Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 3 No. 5 (May) (2025)

Herding Behavior in Cryptocurrency Markets: A Behavioral Perspective

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Abstract
This study examines herding behavior in the cryptocurrency market by utilizing the Cross-Sectional Absolute Deviation (CSAD) and Cross-Sectional Standard Deviation (CSSD) models to assess the dispersion of returns. Additionally, Granger Causality tests were employed to investigate the association between market returns and herding behavior. The data for this analysis are sourced from major cryptocurrency exchanges, covering a range of cryptocurrencies including Binance Coin, Bitcoin, Solana, Ripple and Ethereum. The dataset includes monthly returns over time frame 2019 to 2023, to capture both bullish and bearish market periods. Data is collected from publicly available platforms such as CoinMarketCap, Binance API, and Yahoo Finance. The results indicate the presence of herding, particularly during periods of market stress or strong trends, with asymmetric herding observed between bullish and bearish market conditions. Specifically, herding behavior is more pronounced during bearish days compared to bullish days. However, the Granger causality tests reveal no significant causal relationship between market returns and herding behavior, suggesting that immediate price movements do not directly influence investor herding. This finding implies that other factors, such as market sentiment, investor psychology, and external market events, may play a more significant role in driving herding behavior in cryptocurrency markets. The study highlights the complexity of investor behavior in the cryptocurrency market and calls for further research into alternative drivers of herding, including sentiment analysis and the role of retail versus institutional investors

Keywords: Herding Behavior; Cryptocurrency; CSAD; CSSD; Granger Causality

1. Introduction
The cryptocurrency market, characterized by its high volatility, decentralized structure, and speculative nature, has garnered significant attention in recent

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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years. As digital assets such as Bitcoin, Ethereum, and others gain popularity, understanding the dynamics that drive investor behavior in this market becomes crucial. One key aspect of investor behavior in financial markets, including cryptocurrency markets, is herding behavior. Herding refers to the tendency of investors to mimic the actions of others, often leading to price movements that deviate from underlying fundamentals (Bikhchandani et al., 1992). This phenomenon has been extensively studied in traditional financial markets, where it is seen as a cause of market bubbles and crashes (Chang et al., 2000). However, herding in cryptocurrency markets is a relatively unexplored area, despite its potential implications for market stability and investor welfare.

Herding behavior in financial markets is typically observed when individuals or institutional investors make decisions based on the actions of others rather than their private information. This behavior is often more prominent during periods of market stress or strong trends, where investors may become more susceptible to emotional decision-making, leading to price clustering. Herding can exacerbate market volatility, as investors follow the crowd, contributing to extreme price swings in both upward and downward market movements. The concept was initially created by Bikhchandani et al. (1992) and later expanded in studies by Christie & Huang (1995), Chang et al. (2000), and others, who developed models to detect and quantify herding behavior using market data.

The cryptocurrency market, though relatively young, has demonstrated significant growth and volatility, attracting both retail and institutional investors. Cryptocurrencies are highly speculative assets, and market prices are often driven by sentiment, news, and social media trends rather than traditional economic indicators or fundamentals (Cheah & Fry, 2015). The decentralized nature of cryptocurrency markets further complicates the factors that drive investor behavior. Given the speculative and often emotional nature of cryptocurrency trading, the potential for herding behavior is particularly high.

Several studies have examined herding in traditional financial markets and found that during times of market stress, such as economic downturns or crises, herding behavior tends to increase (Christie & Huang, 1995; Chang et al., 2000). This raises the question of whether similar dynamics exist in the cryptocurrency market. Do investors in the cryptocurrency market tend to herd during periods of market volatility, or do other factors such as social media influence, news events, or speculation play a larger role? This study seeks to address this gap by investigating the existence of herding behavior in cryptocurrency markets.

To detect herding, this study applies two popular models: the CSAD (Cross-Sectional Absolute Deviation) and the CSSD (Cross-Sectional Standard Deviation) models, which are widely used in the financial literature to measure return dispersion. These models compare the returns of individual assets to the market return to assess whether asset returns are clustered together (indicating herding behavior) or dispersed (indicating independent behavior) (Christie & Huang, 1995).

The average absolute deviation of each return from the market return is calculated by the CSAD model. A lower CSAD suggests herding, as returns become more clustered, while a higher CSAD indicates that individual asset returns are more dispersed, suggesting independent behavior. Similarly, the CSSD model, which uses standard deviation rather than absolute deviation, is another measure of return dispersion and has been shown to yield similar results to CSAD in detecting herding (Christie & Huang, 1995).

While the CSAD and CSSD models are effective for detecting herding behavior, it is also important to explore whether market returns themselves Granger cause herding behavior, i.e., whether past market returns can predict future herding. The Granger causality test, developed by Granger (1969), is used to examine whether one time series can be used to predict another. In this context, the test will help determine if market returns (or their volatility) are predictive of future herding behavior in the cryptocurrency market. The Granger causality approach has been applied in numerous studies to investigate the association between market returns and investor behavior, particularly in traditional markets (Jiang et al., 2011).

This study seeks to examine the subsequent aspects; Does herding behavior exist in the cryptocurrency market, and if so, during what conditions (e.g., market trends or stress)? Is herding behavior more pronounced during bullish or bearish market days? Do market returns Granger cause herding behavior, or are there other factors at play?

The primary contribution of this study is the application of established herding detection models (CSAD and CSSD) to the cryptocurrency market, providing insight into the behavioral patterns of investors in this emerging asset class. Additionally, the study examines the direction of causality between market returns and herding behavior, adding a novel aspect to the literature on cryptocurrency markets.

The subsequent sections of the study are structured as follows: Section 2 delineates the theoretical framework of the literature evaluation and the formulation of hypotheses. Section 3 delineates the data sources and variables employed in the analysis. Section 4 delineates the empirical findings, encompassing herding detection and causality analysis. Section 5 presents an analysis of the findings, succeeded by conclusions and recommendations for subsequent research.

2. Literature Review

The study of herding behavior in financial markets has been a prominent area of research for decades, particularly in the context of stock markets, commodities, and other asset classes. With the rise of the cryptocurrency market, it has become increasingly important to investigate whether traditional patterns of investor behavior, such as herding, are applicable to digital assets. This section reviews the existing literature on herding behavior, its detection methods, and its relevance to cryptocurrency markets.

Herding behavior denotes the inclination of individuals to replicate the acts of a bigger group, particularly in situations where they feel uncertain or lack enough information to make independent decisions (Bikhchandani et al., 1992). Investors who engage in herding do not act based on their private information but instead follow the behavior of others, which can lead to market inefficiencies, bubbles, and crashes (Shiller, 2000). In financial markets, herding is often seen as a psychological bias that exacerbates volatility and can distort asset prices away from their fundamental values (Devenow & Welch, 1996).

Early studies on herding behavior were primarily focused on traditional financial markets, where researchers sought to quantify the extent to which investors' actions diverge from rational behavior. Bikhchandani et al. (1992) introduced the concept of informational cascades, where individuals make decisions based on the observations of others rather than on their own private information. This theory has since been applied to various financial markets to explain the dynamics behind bubbles and market crashes (Lakonishok et al., 1992).

A multitude of studies has proven the presence of herding behavior in traditional equity markets. Christie and Huang (1995) used the Cross-Sectional Absolute Deviation (CSAD) model to detect herding in stock markets. They found that herding behavior increased during periods of market stress, such as the 1987 stock market crash, and was more pronounced in downward market movements. Similarly, Chang et al. (2000) applied the CSAD model across several global stock markets and found evidence of herding, particularly in countries with less developed financial markets, where investor behavior is more likely to be influenced by the actions of others.

Lakonishok et al. (1992) also explored the consequences of herding in equity markets and concluded that it could lead to market inefficiencies. Investors who follow the crowd rather than make independent decisions can contribute to the creation of speculative bubbles, which may eventually burst when the herding behavior reverses.

Moreover, the Granger causality test, introduced by Granger (1969), has been frequently used in herding studies to examine the direction of causality between market movements and herding behavior. Several studies have tested whether past market returns cause herding behavior or if the reverse is true (Jiang et al., 2011). The results of these tests are often mixed, with some studies finding significant causality from market returns to herding and others failing to detect such relationships.

The cryptocurrency market presents unique challenges and opportunities for the study of herding behavior due to its high volatility, lack of regulation, and reliance on digital platforms where sentiment and news can spread rapidly. Unlike traditional assets, cryptocurrencies are not subject to the same institutional constraints, making it more likely that retail investors, who are more susceptible to emotional decision-making, dominate the market (Cheah & Fry, 2015). The speculative nature of cryptocurrency trading, often driven by market hype, social media trends, and fear of missing out (FOMO), can further fuel herding behavior.

In the cryptocurrency context, Cheah and Fry (2015) explored speculative bubbles in the Bitcoin market and found evidence that the price of Bitcoin was driven largely by investor sentiment and speculative behavior, rather than by underlying technological or economic fundamentals. Their study emphasized the significance of social media networks, like Reddit and Twitter, where information and sentiment are rapidly disseminated, leading to the amplification of price movements and contributing to herding behavior. Fry and Cheah (2016) further expanded this analysis, noting that the volatility of cryptocurrencies might make herding more likely during extreme market events, such as rapid price increases or crashes.

Other studies have examined the influence of external factors such as media coverage, news events, and social networks on cryptocurrency prices. Zohar et al. (2018) found that social media sentiment and news about cryptocurrencies significantly influenced the trading behavior of retail investors, who were more prone to follow trends and herd together. Their research suggested that the emotional nature of cryptocurrency markets may make investors more likely to mimic each other, especially during periods of market optimism or panic.

Despite the increasing interest in herding behavior in cryptocurrency markets, empirical studies using models like CSAD and CSSD are still limited. Yermack (2017) provided an early analysis of behavior of herding in the Bitcoin market, noting that while speculative bubbles are evident, investor behavior in these markets does not always conform to traditional models of herding. Similarly, Kristoufek (2013) investigated the association among Bitcoin and other financial assets, finding that Bitcoin's price movements were not strongly correlated with those of traditional markets, which further complicates the dynamics of herding in cryptocurrencies.

The detection of herding behavior typically involves examining the dispersion of returns in a market. The most commonly used models for this purpose are the CSAD and CSSD models, both of which measure how individual asset returns deviate from the market average. In the CSAD model, a lower degree of return dispersion (lower CSAD) indicates higher herding behavior. The CSSD model, on the other hand, uses the standard deviation of asset returns and follows a similar logic.

These models have been applied extensively in traditional markets, but their application to cryptocurrency markets remains relatively new. Studies like Chang et al. (2000), Christie and Huang (1995), and Hwang and Salmon (2004) have demonstrated the usefulness of these models in detecting herding behavior in stock markets. However, applying these models to cryptocurrency markets introduces new challenges due to the unique characteristics of these markets, such as high volatility, market sentiment, and social influence (Bariviera et al., 2017).

The connection between market returns and herding behavior has been a key focus of empirical research. In traditional markets, some studies have found that market returns can Granger cause herding behavior, especially during periods of high volatility or extreme price movements (Jiang et al., 2011). However, the results are often inconsistent, with some studies failing to establish such causality.

In the bitcoin market, the swift dissemination of information via social media and news outlets and other digital channels may lead to instantaneous shifts in sentiment that affect investor behavior. This suggests that, in contrast to traditional markets, external factors may play a more prominent role in driving herding behavior in cryptocurrency markets. The Granger causality approach has been applied in some studies, but its effectiveness in capturing the complex interactions between market returns and herding behavior in the cryptocurrency market remains underexplored.

While substantial research has been conducted on herding behavior in traditional financial markets, its application to the cryptocurrency market is still in its infancy. Previous studies suggest that herding behavior is likely to be more pronounced during market stress, speculative periods, and extreme volatility, particularly in retail-dominated markets like cryptocurrencies. However, the role of social media, market sentiment, and external news events complicates the dynamics of investor behavior in this market. This research enhances the existing literature by analyzing whether traditional herding models, such as CSAD and CSSD, can be effectively applied to the cryptocurrency market and whether market returns Granger cause herding behavior.

2.1 Theoretical Foundations of Herding

The impression of herding can be theoretically grounded in models such as informational cascades (Banerjee, 1992; Bikhchandani et al.1992), where

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

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individuals rationally ignore their private information in favor of the observed behavior of others. Another explanation is reputational herding (Scharfstein & Stein, 1990), which occurs when professional investors imitate others to safeguard their reputation. Social influence theories also suggest that group behavior can override individual judgment, especially under conditions of ambiguity or social pressure.

2.2 Empirical Evidence in Traditional Financial Markets

Empirical studies have documented herding in various traditional asset classes. Christie and Huang (1995) and Chang et al. (2000) proposed statistical frameworks such as the Cross-Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) to detect herding. These models have been widely applied in stock markets across both developed and emerging economies, generally showing that herding behavior is particularly evident during times of market distress or significant returns.

2.3 Behavioral Finance and Cryptocurrency Markets

The cryptocurrency market presents a unique context for studying herding behavior due to its lack of intrinsic valuation models, high volatility, and strong influence from non-fundamental factors like social media sentiment and celebrity endorsements. According to Urquhart (2016) and Corbet et al. (2018), cryptocurrencies display characteristics inconsistent with market efficiency, making them particularly susceptible to behavioral biases. Research by Vidal-Tomás (2019) found evidence of herding in major cryptocurrencies, particularly during market downturns. Similarly, Blasco and Corredor (2021) observed herding among retail investors in Bitcoin markets, linking it to social contagion and speculative motives.

2.4 Gaps in the Literature

While herding behavior has been significantly explored in equity and bond markets, its presence in cryptocurrency markets is still an emerging area of research. Existing studies often focus on price dynamics or speculative bubbles, with limited attention to psychological and behavioral drivers. Moreover, few studies differentiate between rational (information-based) and irrational (emotion-driven) herding. The role of social media, peer influence, and digital community culture in amplifying herding remains underexplored. This study aims to bridge these gaps by adopting a behavioral finance perspective to assess herding patterns in the cryptocurrency market.

2.4 Theoretical Framework and Hypotheses Development

Herding behavior challenges the rational agent model of traditional finance by demonstrating that individuals frequently rely their decisions on the behaviors of others instead of their own confidential knowledge or analysis. This behavior is particularly salient in cryptocurrency markets, where high volatility, lack of regulation, and rapid information dissemination through digital channels create an environment conducive to irrational investment behavior.

2.4.1 Theoretical Underpinnings

a) Behavioral Finance Theory

Behavioral finance provides the foundational lens through which herding behavior can be understood. Investors are not always rational; instead, they are subject to cognitive biases, limited information-processing capacity, and social influence (Thaler, 1980). In the context of cryptocurrency, behavioral factors such as *fear of missing out (FOMO)*, *overconfidence*, and *loss aversion* amplify herding tendencies, as investors react emotionally to market trends and peer behavior.

b) Informational Cascades Theory

Informational cascade theory (Bikhchandani et al., 1992) suggests that when individuals make decisions sequentially, they may ignore their own information in favor of the activities of others, resulting in herd behavior. In the crypto market, where price signals and trading decisions are highly visible and shared in real-time, informational cascades can occur quickly and drive asset prices away from fundamental values.

c) Social Learning and Digital Influence

Cryptocurrency markets are deeply embedded in online communities (e.g., Reddit, Twitter, Discord), where information spreads rapidly and investors often seek validation. This creates a feedback loop where price movements and social sentiment reinforce each other, fueling coordinated actions and crowd behavior.

2.5 Hypotheses Development

Based on the theoretical foundation and empirical gaps identified in the literature, the subsequent hypotheses are proposed:

H1: Cryptocurrency markets have significant evidence of herding tendencies.

Investors are likely to mimic the trading behavior of others, especially in the absence of clear fundamental valuation models. This hypothesis aims to establish whether herding behavior can be detected in the cryptocurrency market, based on the clustering of asset returns during specific market conditions, such as periods of market stress or strong trends.

H2: Herding behavior is more obvious during periods of extreme market returns (bullish or bearish).

Investors may abandon individual judgment during market uncertainty, relying on collective behavior to guide decisions. This hypothesis tests whether investors are more likely to herd during market downturns, where fear and panic may drive collective behavior in an effort to avoid losses.

H3: Retail investor activity contributes more significantly to herding behavior than institutional investor activity.

Retail investors are more susceptible to behavioral biases and social influence due to lower financial literacy and access to private information. This hypothesis aims to examine whether past market returns (either positive or negative) can predict future herding behavior in the cryptocurrency market. This will be tested using Granger causality to investigate the direction of causality between market returns and return dispersion (a proxy for herding).

H4: Social media sentiment positively correlates with herding intensity in cryptocurrency markets.

Online platforms act as echo chambers that amplify consensus behavior, contributing to coordinated investment actions. This hypothesis aims to examine

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www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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whether past market returns (either positive or negative) can predict future herding behavior in the cryptocurrency market. This will be tested using Granger causality to investigate the direction of causality between market returns and return dispersion (a proxy for herding).

3. Methodology

Investigating the existence of herding behavior in cryptocurrency markets is the aim of this study. To achieve this, we employ the Cross-Sectional Absolute Deviation (CSAD) model, a widely used approach in financial literature (Chang et al., 2000; Christie & Huang, 1995). Herding is often identified when returns become more closely clustered, suggesting that investors are mimicking the behavior of others rather than making independent investment decisions.
In particular, we hypothesize that during periods of market stress or strong market trends, investors may exhibit herding behavior, leading to a higher concentration of returns across assets. This clustering can be detected by observing the dispersion of asset returns in the market.
The methodology for this study is divided into three main parts: detecting herding behavior, examining asymmetric herding, and testing for Granger causality. Below, we provide a detailed explanation of each step.

3.1 Data

Major cryptocurrency exchanges provided the data for this investigation, which covered a variety of cryptocurrencies like as Ethereum, Bitcoin, Binance Coin, Solana, and Ripple.The dataset includes monthly returns over time frame (2019 to 2023) to capture both bullish and bearish market periods. Data is collected from publicly available platforms such as CoinMarketCap, Binance API, and Yahoo Finance. The CSAD and CSSD models will be estimated using ordinary least squares (OLS) regression. The Granger causality test will be performed using lagged market returns to test the predictive power of past returns on herding behavior. By combining these methodologies, this study aims to provide valuable insights into the dynamics of herding in the cryptocurrency market and its potential implications for market stability.

3.2 Variables and Measures

In this section, we define the key variables and measures used to analyze herding behavior in the cryptocurrency market using the CSAD model.

3.2.1 Market Return (Rm,t)

The Market Return at time t represents the average return of all cryptocurrencies in the sample. It is calculated as:
$R_{m,t}=1/N\ N\sum i=1R_{i,\ t}$
Where, $R_{m,t}$ is the market return at time t, N is the total number of cryptocurrencies in the sample, $R_{i,t}$ is the return of cryptocurrency i at time t. The market return is a key indicator of the overall market performance at any given time and serves as a benchmark for individual asset returns.

3.2.2 Individual Asset Return ($R_{i,t}$)

The Individual Asset Return for each cryptocurrency iii at time ttt is defined as the percentage change in the price of cryptocurrency iii from the previous time period.

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www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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It is given by:
$R_{i,t} = P_{i,t} - P_{i,t-1} / P_{i,t-1}$
Where, $R_{i,t}$ is the return of cryptocurrency i at time t, $P_{i,t}$ is the price of cryptocurrency i at time t, $P_{i,t-1}$ is the price of cryptocurrency i at time t−1.
This measure reflects the return of each individual cryptocurrency over a given period and is critical for calculating the cross-sectional dispersion of returns across all assets in the sample.

3.2.3 Cross-Sectional Absolute Deviation (CSAD)

The main metric for evaluating how returns are distributed among cryptocurrencies in the market is the Cross-Sectional Absolute Deviation (CSAD). It determines the average absolute divergence between the mean market return and the returns on individual assets. The equation is:
$CSAD_t = 1/N \; N\sum i=1 \; |R_{i,t} - R_{m,t}|$
where N is the total number of cryptocurrencies in the sample, Ri,t is the cryptocurrency's return at time t, Rm,t is the market return at time t, and CSADt is the cross-sectional absolute deviation at time t.
CSAD measures the degree to which individual cryptocurrency returns deviate from the market return. High values of CSAD suggest greater dispersion in returns, indicating that investors are acting independently, while lower values of CSAD suggest that returns are more clustered, possibly due to herding behavior where investors follow similar strategies or trends.
A low value of CSAD at time t indicates that the returns of individual cryptocurrencies are closely aligned with the market return, suggesting possible herding behavior, especially in times of strong market trends or stress. A high value of CSAD at time t suggests that there is greater dispersion in the returns, implying that individual assets are behaving independently, without a strong tendency to follow the market direction.
By analyzing the CSAD, we can infer the degree of market conformity and herding, which is essential for understanding investor behavior in cryptocurrency markets during periods of market volatility or strong trends.

3.3 Additional Tests

To further explore herding behavior in the cryptocurrency market, we introduce additional tests to refine our analysis and provide robustness to the results. These tests include the examination of asymmetric herding during bullish and bearish market conditions, as well as a robustness check using the Cross-Sectional Standard Deviation (CSSD) model.

3.3.1 Asymmetric Herding

To assess whether herding behavior is more pronounced during bullish (positive) or bearish (negative) market days, we perform separate models for these two conditions. Specifically, we distinguish between positive market returns (bullish days) and negative market returns (bearish days), testing whether herding behavior differs in these market environments.
The modified CSAD model for bullish and bearish days is as follows:
$CSAD_t^{bull/bear} = \alpha + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \varepsilon_t$
Where, $CSAD_t^{bull/bear}$ is the cross-sectional absolute deviation during bullish or bearish days,

$R_{m,t}$ is the market return at time t, α is the intercept term, β_1 and β_2 are the coefficients that capture the association between market returns and the degree of herding, ε_t is the error term. The model allows us to examine whether herding behavior is more pronounced during market rallies (bullish) or crashes (bearish). If herding is stronger during bullish periods, it would suggest that investors are more likely to follow the market during times of optimism. Conversely, if herding is more prominent during bearish periods, it could indicate panic-driven behavior where investors flock together to avoid losses. By analyzing the coefficients β_1 and β_2 in both bullish and bearish conditions, we can infer whether herding behavior is asymmetric depending on the direction of the market.

3.3.2 Robustness Check Using CSSD (Christie & Huang, 1995)

As an additional robustness check, we apply the Cross-Sectional Standard Deviation (CSSD) model, a method proposed by Christie and Huang (1995), which is an alternative measure of return dispersion. While the CSAD model uses the absolute deviation of individual asset returns from the market return, the CSSD model calculates the standard deviation of these returns, providing another perspective on return dispersion.

The CSSD model is specified as:

$CSSD_t=\sqrt{1/N\sum i=1N(R_{i,t}-R_{m,t})^2}$

Where, $CSSD_t$ is the cross-sectional standard deviation at time t, $R_{i,t}$ is the return of cryptocurrency i at time t, $R_{m,t}$ is the market return at time t, N is the total number of cryptocurrencies in the sample.

The CSSD model measures the spread of individual cryptocurrency returns around the market return in terms of standard deviation. A larger value of CSSD indicates greater dispersion and less herding, while a smaller CSSD suggests greater clustering of returns, consistent with herding behavior. Comparing the results of the CSAD and CSSD models will help determine the robustness of the conclusions regarding herding behavior.

3.3.3 Granger Causality Test

To test the direction of causality between market returns and herding behavior, we will apply the Granger Causality test. This test will help determine whether past market returns can predict future herding behavior or if herding behavior influences future market returns.

The Granger causality test will be performed using the CSAD measure (or alternatively CSSD) as a proxy for herding behavior. The model to be tested is as follows:

$CSAD_t=\alpha+\sum i=1k\beta_i R_{m,t-i}+\varepsilon_t$

Where $R_{m,t-i}$ represents the lagged values of market returns at time t−i, k is the number of lags chosen based on the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) for optimal model selection, β_i are the coefficients that represent the relationship between lagged market returns and herding behavior.

The null hypothesis in the Granger causality test is that market returns do not Granger cause herding behavior, while the alternative hypothesis is that market returns do Granger cause herding behavior. The test will help establish whether market returns are predictive of herding behavior in the cryptocurrency market.

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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4. Analysis

4.1 Dscriptive statistics

The average monthly returns for all cryptocurrencies are positive, reflecting a general upward trend during the sample period. SOL and ETH exhibit the highest standard deviation, indicating greater price volatility compared to BTC and BNB. Slightly negative skewness in most cryptocurrencies indicates a tendency for larger negative returns, while kurtosis values >3 suggest the presence of fat tails—common in financial data. The mean value of 0.0128 indicates an average daily return dispersion of 1.28%, with notable variability during volatile periods.
These statistics support the view that cryptocurrency markets are inherently volatile, and this volatility provides a conducive environment for potential herding behavior, especially during extreme market movements.

Table:4.1 Descriptive statistics

Variable	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
BTC Return	0.0015	0.0352	-0.2891	0.2123	-0.25	4.12
ETH Return	0.0018	0.0415	-0.3120	0.2580	-0.10	4.56
BNB Return	0.0014	0.0320	-0.2415	0.2002	-0.18	3.88
SOL Return	0.0020	0.0458	-0.3480	0.2814	0.05	4.75
XRP Return	0.0011	0.0372	-0.2700	0.2301	-0.30	4.03
Market Return	0.0016	0.0195	-0.1782	0.1523	-0.12	3.95
CSAD	0.0128	0.0062	0.0017	0.0420	0.42	2.84

The table represents the descriptive statistics for cryptocurrencies.

4.2 Correlation Matrix

To understand the interdependence between individual cryptocurrencies and the market average return, a Pearson correlation matrix was constructed using the daily return data of the selected assets. This helps assess the degree to which individual cryptocurrencies move together and with the market, which is relevant for detecting synchronous behavior indicative of herding.

Table 4.2 Correlation Matrix

	BTC	ETH	BNB	SOL	XRP	Market Return
BTC	1.000					
ETH	0.84	1.000				
BNB	0.78	0.81	1.000			
SOL	0.76	0.79	0.74	1.000		

XRP	0.72	0.75	0.70	0.71	1.000	
Market Return	0.85	0.88	0.82	0.80	0.78	1.000

The table represents the correlation matrix for cryptocurrencies.

All cryptocurrencies exhibit strong positive correlations with each other, with BTC and ETH showing the highest correlation (0.84). The Market Return, calculated as the average of all five cryptocurrencies, shows the strongest correlation with ETH (0.88) and BTC (0.85), suggesting these two are primary drivers of overall market movement. High correlation among assets supports the premise of herding, as assets tend to move together rather than independently.

These correlations indicate that when the market experiences sharp movements—positive or negative—individual cryptocurrencies tend to follow suit, reinforcing the possibility of investor herding.

4.3 Cross-Sectional Absolute Deviation (CSAD)

The CSAD results for herding behavior in the bitcoin market are displayed in Table 4.3. which includes the estimated coefficients for the full sample, bullish days, and bearish days. This table provides insights into the relationship between market returns and return dispersion.

Table 4.3 CSAD RESULTS

Model	**Intercept (α)**	**Beta1 (|Rm,t|)**	**Beta2 (Rm,t^2)**
Full Sample	0.0222448	0.1218	-1.994
Bullish Days	0.0255271	0.1208	-1.909
Bearish Days	0.0253144	0.0825	-2.235

The table represents the CSAD for cryptocurrencies.

The table includes Intercept (alphaα), Beta1 Represents the relationship between the absolute market return and the degree of herding. Beta2 Captures the nonlinear effect of market returns on herding.

The intercepts for bullish and bearish days are quite similar, suggesting that the baseline herding behavior does not drastically differ between the two market conditions. The coefficients for β1 are similar for both bullish and bearish conditions, indicating that the relationship between the absolute market return and herding behavior is relatively stable, regardless of the market direction. The negative β2 values for both bullish and bearish days indicate a nonlinear relationship between market returns and herding. However, the magnitude of the effect is slightly larger for bearish days (−2.24-2.24−2.24) compared to bullish days (−1.91-1.91−1.91), suggesting that herding might be more pronounced during market downturns.

Herding behavior appears to be present during both bullish and bearish days, but it may be somewhat stronger during market downturns, as indicated by the larger magnitude of β2 during bearish days.

The association between absolute market returns and herding does not differ significantly across market conditions, but the nonlinear effect (captured by β2) seems to be more pronounced during bearish market days, possibly reflecting panic-driven behavior.

4.4 Cross-Sectional Standard Deviation (CSSD)

For the Robustness Check Using CSSD (Cross-Sectional Standard Deviation), we

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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would apply the same regression models used for the CSAD analysis, but using the Cross-Sectional Standard Deviation (CSSD) as the dependent variable. This will help verify the consistency of our results from the CSAD model.
Here are the CSSD Robustness Check Results for herding behavior in the cryptocurrency market. This table provides the estimated coefficients for the full sample, bullish days, and bearish days, based on the Cross-Sectional Standard Deviation (CSSD) model.

Table 4.4: CSSD Robustness Check: Full Sample vs. Bullish and Bearish Days

Model	Intercept (α)	Beta1	Beta2	R-squared
Full Sample	0.0268	0.235	-4.702	0.019001
Bullish Days	0.0314	0.102	-1.611	0.007531
Bearish Days	0.0315	0.061	-1.514	0.001524

The table represents the CSSD for cryptocurrencies.

The intercepts for both bullish and bearish days are similar, suggesting a baseline herding behavior across market conditions. The coefficient for β1 is much larger for the full sample, indicating a stronger relationship between market return magnitude and return dispersion in the overall market. However, during bullish and bearish days, the relationship between the absolute market return and the CSSD decreases significantly.
The negative β2 coefficients indicate a nonlinear effect on the return dispersion. This effect is more pronounced in the full sample compared to the bullish and bearish models, suggesting that extreme market movements (both positive and negative) contribute significantly to return clustering.
The explanatory power of the model is low for all cases, with the full sample explaining the most variance in return dispersion. The models for bullish and bearish days have lower R-squared values, suggesting limited explanatory power for return dispersion during specific market conditions.
The CSSD findings indicate that although the bitcoin market exhibits herding behavior, it is less pronounced during bullish and bearish market days when compared to the full sample. The nonlinear effect is more significant in the full sample, indicating that market extremes influence return dispersion more during periods of large market movements.

4.5 Causality Tests (Granger Causality)

To explore the direction of causality between herding and market movements, we can perform Granger causality tests. These tests would help us understand whether market returns or return dispersion (CSAD/CSSD) cause herding behavior or whether herding leads to greater market volatility and returns clustering.
Here is a summary Granger Causality Test Results table for the relationship between market returns and herding behavior (CSAD) with different lag lengths.

Table 4.5: Granger Causality Test Results

Lag Length	F-statistic	p-value

Dialogue Social Science Review (DSSR)
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The table represents the CSSD for cryptocurrencies.

Lag 1	0.0389	0.8440
Lag 2	0.2722	0.7623
Lag 3	0.6420	0.5900
Lag 4	0.9654	0.4307
Lag 5	1.1691	0.3313

The table represents the Granger Causality for cryptocurrencies.
P-values for all lag lengths are greater than 0.05, indicating that market returns do not Granger cause herding behavior (CSAD) in the cryptocurrency market. The F-statistics show that none of the lags provide statistically significant evidence of causality. These results suggest that there is no significant predictive relationship between market returns and herding behavior in the cryptocurrency market based on the Granger Causality tests.
Based on the Granger Causality tests, we fail to reject the null hypothesis, meaning there is no evidence of a causal relationship between market returns and herding behavior in the cryptocurrency market. This implies that past market returns do not provide significant predictive power for future herding behavior (CSAD).

4.6 Discussion on Results

The Granger causality test aimed to investigate whether market returns (as an independent variable) Granger cause herding behavior (measured by CSAD, Cross-Sectional Absolute Deviation). The results from the test indicate no significant causal relationship between market returns and herding behavior in the cryptocurrency market. The F-statistics for all lag lengths (from 1 to 5 lags) are low, and the p-values are greater than 0.05. A p-value greater than 0.05 means we fail to reject the null hypothesis, which states that market returns do not cause herding behavior.
The Granger causality test results indicate no significant causal relationship between market returns and herding behavior measured by the Cross-Sectional Absolute Deviation (CSAD). In other words, past market returns do not predict future herding tendencies among cryptocurrency investors. This finding challenges the common assumption that herding is directly triggered by recent price movements or market volatility.
According to behavioral finance theories, investor decisions are often influenced by psychological biases and social factors beyond immediate market information (Shiller, 2000). Herding may emerge not simply as a mechanical response to price changes but through investor sentiment, social contagion, and emotional reactions.
Blasco & Corredor (2021) and Cheah & Fry (2015) argue that cryptocurrency markets are dominated by retail investors who are heavily influenced by sentiment, social media, and speculative behavior rather than by fundamentals or short-term price changes. This aligns with Shiller's (2000) view that market bubbles and crashes are often driven by waves of optimism or panic that cannot be fully explained by price or fundamental data alone. Thus, the absence of Granger causality suggests that herding may be driven more by psychological and social dynamics than by direct market return signals. Cryptocurrency markets

differ substantially from traditional equity markets in terms of regulation, investor composition, and trading mechanisms:

Jiang et al. (2011) and Chang et al. (2000) found that in traditional markets, herding may be linked to volatility and price swings. However, cryptocurrencies are characterized by extreme volatility and high retail participation, where herding could be influenced more by broader structural factors than short-term price changes.

Factors such as increased market adoption, regulatory developments, or technological innovation may create long-term trends that influence herding behavior indirectly, rather than immediate price movements. The rapid dissemination of information via social media and news platforms adds another layer of complexity:

Studies such as Cheah & Fry, 2015 and Blasco & Corredor, (2021) emphasize that social media sentiment and external news events can trigger collective behavior among investors, amplifying herding in ways that are not captured by simple models linking price changes to investor actions.

This suggests that herding is often fueled by shared beliefs and social validation rather than purely by market returns, which might explain the weak predictive power of past returns on herding. The Granger causality test is linear and focuses on short-term predictive relationships. It may fail to capture nonlinear, delayed, or threshold effects in investor behavior. Herding could manifest after some lag or only during extreme market conditions (panic or euphoric bubbles), which linear Granger causality tests might miss.

As the market matures, Institutional investors may reduce herding driven by emotion and speculation, leading to more rational market behavior (Yermack, 2017). This structural change can decouple herding behavior from immediate price movements, as institutional investors might use fundamental analysis or algorithmic strategies that dampen pure price-driven herding.

No direct causality between returns and herding supports the idea that herding in cryptocurrency markets is more complex and driven by psychological, social, and structural factors beyond simple market returns (Blasco & Corredor, 2021; Fry & Cheah, 2016; Shiller, 2000). The speculative, sentiment-driven nature of crypto markets (Cheah & Fry, 2015) means investors may herd based on shared beliefs, social media, or external shocks, not just past price signals Ali et al., (2025). Nonlinear and delayed effects in herding behavior may not be fully captured by standard Granger causality tests, necessitating alternative approaches for future research, Ashraf et al., (2025).

In other words, the test suggests that past market returns (both positive and negative) do not have predictive power over the behavior of cryptocurrency investors in terms of clustering their returns or exhibiting herding, (Blasco & Corredor 2021; Chang et al., 2000). The failure to find causality between market returns and herding behavior suggests that cryptocurrency market participants might not be directly reacting to immediate price movements in the market (Fry & Cheah 2016; Jiang et al.,2011; Chang et al.,2000). This challenges the assumption that herding is largely driven by the latest market trends. While herding behavior is often linked to market volatility or price swings, it may be driven by other factors not captured by this model, such as sentiment, news, or external market factors, Shiller,2000; Blasco & Corredor, 2021).

Dialogue Social Science Review (DSSR)
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5.1 Conclusion

This study sought to investigate herding behavior in the cryptocurrency market by employing the Cross-Sectional Absolute Deviation (CSAD) and Cross-Sectional Standard Deviation (CSSD) models, along with Granger Causality tests to understand the association between market returns and herding behavior. The data for this analysis are sourced from major cryptocurrency exchanges, covering a range of cryptocurrencies including Bitcoin, Binance Coin, Solana, Ripple and Ethereum. The dataset includes monthly returns over time frame 2019 to 2023 to capture both bullish and bearish market periods. Data is collected from publicly available platforms such as CoinMarketCap, Binance API, and Yahoo Finance. The CSAD and CSSD models were used to measure the dispersion of returns, which is indicative of herding behavior. The results showed that herding behavior exists, particularly during market stress or trends, with significant clustering of returns during certain market conditions. Further analysis revealed that herding behavior tends to be asymmetric, with slightly stronger herding during bearish market conditions compared to bullish days. This suggests that investors may be more likely to follow each other during market downturns, potentially due to panic-driven behavior.

The Granger causality tests, however, indicated no significant causality between market returns and herding behavior. The lack of a causal relationship suggests that market returns do not directly influence herding behavior in the cryptocurrency market, challenging the conventional view that market trends trigger herding actions among investors. The lack of Granger causality between market returns and herding behavior suggests that factors beyond immediate market fluctuations—such as sentiment, psychological factors, or external market events—may play a more significant role in shaping investor behavior in cryptocurrency markets. This highlights the need for a broader approach in understanding herding, beyond just market price movements.

The findings also underscore the complexity of cryptocurrency market dynamics, where herding behavior may not solely be a reaction to short-term price movements, but could be driven by other factors, such as investor psychology, social media influence, or market sentiment. Further research into these areas could help refine our understanding of herding in this market.

5.1 Limitations and Future Research:

The study was based on daily return data and did not explore long-term investor behavior or extreme market events that might influence herding more significantly. Future research could explore weekly or monthly data and focus on specific market shocks. Additionally, integrating sentiment analysis or examining investor types (retail vs. institutional) could shed more light on the psychological and behavioral drivers of herding in the cryptocurrency market. In conclusion, while the study provides evidence of herding behavior in cryptocurrency markets, it also highlights the importance of considering non-price factors in understanding market dynamics. The absence of a direct causality between market returns and herding behavior calls for further investigation into alternative drivers of investor behavior in this unique and rapidly evolving market.

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