al.* (2023) contribute insights into Fear of Missing Out (FOMO) in the Bitcoin market, revealing asymmetric volatility dynamics indicative of investor behavior influenced by the fear of missing lucrative opportunities. Studies such as Yarovaya *et al.* (2020) on herding behavior during the COVID-19 pandemic and Mandaci and Cagli (2022) analysis of herding behavior's impact on market volatility provide further understanding of investor behavior in cryptocurrency markets. Additionally, Koch and Dimpfl (2023) sheds light on investor preferences, particularly emphasizing the dominance of the Bitcoin market, while Mohamad and Stavroyiannis (2022) exploration of herding behavior across Bitcoin and foreign exchange majors highlights time-varying patterns and anti-herding tendencies within the cryptocurrency landscape.

The primary objective of this paper is to examine the influence of market-wide herding on the cryptocurrency market during two distinct time periods: pre-2019 and post-2019. Given the inherent characteristics of the cryptocurrency market, which often exhibit signs of inefficiency, it is particularly susceptible to irrational behavior. Factors such as regulatory uncertainty, cybercriminal activity, bubble-like tendencies, and recent global crises, including the Covid-19 pandemic and the ongoing financial downturn, contribute to the likelihood of irrational decision-making. The worldwide lockdowns resulting from these crises have injected additional liquidity into the market, attracting new investors seeking higher returns despite the associated risks. However, amidst the current financial crisis, the prices of major cryptocurrencies by the end of 2022 have failed to reclaim the peak levels observed in 2021. This context underscores the importance of exploring how herding behavior interacts with these dynamics within the cryptocurrency market.

In this paper, we employ the Cross-Sectional Absolute Deviation (CSAD) approach proposed by Chiang and Zheng (2010) to detect herding behavior in the cryptocurrency market. Additionally, we incorporate dummy variables to discern the specific types of market movements associated with herding. Herding behavior is identified when dispersion decreases or rises at a rate less than proportional to market returns, indicating a negative relationship between market return and dispersion in the presence of herding. To enhance the robustness of our analysis, we estimate CSAD using quantile regression, which enables us to capture herding tendencies across various quantiles and elucidate their relationship with the magnitude of returns. Furthermore, to gain deeper insights into investor behavior, we utilize Bitcoin as a case study to examine investor reactions to bubbles, employing the Hodrick-Prescott (HP) Filter.

The inclusion of distinct time periods and sophisticated methodologies enhances the robustness of our analysis, offering valuable insights into the underlying mechanisms driving market behavior and the implications for market stability and efficiency. Overall, this paper adds to the ongoing dialogue on cryptocurrency market dynamics and investor behavior, providing valuable insights for policymakers, investors, and researchers navigating this rapidly evolving landscape.

The structure of the paper unfolds as follows. Firstly, the literature review provides a comprehensive overview of the cryptocurrency market, emphasizing the significance of behavioral finance and exploring the concept of herding, including its implications amidst the Covid-19 pandemic. Subsequently, the methodology section delineates the quantitative and qualitative approaches employed in this study, along with an acknowledgment of its limitations. Finally, the discussion section presents the economic outcomes derived from the analysis, offering insights and interpretations within the context of the broader research framework.

Literature review

Prior literature on the cryptocurrency market' features

The roots of cryptocurrency trace back to the evolution of cryptographic protocols, which initially offered anonymity. The inception of the first commercial digital currency, DigiCash, occurred in 1990. Research into anonymous communication can be traced back to the early eighties, with a primary focus on addressing the "double spending" problem. This dilemma pertained to the absence of a mechanism preventing currency holders from utilizing it multiple times. The solution to this problem emerged through the introduction of blockchain technology, initially presented in

2008 by an individual or group operating under the pseudonym Satoshi Nakamoto.

Since the inception of Bitcoin in 2008 as the first decentralized digital currency, the cryptocurrency market has witnessed exponential growth. According to data from https://coinmarketcap.com, as of June 14, 2019, the market boasted 2,236 cryptocurrencies across 18,882 markets, with a cumulative market capitalization of $265.33 billion. Bitcoin, holding a dominant market share of 56.2%, played a pivotal role in shaping the market landscape.

By January 17, 2023, the cryptocurrency ecosystem had expanded significantly, with over 12,000 cryptocurrencies in circulation and a staggering total market capitalization of $990.04 billion. Despite this remarkable growth, Bitcoin's market dominance had slightly declined to 43.12%. Throughout 2023 and extending into 2024, Bitcoin continued to maintain its status as the foremost cryptocurrency in terms of market capitalization and adoption. During this period, Bitcoin's market value experienced notable fluctuations, influenced by factors such as regulatory developments, technological innovations, and shifts in investor sentiment. Despite occasional volatility, Bitcoin remained a favored investment choice for both institutional and retail investors, with its market value serving as a barometer for the broader cryptocurrency market's performance.

Cryptocurrencies, as defined, represent digital "currencies." However, according to Nakamoto's definition (2008), exemplified by Bitcoin, they are often regarded as "alternative" currencies, albeit not fulfilling all criteria for classification as traditional currencies. The traditional view on money, as outlined by Jevons (1896), necessitates that money serves as a medium of exchange, a unit of account, and a store of value.

Firstly, cryptocurrencies function as a medium of exchange, albeit with limitations. Historically associated with illegal activities due to their anonymity feature, they have gradually gained acceptance for everyday transactions, thereby increasing in popularity as a recognized medium of exchange. Secondly, their inherent price volatility poses challenges to their role as a store of value akin to fiat money. The fluctuating value of cryptocurrencies undermines their stability, thus hindering their ability to serve effectively as a reliable store of value. Lastly, while cryptocurrencies theoretically have the potential to function as a unit of account, their lack of oversight by a central authority complicates this role. Without legal regulation, it becomes challenging to ascertain their capacity to serve as a standardized unit of measurement across transactions. While cryptocurrencies exhibit characteristics of traditional currencies, their limited fulfillment of the criteria for serving as mediums of exchange, stores of value, and units of account underscores the ongoing debate regarding their classification and utility within the financial landscape.

Recent literature, as highlighted by Selgin (2015), has classified cryptocurrencies as synthetic commodity money. This categorization stems from their possession of attributes shared by both commodities such as gold and fiat money. Commodity money, like gold, is inherently scarce and primarily valued for purposes beyond serving as a medium of exchange, aligning with the characteristics exhibited by cryptocurrencies. Conversely, fiat money, issued by central banks, is primarily intended for use as a medium of exchange but can also serve as a store of value and unit of account. By encapsulating aspects of both commodity and fiat money, cryptocurrencies occupy a unique position within the monetary landscape, reflecting their hybrid nature as synthetic commodity money.

Cryptocurrencies exhibit scarcity in that their total supply is typically unknown, with only estimations available due to their mining-based generation process. Mining, as the technology underlying coin creation, introduces a competitive dynamic that regulates the cryptocurrency supply. This characteristic aligns cryptocurrencies closely with the concept of commodity money, as they are subject to shocks and price movements without central control, akin to traditional commodities. Unlike fiat money, which is governed by central authorities, cryptocurrencies lack centralized oversight, further emphasizing their resemblance to commodity-based currencies.

Supporters of cryptocurrencies argue that they represent a potential evolution toward a cashless medium of exchange. However, opponents raise concerns about the exposure to cybercriminal activity inherent in this evolution. The focus often centers on the notable price fluctuations experienced by these digital assets. Price inflation in cryptocurrencies is frequently accompanied by episodes of extreme volatility, a phenomenon commonly attributed to regulatory uncertainty and cybercriminal activities.

The study of Corbet *et al.* (2019) introduces the concept of the cryptocurrency trilemma, which identifies regulatory alignment, cyber-criminality, and the potential for inherent bubbles as significant barriers to the evolution of cryptocurrencies. Regulation plays a pivotal role in influencing cryptocurrency prices, as demonstrated by events such as the 50% reduction in Bitcoin's price at the outset of 2018 following announcements of regulatory cooperation between South Korea and China regarding cryptocurrency trading.

The anonymity inherent in cryptocurrencies exacerbates concerns surrounding cybercriminal activities, providing opportunities for illicit practices such as money laundering and cross-border transfers. Furthermore, the extension of Phillips *et al.* (2015) work offers evidence of potential pricing bubbles within Bitcoin and Ethereum markets, underscoring the complexities and risks associated with the cryptocurrency landscape.

The volatility inherent in cryptocurrency markets poses significant short-term risks for users, exacerbated by the minimal correlation between cryptocurrency exchange rates and those of fiat currencies. According to Yermack (2014), cryptocurrencies demonstrate characteristics more aligned with speculative assets rather than functioning as currencies. Bauer *et al.* (2018) corroborate this assertion, revealing that over 30% of Bitcoin is held for investment purposes, with investors predominantly acquiring Bitcoin without engaging in transactions. Research by Ciaian *et al.* (2016) highlights market forces and investor sentiment as primary drivers of Bitcoin prices, with limited evidence suggesting that macro-financial developments influence long-term price trends. Kristoufek (2015) further contends that Bitcoin prices are primarily determined by speculative investments rather than economic theory, with popularity and transactional demand serving as key price influencers. Moreover, the study by Polasik *et al.* (2015) underscore the impact of sentiment and investor behavior on cryptocurrency value, price, and returns. These findings collectively indicate that behavioral finance plays a crucial role in understanding the dynamics of cryptocurrency markets, wherein sentimental value and investor actions exert significant influence.

Bitcoin has garnered significant attention from both investors and the media, with Urquhart (2018) delving into the factors driving this attention. The study suggests that Bitcoin's innovative features, transparency, simplicity, and increasing popularity contribute to its prominence. Policy makers, entrepreneurs and consumers grapple with a multitude of challenges and opportunities posed by Bitcoin's emergence. Analyzing Google Trends data, Urquhart's study reveals that daily volume and volatility serve as primary drivers of attention to Bitcoin. Notably, investor interest surged following substantial increases in trading volume and volatility. Additionally, Yi *et al.* (2018) find that volatility connectedness, or spillover effects, are not correlated with market capitalization. Contrary to expectations, cryptocurrencies with high market capitalization, like Bitcoin, experience volatility shocks, while smaller-cap cryptocurrencies absorb shocks from others. This suggests that Bitcoin's dominance in the market may be less pronounced than commonly believed. Moreover, Ciaian *et al.* (2018) contend that altcoin prices are unaffected by Bitcoin's development in the long run, indicating limited market influence. The observed lack of volatility spillover between cryptocurrencies underscores the market's imperfections, suggesting that investor behavior may wield greater influence.

Recent research indicates that cryptocurrencies offer diversification benefits. Briere *et al.* (2015) find that incorporating a small proportion of Bitcoin can enhance the risk-return profile of a diversified portfolio. However, it is cautioned that this benefit may not hold over the medium to long term. Dyhrberg (2016b) provides evidence suggesting that Bitcoin can serve as a hedge against the US dollar in the short term and against stock market fluctuations, akin to gold.

Overall, these studies shed light on Bitcoin's evolving role in financial markets, suggesting its potential as both a speculative asset and a hedging tool, albeit with caveats regarding its long-term viability and market influence.

Earlier studies on behavioral finance and efficient market hypothesis

The foundation of traditional finance rests upon the Efficient Market Hypothesis (EMH), initially proposed by Fama (1965) and Samuelson (1965) during a time when capital markets were presumed to operate efficiently. Fama (1970) defined an efficient market as one where rational investors actively compete to predict future market values, aiming to maximize profits with freely available information. The EMH encompasses three forms of efficiency: weak, semi-strong, and strong. Weak efficiency incorporates historical information, negating the possibility of abnormal profits and implying a random walk in price evolution. Semi-strong efficiency extends weak efficiency by reflecting both existing and new market information, while strong efficiency includes private information as well.

The EMH is underpinned by assumptions of rationality and arbitrage, positing that even irrational investors' trades cancel each other out and do not affect prices significantly. However, anomalies in the market emerged in the 1980s that challenged the EMH. Nicholson (1968) and Basu (1977) observed discrepancies in stock prices relative to their price-earnings ratios, while calendar effects like the January effect were documented by Keim (1983), casting doubt on the EMH's explanatory power.

The limitations of traditional models led to the emergence of behavioral finance, pioneered by Barberis and Thaler (2003), which integrates psychology and limits to arbitrage. Unlike the EMH, behavioral finance acknowledges the costs and risks associated with arbitrage and emphasizes the psychological underpinnings of investor decision-making. Historical financial crises further underscored the inadequacies of the EMH, with events like the stock market crash in 1987, the dot-com bubble in 2000, and the 2008 financial crisis shaping the evolution of financial markets. Devenow and Welch (1996) demonstrated that influential investors' decisions are influenced by others', highlighting the role of investor psychology in market dynamics.

Behavioral finance gained prominence as a field that seeks to understand how market behavior influences market outcomes, with a focus on quantifying cognitive processes and influences on decision-making. The challenge lies in bridging cognitive psychology and finance to elucidate how individuals think and act in financial contexts.

While literature on the efficiency of cryptocurrency markets, particularly Bitcoin, remains limited, significant research has begun to emerge. Urquhart (2016) and Vidal-Tomas and Ibanez (2018) have examined Bitcoin's efficiency, with findings suggesting efficiency in reacting to news about itself while remaining unaffected by monetary policy news. These studies suggest that Bitcoin may become more efficient over time as investors react more swiftly to market developments.

Prior literature examining the herding behavior

In theory, market participants rely on the assumption of market efficiency and rational investment behavior. However, in reality, the rationality of investors is often called into question. Investors can be influenced by a myriad of variables, including emotions and beliefs, which can lead to irrational decision-making. The main argument against the notion of rational investment is the observed volatility of markets, where panic and fear can drive irrational behavior among investors. Without a clear reference point such as intrinsic value, investors may struggle to make decisions confidently, further contributing to the complexity of market dynamics.

The absence of fundamental value in cryptocurrencies results in prices being determined by collective valuations rather than intrinsic factors. From the perspective of behavioral finance, this collective behavior is often referred to as herding. Herding behavior in markets is characterized by investors following the actions of others rather than relying on their own beliefs or analysis. Herding is a common phenomenon observed in various aspects of life, reflecting normal human behavior influenced by social dynamics. In investment contexts, herding occurs as a result of human decision-making, contributing to market dynamics and potentially influencing asset prices.

Investors may choose to follow others rather than rely on their own judgment for several reasons. One key factor is the herding bias, which arises in situations of uncertainty, fear, or when the potential for significant losses looms large. In such circumstances, individuals may find it psychologically easier to align with the actions of others rather than take independent decisions. Kallinterakis *et al.* (2010) elucidate the concept of the noise bias, wherein less knowledgeable investors emulate the actions of well-informed investors in the hope of gaining financial insight. Additionally, the tendency to herd is influenced by individual investor characteristics such as market knowledge, trading experience, and the quality of their trading history. Individual investors, lacking the expertise of institutional investors and being more exposed to risk, are particularly prone to herding behavior.

Studies, such as the work by Waeru *et al.* (2008), suggest that herding is more prevalent in the context of buying or selling decisions. Investors may be more inclined to follow the actions of others when faced with decisions regarding entering or exiting the market. However, the choice of assets and the volume of assets traded are found to be less susceptible to herding behavior. This suggests that while investors may herd in their trading actions, they are less likely to do so in terms of asset selection or the quantity of assets traded. Understanding these determinants of herd behavior is essential for comprehending market dynamics and the role of collective investor actions in shaping asset prices and market trends.

Gompers *et al.* (2011) have highlighted the significance of risk and volatility as crucial determinants driving herding behavior in financial markets. When investors are confronted with high levels of risk or volatility, they may be more inclined to mimic the actions of others in an attempt to mitigate their perceived overall risk exposure. This behavior aligns with the notion put forth by Tesfatsion (2006), suggesting that investors may imitate others' actions under the belief that doing so will reduce their risk exposure. The tendency for investors to herd can lead to a divergence from the fundamental value of assets, potentially exposing the market to bubbles and crashes. By imitating the actions of the masses, investors may make uninformed decisions, resulting in deviations of expected returns from the equilibrium predicted by models such as the Capital Asset Pricing Model, as noted by Prosad *et al.* (2012). Furthermore, Landberg (2003) has concluded that herding behavior often stems from a combination of risk and the greed factor, which influences investors' perceptions of investment performance. This interplay between risk and the desire for higher returns can drive investors to follow the crowd, leading to herd behavior and contributing to market inefficiencies and fluctuations.

The occurrence of stock market volatility surpassing expected returns often raises questions about the efficiency of the market, as noted by Lux (1995). Christie and Huang (1995) further assert that herding behavior among investors serves as an explanation for this phenomenon, suggesting that when investors follow the crowd, it can exacerbate market volatility. The heightened interest in herd behavior stems from historical financial crises, with arguments positing that these crises are, in part, a consequence of herding behavior spreading among market participants, as highlighted by Chari and Kehoe (2004). Both investors and economists recognize the existence of herding among investors in financial markets, underscoring its significance in shaping market dynamics and influencing asset prices, as evidenced by Devenow and Welch (1996).

Various definitions of herding behavior have been proposed in the literature, each shedding light on different facets of this phenomenon. Banerjee (1992) offers a comprehensive definition, characterizing herding as the tendency for individuals to follow the crowd, even when their private information suggests a different course of action. This definition captures the general form of herding observed in everyday situations. From a behavioral finance perspective, Chiang and Zheng (2010) describe herding behavior as the manifestation of correlations in trades resulting from interactions among market participants. Bikhchandani and Sharma (2001) emphasize the conscious influence of others' actions on investors, suggesting that herding occurs when external information alters their decision-making process. Even in scenarios where investors have already made decisions independently, exposure to information about others' actions can prompt them to change their course, as highlighted by Bikhchandani and Sharma (2001).

In this paper, the definition of herding behavior adopted is that of Hwang and Salmon (2004), which states that herding arises when investors opt to mimic observed decisions or market movements rather than adhere to their own beliefs and information. This definition encapsulates the essence of herding behavior in financial markets, emphasizing the propensity for individuals to abandon independent judgment in favor of conforming to prevailing trends or actions observed in the market.

Herding behavior among investors is often categorized into two distinct types: intentional herding and spurious herding. Intentional herding occurs when investors consciously seek to emulate the actions of others in the market. On the other hand, spurious herding arises when groups of investors, facing similar decision problems and information, independently arrive at similar decisions, leading to a seemingly coordinated outcome that is considered efficient. Distinguishing between intentional and spurious herding is crucial, although it can be challenging in practice. This difficulty stems from the myriads of factors that influence individual decision-making processes, as highlighted by Bikhchandani and Sharma (2001). Given the complex interplay of variables at play in financial markets, identifying the underlying motivations behind investor behavior requires careful analysis and consideration of various contextual factors.

Indeed, various authors offer diverse perspectives on herding behavior in financial markets. Devenow and Welch (1995) delineate between rational and non-rational views of herding. The non-rational view emphasizes externalities, positing that optimal decision-making may be compromised by information asymmetries or incentive issues, as noted by Zemsky (1998). On the other hand, rational herding is attributed to factors such as imperfect competition, compensation structures, and concerns for reputation, as elucidated by Bikhchandani and Sharma (2001). Additionally, Graham (1999) proposes a nuanced classification of herding into four categories: informational cascades, reputational herding, investigative herding, and empirical herding. Informational cascades occur when individuals prioritize following the actions of others over their private information. Reputational herding occurs when individuals imitate the behavior of others to maintain or enhance their reputation. Investigative herding involves individuals relying on the actions of others as signals of valuable information. Empirical herding refers to the observation of collective behavior in the absence of clear information or rational justifications. These various views and classifications provide valuable insights into the multifaceted nature of herding behavior in financial markets, highlighting the interplay of rational and non-rational factors, as well as the diverse motivations driving investors' decisions

Herding driven by imperfect information often manifests as an informational cascade, where individuals disregard their private decisions and instead mimic the actions of others, as suggested by Graham (1999). Informational cascades can be disrupted by various shocks, such as individuals possessing new or superior information, as demonstrated by Welch (1992), who showed that such cascades can lead to market booms and crashes.

Bikhchandani and Sharma (2001) offer an illustrative example of how informational cascades may form. Consider a group of 100 investors deliberating whether to invest in an emerging market. While 80 investors believe the investment is not profitable and 20 believe it is, each investor is unaware of others' beliefs. If these investors were to share their beliefs, the collective decision might be not to invest. However, if the initial investors who believe the investment is profitable act first, their actions may influence some of the 80 skeptics to change their decision, leading to a cascade effect where most investors ultimately make a suboptimal investment decision. Most models, including the one described above and others by Welch (1992), operate under the assumption of a fixed price, which may not accurately reflect real-world market dynamics. This acknowledgment underscores the complexity of modeling herding behavior and its implications for market outcomes.

Reputational herding shares similarities with informational cascades, as it involves disregarding private information in favor of mimicking the actions of others. However, it differs from informational cascades in that reputational herding entails positive information externalities derived from participating in a project or group. Scharfstein and Stein (1990) developed a model of reputational herding, suggesting that it could be rational for managers to emulate the investment decisions of others. In their model, managers are classified as either smart or dumb, receiving either true signals or noise signals about an investment decision. Managers are unaware of their classification until after the decision is made and the investment is executed. If a manager makes a poor investment decision and others do not follow suit, it may indicate poor manager quality. Conversely, if other managers also make the same poor decision, it may suggest a challenging investment climate. However, if enough poorly informed managers herd on a bad investment decision, even well-informed managers may be influenced to avoid being the sole investor in the bad idea. Trueman (1994) proposed that reputational herding could also extend to analysts' forecasts, as analysts often report forecasts similar to historical ones. Another form of rational herding, identified by Bikhchandani and Sharma (2001), involves compensating structures, where managers' compensation is tied to their performance, incentivizing them to herd. This compensation structure provides an incentive for managers to align their decisions with the actions of others in the market.

The remaining categories of herding behavior outlined by Graham (1999) — investigative and empirical herding — hold significant importance in understanding investor behavior. Investigative herding occurs when analysts seek out information, they believe others will also uncover, with the aim of being the first to discover it. Empirical herding, on the other hand, examines whether excessive numbers of investors mimic the actions of others, often manifesting as a tendency to emulate past winners.

The non-rational view of herding, as proposed by Devenow and Welch (1996), is rooted in investor psychology, wherein individuals blindly follow others without engaging in rational analysis. A familiar example of this behavior can be observed in the stock market when investors react impulsively to market declines by selling their stocks to avoid losses, driven by panic rather than reasoned analysis. Similar behavior is evident during bank panics, where depositors withdraw their funds hastily due to fears of imminent bank failure. Market-wide herding occurs when investors overlook asset characteristics and instead follow overall market performance (Henker *et al*., 2006). This phenomenon is not contingent on whether herding is rational or irrational; it is presumed to arise during significant market movements, a characteristic that aligns with the volatile nature of the cryptocurrency market, where outliers and large movements are common occurrences.

Rational asset pricing models operate under the assumption that during periods of significant market movements, investors rely on their private information. This assumption leads to an expected linear relationship between equally weighted market returns and dispersions, where dispersions increase in proportion to market returns. However, herding behavior deviates from this rational expectation. Herding occurs when investors disregard private information and instead follow market performance, resulting in a non-linear relationship between market returns and dispersion of returns (Chiang & Zheng, 2010). Detecting herding involves observing instances where dispersion either decreases or rises at a rate less than proportional to market returns, indicating a negative relationship between market return and dispersion in the presence of herding behavior.

Herding is a significant phenomenon in financial markets due to its substantial impact. Given the limited information available on cryptocurrencies, they are particularly susceptible to herding behavior. The technological advancements underpinning cryptocurrencies, coupled with regulatory uncertainty and the allure of high returns, have attracted widespread investor interest in this speculative asset. Risk-tolerant investors are naturally drawn to such investments, while even risk-averse investors may be swayed if enough risk-tolerant investors validate its potential. Consequently, the likelihood of herding occurring in the cryptocurrency market is considerable. As a speculative asset characterized by significant information gaps, the market is prone to "panic" reactions, increasing the risk of crashes. The market's volatility underscores the pervasive uncertainty in cryptocurrency investments, serving as a catalyst for herding behavior.

Earlier studies towards herding behavior on the cryptocurrency market and COVID-19 crisis

The outbreak of the COVID-19 pandemic triggered extensive research into its repercussions on financial markets. The implementation of global quarantine measures led to shifts in consumer spending habits and increased investor caution, thereby significantly reshaping market dynamics. Research conducted by Yarovaya *et al.* (2020) suggests that while the COVID-19 crisis did not exacerbate herding behavior, evidence points to its existing presence in financial markets.

Examining the impact of the "fear of missing out" (FoMO) phenomenon on the Bitcoin market, Wang *et al.* (2023) delve into its significance, particularly amidst the COVID-19 pandemic. Their study reveals that FoMO drives asymmetric volatility in Bitcoin and other cryptocurrencies, shedding light on its role in shaping market dynamics during times of crisis. In a similar vein, Mandaci and Cagli (2022) delve into the realm of herding behavior, uncovering significant instances, particularly amplified during the pandemic period. Their findings challenge the traditional Efficient

Market Theory by highlighting the substantial influence of behavioral factors, such as herding, in price formation, especially in times of crisis.

Contrasting perspectives emerge from the study conducted by Mohamad and Stavroyiannis (2022), which reveals no evidence of herding within bitcoin and major foreign exchange currencies, even amidst the COVID-19 pandemic. Their analysis of hourly data suggests a prevailing anti-herding behavior among market participants, indicating decisions driven by private information or individual assessments rather than mimicking others' actions. Collectively, these studies offer multifaceted insights into the interplay between herding behavior and the COVID-19 crisis, enriching our understanding of market dynamics during turbulent times. They underscore the significance of behavioral factors in shaping market outcomes and highlight the need for nuanced approaches to market analysis, especially in times of crisis (table 1).

Methods

In this paper, the definition of herding behavior formulated by Hwang and Salmon (2004) is adopted, which states that herding arises when investors opt to mimic observed decisions or market movements rather than adhere to their own beliefs and information. This definition encapsulates the essence of herding behavior in financial markets, emphasizing the propensity for individuals to abandon independent judgment in favor of conforming to prevailing trends or actions observed in the market.

Cross-Sectional Absolute Deviation (CSAD)

To date, only a few methods are available for empirically testing herding behavior. However, this study advocates for the adoption of the Cross-Sectional Absolute Deviation of Returns (CSAD) methodology, initially introduced by Chang *et al.* (2000).

Unlike other methods, CSAD offers a notable advantage by considering absolute deviations rather than squared deviations. This feature makes CSAD less susceptible to the influence of extreme values or outliers in the dataset, thereby enhancing the reliability of herding detection. However, it's crucial to acknowledge a limitation inherent in the model proposed by Chang *et al.* (2000), namely its static nature, where parameters remain constant over time. This lack of dynamism may overlook the evolving dynamics of herding behavior. Nonetheless, the advantages of CSAD, such as robustness against outliers and enhanced reliability in detecting herding, make it a promising tool for studying market phenomena.

The equations outline the methodology for calculating market returns and Cross-Sectional Absolute Deviation (CSAD) in the context of analyzing herding behavior in the cryptocurrency market.

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

Equation (1) where $P_{i,t}$ is the price of cryptocurrency i at time t and $r_{i,t}$ is the individual daily return of cryptocurrency i at time t.

$$r_{m,t} = \frac{\sum_{i=1}^{N} r_{i,t}}{N} \tag{2}$$

Equation (2) where $r_{m,t}$ is the market return at time t, calculated as a weighted average of the sum of the daily individual returns $r_{i,t}$ at time t and N being the number of cryptocurrencies.

$$CSAD_{m,t} = \frac{\sum_{i=1}^{N} |r_{i,t} - r_{m,t}|}{N} \tag{3}$$

Equation (3) where $CSAD_{m,t}$ is the Cross-Sectional Absolute Deviation measuring dispersion by taking the weighted average of the sum of the absolute difference of the individual returns and the market returns.

$$CSAD_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 |r_{m,t}| + \beta_3 r_{m,t}^2 + u_t \tag{4}$$

Equation (4) introduces the regression model aiming to capture herding behavior in response to market returns, encompassing both linear and non-linear relationships between $CSAD_{m,t}$ and market movements. In this equation, α represents the intercept term, accounting for the baseline level of $CSAD_{m,t}$ not explained by market returns. The error term u_t encapsulates unobserved factors affecting $CSAD_{m,t}$ ensuring the model's robustness by capturing residual variation in CSAD beyond the explanatory power of the market returns.

To regress $CSAD_{m,t}$ with the market returns, we include the absolute term $|r_{m,t}|$, the squared market return $r_{m,t}^2$ and the linear term $r_{m,t}$ as proposed by Chiang and Zheng (2010) to account for the asymmetry of investor behavior across different market conditions.

Additionally the inclusion of $r_{m,t}^2$ assumes a non-linear relationship between $CSAD_{m,t}$ and $r_{m,t}$ during periods of wide market movements when herding is more likely to occur. Therefore, a negative and statistically significant coefficient for the non-linear term β_3 would indicate the presence of herding in the data.

The hypothesis testing for Equation (4) can be formulated as follows:
Null Hypothesis (H_0): $\beta_3 = 0$
Alternative Hypothesis (H_1): $\beta_3 \neq 0$

$$CSAD_{m,t} = \alpha + \beta_1(1-D)r_{m,t} + \beta_2 D r_{m,t} + \beta_3(1-D)r_{m,t}^2 + \beta_4 D r_{m,t}^2 + u_t \quad (5)$$

Equation (5) extends the regression model by introducing dummy variables $(1-D)$ and D which are equal to 1 when $r_{m,t} \geq 0$ and $r_{m,t} < 0$ respectively. These variables facilitate the detection of herding during periods of upward or downward market movements. In this context, a downward market movement refers to a situation where the overall market experiences a decrease in value, leading to negative returns. Conversely, an upward market movement denotes a scenario where the market shows an increase in value, resulting in positive returns. A negative and statistically significant coefficient β_3 would imply herding detection during downward market movements, , indicating that investors are more likely to herd during times of market decline.

Quantile Regression (QR)

Quantile regression, proposed by R. J. Boskovic in 1760, originally intended for estimating median regression, has evolved into a powerful tool known for its effectiveness in analyzing conditional quantiles. Particularly useful when extreme quantities of return distribution are of interest, quantile regression (QR) has gained traction in detecting herding behavior, especially in the volatile cryptocurrency market where outliers abound. Its robustness in identifying outliers is well-documented, making it an apt choice for studying herding dynamics (Koenker, 2004). Moreover, QR's suitability for non-normally distributed financial data and its ability to accommodate market stress models further bolster its appeal.

QR's flexibility allows researchers to explore the effects across various points of the market return distribution, providing insights into herding behavior at different quantiles. By setting the quantile parameter t to values like 0.1 or 0.25, analysts can obtain estimates for low returns, while setting it to 0.75 or 0.90 yields estimates for extremely high returns. This granularity enables a comprehensive examination of herding tendencies across the entire spectrum of market conditions.

Empirical studies have showcased QR's efficacy in diverse financial contexts. For instance, Chiang *et al.* (2010) applied QR to the Chinese stock market and found that QR estimates outperformed those from ordinary least squares (OLS) regression, offering higher coverage and efficiency across different quantiles. Similarly, Barnes and Hughes (2002) demonstrated QR's utility in detecting extreme values with fat tails or skewed distributions, underscoring its relevance in capturing nuanced features of financial data.

HP Filter (HP) and bubbles

The current literature has utilized the Hodrick-Prescott filter to identify speculative bubble cycles in Bitcoin. A study by M'bakob (2024) demonstrated evidence of "super cycles" in Bitcoin and Ethereum between 2019 and 2022. The study employed the HP Filter to verify that the halving mechanism serves as the primary factor driving the formation of cyclical speculative bubbles in Bitcoin and Ethereum during the years 2013, 2017, and 2021.

As the fundamental value of cryptocurrencies is hard to calculate, the use of HP (Hodrick-Prescott) Filter comes in use to find a definition of a "fundamental value", thus' the value of F_t is presented by the result of the HP filter at time t . P_t is represented by the log value of the price of the cryptocurrency i at time t. The difference between the price and the fundamental value represents the bubble B_t.

$$\begin{gathered} B_t = P_t - F_t \\ B_t = f(x) \end{gathered} \tag{6}$$

$$B_t = \alpha + \beta B_{t-1} + \gamma D_{Ht} + \varepsilon_t \quad (7)$$

where:

$$D_{Ht} = \begin{cases} 1, R_m^2 > threshold \\ 0, otherwise \end{cases}$$

Regressing B_t with the bubble at time *t-1* and the dummy variable it can be observed how a bubble reacts based on the changes in those independent variables. The dummy variable, D_{Ht} equals to 1 when R_m^2 is higher than the herding threshold based on the percentile of R_m^2 when in that sample herding using Equation 7. In simpler terms the dummy variable equals *1* when herding occurs. This allows the relation between the bubble and herding to be seen.

Results

Considering the market fluctuations observed over the past eight years within the cryptocurrency market, this study delineates two distinct timeframes for analysis: pre-2019 and post-2019. To discern herding behavior, a market portfolio is constructed for each of these periods. This portfolio is compiled from the daily closing prices of the top 20 cryptocurrencies, determined by their market capitalization levels, as sourced from https://coinmarketcap.com.

Econometric findings for the pre-2019 period

Data and descriptive statistics

To construct the portfolio for the pre-2019 period, a selection of daily prices of 9 out of 20 cryptocurrencies is made based on their market capitalization as of March 24, 2019, as provided by data from https://coinmarketcap.com. The sample period spans from January 1, 2016, to February 1, 2019. The details of the selected cryptocurrencies and their market capitalization can be observed in Table 2.

An examination of the descriptive statistics of the log returns of these nine cryptocurrencies for the period from January 1, 2016, to February 1, 2019 is presented in Table 3. Notably, apart from Bitcoin (BTC), all other cryptocurrencies exhibit a right-skewed distribution, indicating a tendency towards higher positive returns. Additionally, all cryptocurrencies demonstrate peakedness relative to a normal distribution, suggesting higher kurtosis in their return distributions

Further the CSAD and $r_{m,t}^2$ for the nine cryptocurrencies was computed based on the methodology. Analyzing the descriptive statistics, it can be observed in Table 4 that $CSAD_{m,t}$ has a positive skewness indicating a long right tailed distribution and kurtosis being higher than 3 means that the distribution is peaked relative to normal. While $r_{m,t}^2$ indicated a negative skewness meaning a long left tailed distribution and kurtosis indicates that the distribution is also peaked relative to normal. It can be observed that the mean of the market dispersion is higher than the return of the market. The market return shows that the maximum value of 0.071396 and minimum value of -0.07822 showing the volatility of the market during the period of the sample.

Empirical results of the estimated regression models

The statistical analyses and data processing for these results were conducted using EViews version 10 and Microsoft Excel 2013.

Based on the estimation of Equation (4) using least squares, the results presented in Table 5 indicate that approximately 39.15% of the variations in the dispersion of returns are explained by the independent market return variables. Specifically, the coefficient β_3 is estimated to be -0.434971, which is negative, supporting the alternative hypothesis $H_1: \beta_3 \neq 0$. This negative coefficient provides evidence of herding behavior, as it suggests that the Cross-Sectional Absolute Deviation $CSAD_{m,t}$ tends to decrease with an increase in the market return. Additionally, the Durbin-Watson statistic value of 1.387238, which exceeds the critical threshold of 1.3, indicates less evidence of autocorrelation in the regression, suggesting that the model's residuals are independent of each other.

Estimation of Equation (4) using quantile regression was conducted with 100 quantiles, the results of which are presented in Table 6. Analysis reveals statistically significant negative coefficients at higher quantiles, ranging from 0.780 to 0.810 and again from 0.920 to 0.980. Notably, two coefficients at quantiles 0.940 and 0.960 are negative at the 1% significance level, indicating a propensity for herding behavior at higher returns. Additionally, smaller quantiles, ranging from 0.110 to 0.260, exhibit statistically negative coefficients, with quantile 0.180 showing significance at the 1% level. This suggests that herding is also prevalent at lower returns, albeit to a lesser extent compared to higher returns.

The analysis of the distribution of Equation (4) using the t-statistic and a threshold of ±1.65 (10%) is depicted in Figure 1. It is important to note that when the t-statistic exceeds the negative threshold of -1.65, it indicates the occurrence of herding within the distribution. Consistent with expectations, the results reveal instances of herding occurring at the extremes of the distribution, both at higher returns and smaller returns. Specifically, the lowest t-statistic value recorded is -2.7038, observed at the 0.1233% percentile of $r_{m,t}^2$. This finding suggests that herding is more likely to occur at higher percentiles, corresponding to higher returns in the market.

Equation (5) extends the regression model to further analyze the nature of market movements during which herding occurs. By estimating Equation (5) using least squares, the coefficient β_4 found to be negative, indicating that herding is expected to occur during downward market movements.

Subsequently, Equation (5) is estimated using quantile regression, and the quantile process estimates of the coefficients are presented in Table 8. Notably, at the 1% significance level, quantile 0.970 exhibits the lowest value, signifying that herding occurs at high market returns. This observation aligns with the trend observed in the quantile estimates of Equation (4), where herding is prominent at either very low or high quantiles.

To analyze when herding events occurred Figure 2 was made using the market return and t-stat percentiles to identify if herding events occurred on the specific timeframes. A herding event equals 1 when the market return squared $r_{m,t}^2$ is higher than t_1=0.11 (0.0002% percentile) or lower than t_2=0.26 (0.013% percentile) or higher than t_3= 0.78 (0.0293% percentile). Results from this analysis reveal significant herding events during the summer of 2017 and starting from January 1, 2018.

To evaluate the herding effect during time, $r_{m,t}^2$ value was spread for the period of the analysis meaning 1/1/2016-2/1/2019 presented in Figure 3. The herding threshold was chosen based on the 0.780 quantile estimate for Equation (4) seen in Table 6, by taking the 0.78 percentile of the market returns squared, resulting in a value of 0.000293, indicated by the red line. Any value of $r_{m,t}^2$ surpassing this threshold indicates that herding occurs.

The empirical findings suggest that herding predominantly occurs during downward market movements or at high returns. To contextualize these findings, the log price of Bitcoin in USD is included in the plot in green, facilitating a comparison between instances of herding and Bitcoin price fluctuations. Notably, when Bitcoin reached its peak value at the end of 2017 and subsequently began to decline in early January, herding events were observed at very high values, reinforcing the notion that herding coincides with downward market movements.

Quantitative results for the post-2019 period

Data and summary statistics

The sample for the post-2019 period, spanning from January 1, 2019, to July 1, 2022, comprises daily closing prices of the top 20 cryptocurrencies, sourced from https://coinmarketcap.com, as depicted in Table 9.

Analysing the descriptive statistics of the individual log returns, as presented in Table 10, reveals notable trends. With the exception of BSV, DOGE, DOT, SHIB, USDT, and XLM, all other cryptocurrencies exhibit left-tailed distributions, indicated by negative skewness values. Additionally, these cryptocurrencies demonstrate peakedness relative to a normal distribution, as evidenced by kurtosis values exceeding 3. These characteristics highlight deviations from normality in the distribution of log returns across most cryptocurrencies in the post-2019 period.

Econometric outcomes of the estimated regression models

Analysing the descriptive statistics of the variables observed in Table 11, we observe that both $CSAD_{m,t}$ and $r_{m,t}$ present a kurtosis higher than 3 and positive skewness. These findings suggest a distribution that is relatively peaked compared to the normal distribution and exhibits right-tailedness.

Estimating Equation (4) using both least squares and quantile regression methods, the results in Table 12 and Table 13, respectively, indicate that the coefficient β_3 is negative, suggesting evidence of herding. However, this coefficient is statistically significant at the 1% level only when the equation is estimated under the quantile regression framework. This finding supports the expectation that $CSAD_{m,t}$ decreases with the market return, indicating the presence of herding behaviour.

Estimating Equation (4) via quantile regression involved the utilization of 100 quantiles, the results of which are detailed in Table 14. It is notable that statistically significant negative coefficients at the 1% level begin to emerge at lower quantiles, specifically between 0.34 and 0.68, and reappear at higher quantiles from 0.92 to 0.99. This suggests that herding is more likely to occur at higher returns; however, there is also evidence indicating that herding takes place with a lesser impact at smaller quantiles.

Analyzing the distribution of Equation (4) using the t-statistic and a threshold of ±1.65(10%) is illustrated in Figure 3. Remarkably, the lowest recorded t-statistic value stands at -7.5394, identified at the 0.015% percentile of $r_{m,t}^2$. This finding suggests that during the post-2019 period, herding tendencies are more likely to manifest at moderate levels of returns. In financial terms, "medium returns" denote average or moderate levels of investment performance, falling neither in the high nor low extremes, but rather within a middle range.

For further investigation into the specific type of market movement where herding is detected, Ordinary Least Squares (OLS) and Quantile Regression (QR) estimations of Equation (5) were conducted, with results presented in Table 15 and Table 16 respectively. The OLS estimation indicates that neither coefficients β_3 nor β_4 are statistically significant at the 1% level, despite both exhibiting negative values. This could potentially lead to a misleading conclusion. Conversely, the QR estimation reveals that only the negative coefficient β_4 is statistically significant at the 1% level, suggesting that herding may occur during upward market movements.

Estimation of Equation (5) using quantile regression was made using 100 quantiles and an extraction for the 1% statistically significant quantiles of $Dr_{m,t}^2$ are presented in Table 17. Analysing the statistically significant quantiles we can imply that herding is more likely to occur at higher returns but also at smaller returns as negatively statistically coefficients start at 0.34 until 0.59 and start again at 0.92 until 0.98. The lowest t-stat value is 15.9028 at 0.098% percentile of $r_{m,t}^2$, indicating that during the post-2019 period, higher returns have a more significant impact, suggesting a higher likelihood of herding during upper market movements.

To analyze the herding effect during time, Figure 5 presenting the market return $r_{m,t}^2$ and herding events. Herding events were computed starting from using the t-stat percentiles to identify if herding events occurred on the specific timeframes. A herding event equals 1 when the market return squared if $r_{m,t}^2$ is higher tha t_1=0.11 (0.0003% percentile) or lower than t_2=0.26 (0.0020% percentile) or higher than t3= 0.78 (0.00341% percentile).

Finally Figure 6 presents the evolution of BTC/USD, $r_{m,t}^2$ and the herding threshold selected from t_3=0.79 (0.00341%) implying that if $r_{m,t}^2$ surpasses the threshold there is herding. As BTC is a significant signal for other cryptocurrencies, we can analyze on the plot if there is a significant herding event during the same time a market movement occurred in BTC. Notably, interesting results emerge in May 2021, where herding coincides with a notable down-market movement, whereas in September 2021, herding occurs during an upward market movement. This is followed by another instance of herding in May 2022, preceding another significant down-market movement.

HP Filter and bubbles

Given Bitcoin's prominence as the cryptocurrency with the largest market capitalization, it is anticipated that news related to Bitcoin could significantly influence or direct investor behavior. Vidal-Thomas and Ibanez (2018) presented evidence suggesting that investors primarily react to news concerning Bitcoin.

Estimating linearly Equation (7) for the sample of Bitcoin daily log prices from 1/1/2016 to 1/1/2019 the results can be observed in Table 18. As γ is negative this shows evidence that if the dummy variable rises by one unit than the dependent variable $B_t$decreases by 0.003203. This suggests that herding is more likely to occur following the burst of a bubble.

Discussion

The outcomes of this research align with significant cryptocurrency market events observed during the respective timeframes investigated, drawing parallels to recent studies. In the pre-2019 period, marked by notable volatility, particularly exemplified by Bitcoin's surges and subsequent corrections (Vidal-Tomas & Ibanez, 2018), our findings suggest a likely occurrence of herding behavior among investors, especially during downward market movements. This trend resonates with research by Mohamad and Stavroyiannis (2022), which revealed anti-herding behavior in Bitcoin and major foreign exchange currencies during the same period, indicating decisions made based on private information or individual assessments rather than mimicking others' actions.

Transitioning to the post-2019 era, the onset of the COVID-19 pandemic brought about unparalleled economic uncertainty, affecting both traditional financial markets and cryptocurrencies. The sharp decline in cryptocurrency prices, coinciding with the pandemic's onset in early 2020, likely exacerbated herding tendencies among investors, as evidenced by our study's findings of herding occurring during both upward and downward market movements. This finding resonates with the research by Yarovaya *et al.* (2020), which found that the pandemic did not significantly alter herding patterns in cryptocurrency markets, suggesting resilience to psychological biases induced by global crises.

Moreover, regulatory developments played a pivotal role in shaping cryptocurrency market dynamics during the post-2019 period, as evidenced by the study by Mandaci and Cagli (2022). Ongoing regulatory discussions and actions worldwide regarding cryptocurrency oversight introduced additional layers of uncertainty, potentially influencing observed patterns of herding. Comparing results between distinct periods sheds light on historical movements within the cryptocurrency market. Despite challenges in constructing comprehensive market portfolios during the pre-2019 accumulation phase, our study ensures a robust analysis of market dynamics across both periods, aligning with recent literature emphasizing the importance of analyzing herding behavior in cryptocurrency markets amidst evolving regulatory landscapes and market stressors. The alignment of our findings with recent studies underscores the intricate interplay between market dynamics, external factors, and investor behavior within the cryptocurrency ecosystem, offering valuable insights for policymakers, investors, and researchers navigating this rapidly evolving landscape.

Conclusions

This paper investigates the presence of market-wide herding in the cryptocurrency market during two distinct periods: pre-2019 and post-2019. Utilizing the Cross-Sectional Absolute Deviation of returns (CSAD) model, augmented with modifications proposed by Chiang and Zheng (2010) to account for asymmetric investor behavior, herding behavior is detected.

Quantile Regression is employed to handle outliers prevalent in the volatile cryptocurrency market, while T-stat and Quantile Process Estimates are analyzed to gauge the magnitude of return impacts. Additionally, an analysis using the Hodrick-Prescott (HP) filter examines the relationship between herding and Bitcoin price bubbles, inspired by research indicating that investors predominantly respond to Bitcoin news.

The findings reveal evidence of herding behavior in the pre-2019 period, particularly during downward market movements, underscoring the significance of understanding behavioral finance perspectives. During market downturns, investors tend to act impulsively to minimize losses, reacting based on market information in hopes of mitigating their losses. Notably, herding around Bitcoin is observed to be more prevalent following the bursting of bubbles, serving as a signal to investors that losses are likely and incentivizing them to herd.

Conversely, results from the post-2019 period show evidence of herding during upward market movements, contrasting with the pre-2019 period. This discrepancy can be attributed to the cryptocurrency market's peak in 2022, followed by a rapid decline exacerbated by the COVID-19 crisis. While the crisis does not amplify herding, it does facilitate its presence, according to Yarovaya *et al.* (2020).

However, the study has limitations, including the combination of cryptocurrencies and tokens in the portfolio, despite variations in investor reactions. Furthermore, the static nature of the CSAD model does not fully capture the dynamic aspects of herding behavior. Future research could address these limitations by employing additional robustness analyses, such as estimating the CSAD model with GARCH to minimize heteroskedasticity.

In conclusion, the study contributes to understanding the implications of the cryptocurrency market's rapid evolution as a speculative investment. The absence of fundamental value and susceptibility to news underscores the need for further examination, particularly regarding the market's volatility and liquidity. Future research avenues include exploring the contagiousness of volatility across markets and examining the impact of historical herding on future price movements.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Annex

Table 1. Overview of recent cryptocurrency literature

Author	Period	Variables	Methods	Empirical outcomes
M'bakob (2024)	2013–2023	Bitcoin (BTC) and Etherum (ETH)	Hodrick-Prescott (HP) filter and Autoregressive Distributed Lag (ARDL)	Halving mechanism serves as the primary factor driving the formation of cyclical speculative bubbles
Gamayel & Preda (2024)	2016–2019	119 cryptocurrencies transaction level data	LSV measure; FHW measure; Sias measure; Investor Herding measure	Fear of missing out (FOMO), plays a significant role in trading behavior during downturns.
Wang *et al.* (2023)	2015–2022	Bitcoin (BTC)	(GJR) GARCH model	positive asymmetric volatility behavior in Bitcoin, confirming the presence of FOMO(Fear-Of-Missing-Out)
Yarovaya *et al.* (2020)	2019–2020	Bitcoin (BTC), Etherum (ETH) and Litecoin (LTC)	CSAD, MS with EM algorithm, TVR model	COVID-19 did not significantly alter herding patterns but remained dependent on market conditions (up or down days)
Mandaci & Cagli (2022)	2019–2021	Bitcoin (BTC) and 8 altercoins	Granger Causality; Fourier approximation	Significant herding behavior during COVID-19 outbreak; herding had significant effect on market volatility.
Koch & Dimpfl (2023)	2017–2021	Bitcoin (BTC), Etherum (ETH), Litecoin (LTC), Monero (XMR); S&P 500, CBOE VIX and Gold.	Realized Correlations; S Y N C measure; VAR model	Main focus of the investors lies on the Bitcoin market
Mohamad & Stavroyiannis (2022)	2018–2022	Bitcoin (BTC) & foreign exchange (FX) majors	CSAD static model, TVP model, Wavelet coherence	Herding between FX majors is time-varying and horizon dependent; presence of anti-herding in Bitcoin (BTC)

Table 2. Sample for pre-2019 Period

Cryptocurrency	Market Cap($)	Price($)	Volume	Circulating Supply	Date Samples
Bitcoin(BTC)	70.8 B	4,022	8.8 B	17.6M	1/1/2016-2/1/2019
Etherum(ETH)	14.5 B	137	4 B	105.3M	1/1/2016-2/1/2019
Ripple(XRP)	12.8 B	0.3	593 M	41.6B	1/1/2016-2/1/2019
Litecoin(LTC)	3.6 B	60	2.1 B	61.0 M	1/1/2016-2/1/2019
Stellar(XLM)	2 B	0.1	194M	19.2 B	1/1/2016-2/1/2019
Tether(USDT)	2 B	1.0	7.4 B	2 B	1/1/2016-2/1/2019
Monero(XMR)	908 M	54	84.1 M	16.8 M	1/1/2016-2/1/2019
DASH(DASH)	807M	93	247M	8.7 M	1/1/2016-2/1/2019
NEM(XEM)	461 M	0.1	14M	8.9 B	1/1/2016-2/1/2019

Source: Extracted on 24.3.2019 from https://coinmarketcap.com/

Table 3. Descriptive Statistics for 9/20 selected cryptocurrencies (pre-2019) period
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Cryptocurrency	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis
Bitcoin (BTC)	0.0008	0.0971	- 0.0878	0.0174	- 0.1469	7.4936
Etherum(ETH)	0.0018	0.1243	- 0.1389	0.0280	0.2030	6.3084
Ripple (XRP)	0.0015	0.4465	- 0.2836	0.0362	2.4955	32.9013
Litecoin (LTC)	0.0009	0.2252	- 0.1698	0.0257	1.2537	15.4328
Tether (USDT)	0.0000	0.0248	- 0.0206	0.0029	0.5549	18.0844
Stellar (XLM)	0.0015	0.3058	- 0.1448	0.0374	2.0572	17.5341
Monero (XMR)	0.0018	0.2465	- 0.1267	0.0315	1.0165	9.9782
Dash (DASH)	0.0011	0.1664	- 0.1057	0.0267	0.7786	7.9169
NEM (NEM)	0.0021	0.4640	- 0.1871	0.0385	2.5212	27.2332

Source: Own computation in EViews.

Table 4. Descriptive statistics of cross-sectional absolute deviation of returns (CSAD) and market return for pre-2019 period

Variables	Mean	Max	Min	St. Dev	Skewness	Kurtosis	N
$CSAD_{m,t}$	0.0180	0.1054	0.0025	0.0118	2.0065	9.5907	1128
$r_{m,t}$	0.0013	0.0714	- 0.0782	0.0166	- 0.0870	5.3283	1128

Source: Own computation in EViews.

Table 5. OLS Estimation of Equation (4) for pre-2019 period

$\propto$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\overline{\boldsymbol{R^2}}$	*N*	***Durbin-Watson stat***
0.0105	0.0972	0.6284	- 0.4350	0.3915	1128	1.3872

Source: Own computation in EViews.

Table 6. Quantile Estimates of Equation (4) for pre-2019 period

$r_{m,t}^2$	Quantile	Coefficient	Std. Error	t-stat	p-value
	0.11	- 1.7736	0.9788	- 1.8121	0.0702
	0.12	- 2.2816	1.0423	- 2.1890	0.0288
	0.13	- 2.4617	1.0821	- 2.2750	0.0231
	0.14	- 2.1038	1.0929	- 1.9251	0.0545
	0.15	- 2.6803	1.0907	- 2.4574	0.0141
	0.16	- 2.2683	1.1039	- 2.0547	0.0401
	0.17	- 2.7426	1.1310	- 2.4249	0.0155
	0.18	- 3.1312	1.1677	- 2.6815	0.0074
	0.19	- 2.6449	1.2248	- 2.1594	0.0310
	0.2	- 2.7243	1.2902	- 2.1115	0.0349
	0.21	- 2.8860	1.3052	- 2.2112	0.0272
	0.22	- 2.8266	1.4823	- 1.9069	0.0568
	0.26	- 3.2174	1.9053	- 1.6887	0.0916
	0.78	- 2.4288	1.4262	- 1.7030	0.0889
	0.79	- 2.4234	1.4623	- 1.6573	0.0977
	0.8	- 3.2215	1.4154	- 2.2761	0.0230
	0.81	- 2.8703	1.6932	- 1.6952	0.0903
	0.92	- 4.4800	1.9008	- 2.3569	0.0186
	0.93	- 4.0392	1.8629	- 2.1682	0.0304
	0.94	- 4.6695	1.7270	- 2.7038	0.0070
	0.95	- 5.0434	2.0180	- 2.4992	0.0126

Table 6. Continued

$r_{m,t}^2$	Quantile	Coefficient	Std. Error	t-stat	p-value
	0.96	- 5.8084	2.1835	- 2.6601	0.0079
	0.97	- 5.9177	2.3110	- 2.5607	0.0106
	0.98	- 6.4430	2.7207	- 2.3682	0.0180

Source: Own computation in EViews.

Table 7. Estimation of Equation (5) for pre-2019 period

$\propto$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_4}$	$\overline{\boldsymbol{R^2}}$	N
0.0106	0.6966	- 0.5550	0.4191	- 1.1405	0.3914	1,128

Source: own computation in EViews.

Table 8. Quantile Estimates of Equation (5) for pre-2019 period

$(\mathbf{1}-\mathbf{D})\mathbf{r}_{\mathbf{m,t}}^{\mathbf{2}}$	Quantile	Coefficient	Std. Err	t-Statistic	p-value
	0.14	- 2.1373	1.2493	- 1.7108	0.0874
	0.15	- 2.6335	1.3730	- 1.9181	0.0554
	0.16	- 2.2325	1.1910	- 1.8745	0.0611
	0.17	- 2.3880	1.2164	- 1.9632	0.0499
	0.18	- 2.5521	1.2459	- 2.0483	0.0408
	0.19	- 2.7345	1.2752	- 2.1444	0.0322
	0.2	- 2.5926	1.2964	- 1.9998	0.0458
	0.21	- 2.9075	1.3364	- 2.1756	0.0298
	0.23	- 2.6189	1.5323	- 1.7091	0.0877
$\mathbf{Dr}_{\mathbf{m,t}}^{\mathbf{2}}$	0.11	- 2.6387	1.5224	- 1.7333	0.0833
	0.12	- 2.7047	1.5617	- 1.7319	0.0836
	0.13	- 3.2518	1.6045	- 2.0267	0.0429
	0.14	- 3.1726	1.6355	- 1.9399	0.0526
	0.15	- 3.3274	1.6727	- 1.9892	0.0469
	0.17	- 3.0476	1.7354	- 1.7562	0.0793
	0.18	- 3.3973	1.7460	- 1.9458	0.0519
	0.19	- 3.5993	1.7745	- 2.0284	0.0428
	0.2	- 3.8001	1.7338	- 2.1918	0.0286
	0.21	- 3.7510	1.7593	- 2.1321	0.0332
	0.22	- 3.9275	1.7472	- 2.2479	0.0248
	0.79	- 2.7545	1.5073	- 1.8275	0.0679
	0.8	- 3.1942	1.6989	- 1.8802	0.0603
	0.81	- 3.0093	1.5676	- 1.9197	0.0551
	0.91	- 4.1388	2.0854	- 1.9847	0.0474
	0.92	- 4.1455	1.9355	- 2.1418	0.0324
	0.93	- 3.7596	1.7670	- 2.1276	0.0336
	0.94	- 4.3535	1.6437	- 2.6486	0.0082
	0.95	- 4.5357	1.8323	- 2.4754	0.0135

Table 8. Continued

$(1-D)r_{m,t}^{2}$	Quantile	Coefficient	Std. Err	t-Statistic	p-value
	0.96	- 5.6530	2.3797	- 2.3755	0.0177
	0.97	- 5.9132	2.2639	- 2.6120	0.0091
	0.99	- 18.0423	10.2671	- 1.7573	0.0791

Source: Own computation in EViews.

Table 9. Sample for post-2019 period

Cryptocurrency	Market Cap($)	Price ($)	Volume	Circulating Supply	Data Samples
Bitcoin (BTC)	327.335B	16,986	19.01B	19.23M	01/01/2019-01/07/2022
Etherum (ETH)	154.412B	1,260	5.4B	122M	01/01/2019-01/07/2022
Tether (USDT)	65.584B	1	25.54B	65.58B	01/01/2019-01/07/2022
Ripple (XRP)	19.248B	0	874.23M	50.26B	01/01/2019-01/07/2022
Cardano (ADA)	10.949B	0	171.21M	34.46B	01/01/2019-01/07/2022
Binance (BNB)	46.294B	289	619.52M	159.97M	01/01/2019-01/07/2022
Doge Coin (DOGE)	13.42B	0	791.68M	132.67B	01/01/2019-01/07/2022
Litecoin (LTC)	5.765B	80	705.01M	71.77M	01/01/2019-01/07/2022
Solana (SOL)	5.143B	14	324.42M	363.96M	11/04/2020-01/07/2022
Polkadot (DOT)	6.285B	5	158.51M	1.14B	21/08/2020-01/07/2022
Stellar (XLM)	2.21B	0	40.53M	25.72B	01/01/2019-01/07/2022
NEM (XEM)	294.595M	0	7.14M	9.00B	01/01/2019-01/07/2022
Zcash (ZEC)	731.153M	46	36.97M	15.86M	01/01/2019-01/07/2022
Miota (IOTA)	593.533M	0	10.79M	2.78B	01/01/2019-01/07/2022
Eos (EOS)	1.002B	1	85.61M	1.08B	01/01/2019-01/07/2022
Bitcoin Cash (BCH)	2.15B	110	171.64M	19.25M	01/01/2019-01/07/2022
Tron (TRX)	4.867B	0	183.15M	92.11B	01/01/2019-01/07/2022
Maker (MKR)	623.862M	638	19.79M	977.63k	01/01/2019-01/07/2022
Shiba Inu (SHIB)	5.145B	0	149.38M	549.06T	17/04/2021-01/07/2022
Bitcoin SV (BSV)	800.759M	42	24.07M	19.24M	01/01/2019-01/07/2022

Source: Extracted on (01/07/2022) from https://coinmarketcap.com/.

Table 10. Descriptive statistics of individual log returns for post-2019 period

Cryptocurrency	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis
ADA	0.0008	0.1214	- 0.2187	0.0252	- 0.276	9.463
BCH	- 0.0002	0.1828	- 0.2438	0.0252	- 0.535	17.833
BNB	0.0012	0.2298	- 0.2359	0.0240	- 0.209	20.999
BSV	- 0.0002	0.3847	- 0.2434	0.0296	1.854	38.049
BTC	0.0005	0.0746	- 0.2018	0.0169	- 1.296	20.713
DOGE	0.0011	0.6585	- 0.2237	0.0351	6.031	109.362
DOT	0.0005	0.1931	- 0.2071	0.0313	0.204	9.382
EOS	- 0.0004	0.1909	- 0.2190	0.0261	- 0.702	15.024
ETH	0.0007	0.1002	- 0.2392	0.0216	- 1.330	17.394
IOTA	- 0.0001	0.1386	- 0.2361	0.0264	- 0.813	13.861
LTC	0.0002	0.1167	- 0.1950	0.0234	- 0.888	12.200
MKR	0.0002	0.1836	- 0.3553	0.0270	- 0.951	31.819
SHIB	0.0023	0.7270	- 0.3010	0.0687	3.098	36.936
SOL	0.0019	0.1682	- 0.2021	0.0355	- 0.091	6.297
TRX	0.0004	0.1451	- 0.2272	0.0240	- 0.745	13.522
USDT	- 0.0000	0.0232	- 0.0228	0.0016	0.336	74.730
XEM	- 0.0002	0.1423	- 0.1836	0.0264	- 0.415	9.833
XLM	- 0.0000	0.2429	- 0.1780	0.0246	0.699	17.481
XRP	- 0.0000	0.1932	- 0.2391	0.0256	- 0.114	18.934
ZEC	- 0.0000	0.1098	- 0.2343	0.0262	- 0.836	11.431

Source: Own computation, EViews Output.

Table 11. Descriptive statistics of cross-sectional absolute deviation of returns (CSAD) and market return for post-2019 period

Variable	Mean	Max	Min	St. Dev	Skewness	Kurtosis	N
$CSAD_{m,t}$	0.0369	0.7763	0.0020	0.0486	5.4382	57.8227	1277
$r_{m,t}$	0.0004	0.0402	0.0000	0.0016	18.2415	417.8505	1277

Source: own computation, EViews Output.

Table 12. OLS Estimation of Equation (4) for post-2019 period

$\propto$	β_1	β_2	β_3	N
0.0231	0.1776	1.1224	-2.6656	1,277

Source: Own computation, EViews Output.

Table 13. QR Estimation of Equation 4 for post-2019 period

∝	β1	β2	β3	N
0.0112	0.116066	1.1928	-4.4336***	1,277

Note: ***statistically significant at 1%

Source: Own computation, EViews Output.

Table 14. Quantile Process Estimates of Equation 4 for post-2019 period

	Quantile	Coefficient	Std. Error	t-stat	p-value
$r_{m,t}^2$	0.01	0.60119	0.1467	4.0988	0.0000
	0.02	0.47259	0.1734	2.7247	0.0065
	0.34	-2.04727	0.7666	-2.6705	0.0077
	0.35	-2.09099	0.7737	-2.7025	0.007
	0.36	-2.24654	0.7767	-2.8925	0.0039
	0.37	-2.80931	0.7682	-3.657	0.0003
	0.38	-3.06196	0.7587	-4.0359	0.0001
	0.39	-3.25496	0.7449	-4.3697	0.0000
	0.4	-3.21334	0.752	-4.2731	0.0000
	0.41	-3.30243	0.7359	-4.4877	0.0000
	0.42	-3.52512	0.7133	-4.942	0.0000
	0.43	-3.68737	0.6953	-5.303	0.0000
	0.44	-4.32452	0.6607	-6.5449	0.0000
	0.45	-4.23409	0.6712	-6.3082	0.0000
	0.46	-4.21882	0.6759	-6.2421	0.0000
	0.47	-4.24725	0.6806	-6.2401	0.0000
	0.48	-4.18996	0.6872	-6.0973	0.0000
	0.49	-4.41032	0.6866	-6.4233	0.0000
	0.5	-4.43365	0.6853	-6.4694	0.0000
	0.51	-4.41716	0.6846	-6.4518	0.0000
	0.52	-4.37023	0.6863	-6.3677	0.0000
	0.53	-4.41627	0.6783	-6.5111	0.0000
	0.54	-4.44268	0.6741	-6.5908	0.0000
	0.55	-4.50839	0.6658	-6.7716	0.0000
	0.56	-4.82531	0.6564	-7.3517	0.0000
	0.57	-4.70661	0.6587	-7.1452	0.0000
	0.58	-4.87547	0.667	-7.3094	0.0000
	0.59	-4.83444	0.668	-7.2368	0.0000
	0.6	-4.81943	0.6674	-7.2212	0.0000
	0.61	-4.97815	0.6603	-7.5394	0.0000
	0.62	-4.87205	0.6585	-7.3989	0.0000
	0.63	-4.71669	0.6799	-6.9372	0.0000
	0.64	-4.6084	0.7359	-6.2621	0.0000
	0.92	-8.67247	2.7179	-3.1908	0.0015
	0.93	-8.20987	2.6619	-3.0842	0.0021
	0.94	-8.15351	2.8005	-2.9114	0.0037

Table 14. Continued

	Quantile	Coefficient	Std. Error	t-stat	p-value
$r_{m,t}^2$	0.96	-9.65025	3.5877	-2.6898	0.0072
	0.97	-17.76575	3.2018	-5.5486	0.0000
	0.98	-16.49019	2.8915	-5.703	0.0000
	0.99	-35.91176	13.8573	-2.5915	0.0097
	0.99	-35.91176	13.8573	-2.5915	0.0097

Source: Own computation, EViews Output.

Table 15. OLS Estimation of Equation (5) for post-2019 period

∝	β_1	β_2	β_3	β_4	N
0.02231	1.527556	-0.95987	- 8.092990	-2.56022	1,277

Source: Own computation, EViews Output.

Table 16. QR Estimation of Equation (5) for post-2019 period

∝	β_1	β_2	β_3	β_4	N
0.01015	1.47344	-1.0979	- 9.071967	-4.5194***	1,277

Note: *** statistically significant 1%

Source: Own computation, EViews Output.

Table 17. Quantile Process Estimates of Equation (5) for post-2019 period

	Quantile	Coefficient	Std. Error	t-stat	p-value
$Dr_{m,t}^2$	0.01	0.5936	0.1473	4.0297	0.0001
	0.02	0.4647	0.1740	2.6704	0.0077
	0.34	- 2.1038	0.7715	- 2.7270	0.0065
	0.35	- 2.2625	0.7784	- 2.9065	0.0037
	0.36	- 2.3278	0.7799	- 2.9848	0.0029
	0.37	- 2.8403	0.7750	- 3.6647	0.0003
	0.38	- 2.9857	0.7691	- 3.8818	0.0001
	0.39	- 3.2413	0.7543	- 4.2970	0.0000
	0.4	- 3.2455	0.7558	- 4.2939	0.0000
	0.41	- 3.3868	0.7430	- 4.5585	0.0000
	0.42	- 3.5871	0.7283	- 4.9252	0.0000
	0.43	- 3.7982	0.7026	- 5.4059	0.0000
	0.44	- 4.3707	0.6699	- 6.5245	0.0000
	0.45	- 4.3076	0.7633	- 5.6434	0.0000
	0.46	- 4.3265	0.7677	- 5.6353	0.0000

Table 17. Continued

	Quantile	Coefficient	Std. Error	t-stat	p-value
$Dr^2_{m,t}$	0.47	- 4.3018	0.7734	- 5.5625	0.0000
	0.48	- 4.2444	0.7376	- 5.7544	0.0000
	0.49	- 4.5849	0.7801	- 5.8770	0.0000
	0.5	- 4.5194	0.7406	- 6.1022	0.0000
	0.51	- 4.4758	0.6866	- 6.5187	0.0000
	0.52	- 4.2699	0.7101	- 6.0129	0.0000
	0.57	- 4.4874	0.9746	- 4.6045	0.0000
	0.58	- 4.5149	0.8526	- 5.2958	0.0000
	0.59	- 4.9851	0.6730	- 7.4076	0.0000
	0.92	- 9.3073	2.6237	- 3.5474	0.0004
	0.93	- 8.8609	2.7307	- 3.2449	0.0012
	0.94	- 8.3949	3.4645	- 2.4231	0.0155
	0.98	- 15.9028	2.9431	- 5.4034	0.0000

Source: Own computation, EViews Output.

Table 18. Results of OLS Estimation for Equation (7)

α	β	γ	$\overline{R^2}$	N	Durbin-Watson stat
0.0006	0.9721	-0.0032	0.9418	1096	1.992

Source: Own computation, EViews Output.

Figure 1. t-stat disribution of Equation (4) pre-2019 period

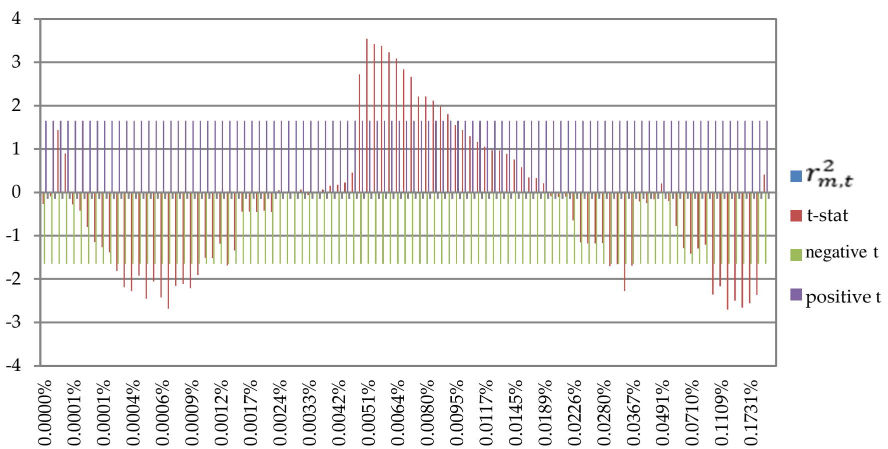

Figure 2. Herding events for pre-2019 period

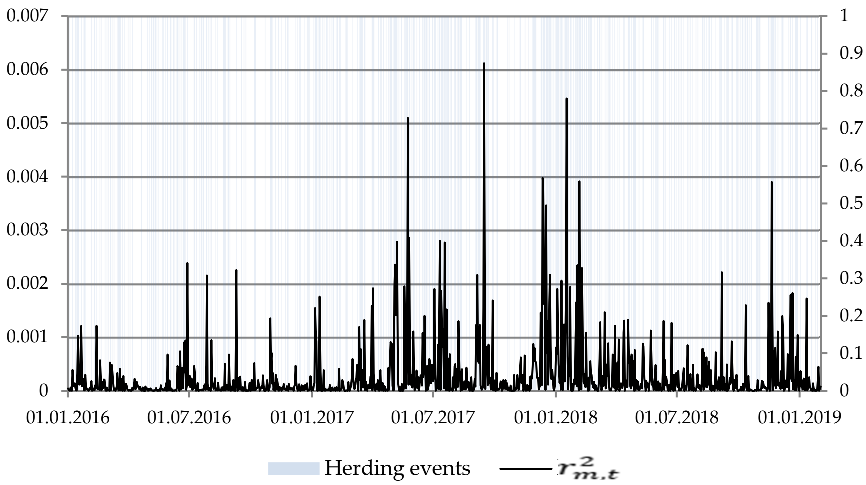

Figure 3. Herding effect during time, BTC analysis

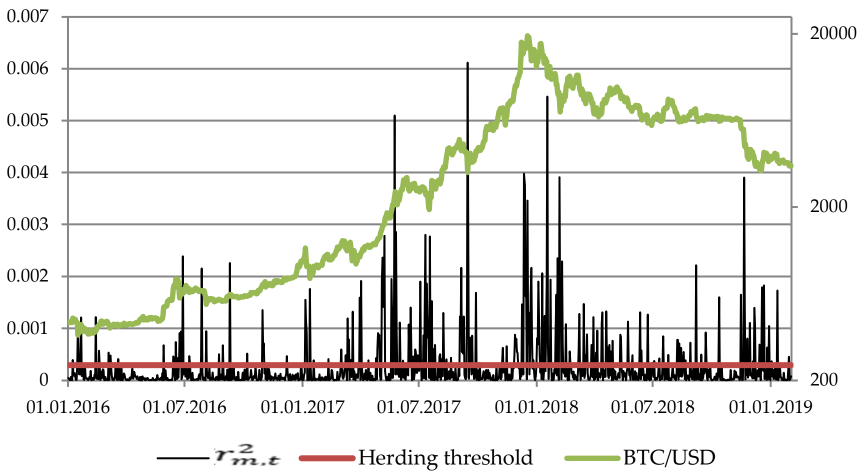

Figure 4. T-stat distribution of Equation (4)

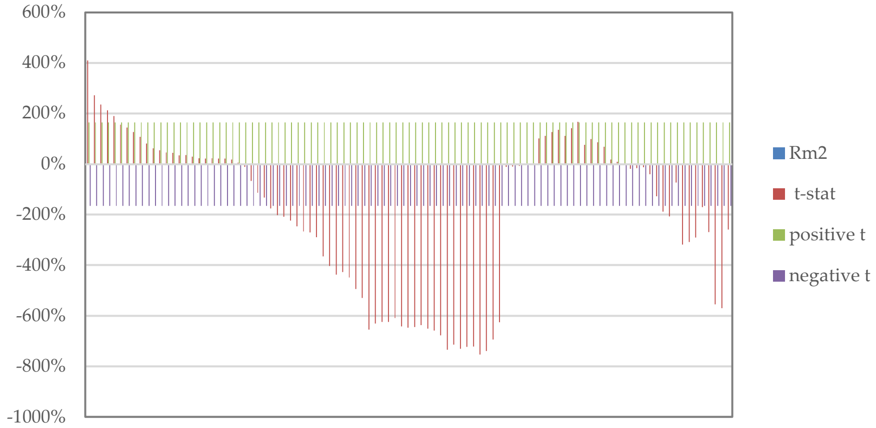

Figure 5. Herding events for post-2019 period

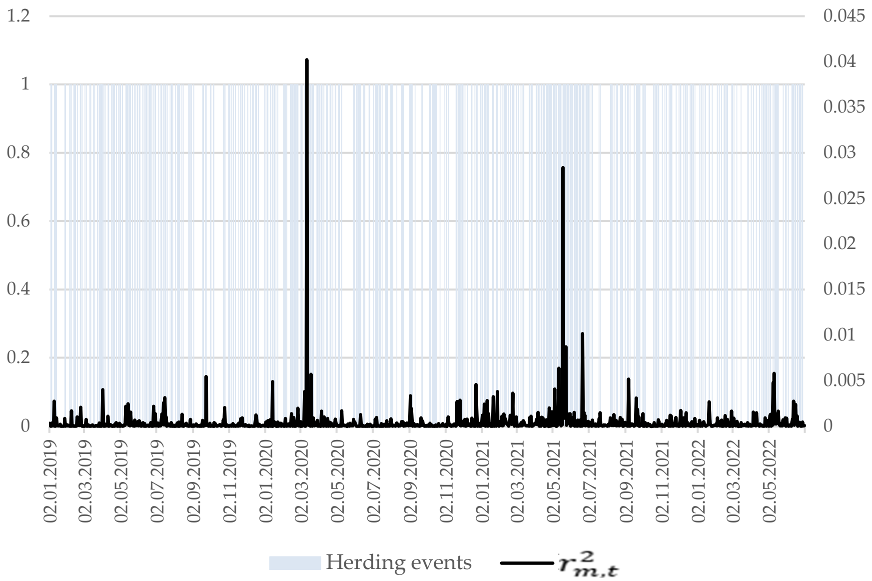

Figure 6. Herding effect during time with BTC/USD reference for post-2019 period