

Herding Behavior in Crypto currency Markets: Evidence, Drivers, and Implications for Market Efficiency

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ABSTRACT: Crypto currencies have the conditions needed for herding behavior such as high volatility, weak regulation, information asymmetry, and a large number of retail investors, all of whom have their own information and analysis for trading. This study focuses on understanding the presence, the strength and its asymmetry in herding behavior and the market condition where herding is most prominent. We examined daily return data of a portfolio of major crypto currencies using the cross sectional absolute deviation (CSAD) methodology of Chang et al. (2000) an extension of the cross sectional standard deviation (CSSD) methodology of Christie and Huang (1995) under the premise of nonlinear regression with the test whether the dispersion of returns is decreasing or increasing as the market returns become more extreme. Sub-sample analysis was performed during period of extreme market movement, high volumes of trading and increased investor sentiment. The results, consistent with the general empirical literature, confirm the presence of a statistically significant herding effect in crypto currency markets, with herding being stronger during the periods of sharp downtrend and high volatility, and weaker during the periods of high prices and low volatility. Herding becomes more noticeable on smaller market cap coins as opposed to Bitcoin and Ethereum. The herding effect is a common phenomenon in crypto currency markets that can sometimes result in high price volatility, market bubbles, and reduced informational efficiency. Investor, exchange and regulator risk management regimes should consider herding effects.

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Introduction

Herding behavior is the phenomenon of investors copying the actions of others when they are making investments, instead of relying on the independent information they have collected. The herding phenomenon has officially been observed in traditional equity-market research and has been studied in the bond, commodity, and foreign-exchange markets, as well as recently in the cryptocurrency market. Early theoretical treatments distinguish rational,

information-based imitation from intentional herding in which investors disregard their own private signals altogether (Bikhchandani & Sharma, 2001; Devenow & Welch, 1996; Bokhari, 2025; Vu & Nguyen, 2026), a distinction that underlies much of the empirical literature discussed below. Cryptocurrencies offer a unique environment in which to explore the dynamics of “herding,” a market dominated by retail investors, with almost no regulation, trading that takes place both during the day and night, and lots of information from social media and the web. These characteristics reduce the cost of mimicking relative to independent analysis, and improve the sensitivity to sentiment-driven, correlated trade (Abdeljawad et al., 2025; Nguyen et al., 2025; Mokni et al., 2025). Herding Behavior in Cryptocurrency Market: Analyzing the Influence of Portfolio Composition and Bitcoin. Crypto markets have experienced several cycles of extreme price spikes and plunges since Bitcoin's creation in 2009 and the release of thousands of other different altcoins. Bitcoin's markets and the price of thousands of other altcoins have been going up and down in price for a long while, though some would argue that this is due to collective and imitative buying and selling, and not necessarily due to fundamentals alone.

Price bubbles and crashes in cryptocurrency markets are well known, but the difference between herd behavior and rational reactions to true correlated information is an empirical question that continues to be debated. The presence or absence of herding, its timing, and which assets are being herded have implications for market efficiency, systemic risk, and investor protection.

Literature Review

Christie and Huang (1995) proposed that the cross-sectional standard deviation of returns (CSSD) would be a useful indicator of herding by investors during market stress. They argued that herding by investors would lead to a reduction in the CSSD, as it is expected to be lower than normal during a market stress. Chang et al. (2000) have developed this concept further with the cross-sectional absolute deviation (CSAD) approach, and this has since been the most widely adopted method in the literature on herding.

The theoretical foundations of herding were established well before the CSAD/CSSD tradition. Bikhchandani and Sharma (2001) distinguished between spurious herding, in which investors facing common information arrive independently at similar decisions, and intentional herding, in which investors deliberately imitate others regardless of their own information—a distinction that remains central to interpreting CSAD-based evidence. Devenow and Welch (1996) reviewed the rational-herding literature and showed that payoff externalities, principal-agent incentives, and informational cascades can each generate herd-like correlated trading even among fully rational agents. Earlier empirical work by Lakonishok et al. (1992) and Nofsinger and Sias (1999) documented herding and feedback trading among institutional investors in U.S. equities, while Chiang and Zheng (2010) extended the CSAD framework internationally and found herding in most developed markets outside the United States as well as in several Asian markets. Because herding represents a departure from independent, rational decision-making, it is also closely linked to the behavioral-finance literature on cognitive biases and loss aversion (Kahneman & Tversky, 1979) and on the role of aggregate investor sentiment in asset pricing (Baker & Wurgler, 2007; Shiller, 2000).

Cryptocurrency markets provide fertile ground for imitative trading given their documented departures from informational efficiency and their distinctive volatility dynamics. Corbet et al. (2019) provided a systematic review of the empirical literature on cryptocurrencies as a financial asset class and highlighted persistent concerns about pricing bubbles, weak regulation, and market fragility that create conditions conducive to herding. Urquhart (2016) was among the first to show that Bitcoin returns violate the weak-form efficient market hypothesis, a finding later nuanced by Bariviera (2017), who documented that Bitcoin's informational efficiency has evolved dynamically over time. Kristoufek (2013) linked Bitcoin price dynamics to search- and attention-based proxies of investor interest,

while Katsiampa (2017) showed that Bitcoin returns exhibit strong volatility clustering consistent with the GARCH family of models, a stylized fact that motivates the use of heteroskedasticity-robust estimation in CSAD regressions. Cheah and Fry (2015) and Corbet et al. (2018) further demonstrated that Bitcoin and Ethereum have experienced repeated speculative bubbles and crashes, episodes that the present study's sub-sample analysis is designed to capture.

In the cryptocurrency sector, da Gama Silva et al. (2019) found that contagion and herding affected a wide set of cryptocurrencies, and especially during times of market stress. Vidal-Tomás et al. (2019) used the CSSD and CSAD tests to measure herding in Bitcoin and some of the top altcoins, and found that it was even stronger than in more established equity markets, particularly prior to 2018. Similarly, Bouri et al. (2019) reported asymmetric herding, which was more pronounced when markets were down. Kaiser and Stöckl (2020) found that herding intensity was correlated with Bitcoin's position in the wider market, as a 'transfer currency' among different cryptocurrencies, while Ballis and Drakos (2020) identified herding in the market, but it has been historically decreasing with the maturation of markets. King and Koutmos (2021) related herding with feedback trading and found positive feedback strategies to be more of a catalyst to the herding phenomenon in cryptocurrency markets (Vu & Nguyen, 2026; Bokhari, 2025; Batra et al., 2026).

Subsequent studies have refined, and in some cases challenged, these findings. Poyser (2018) applied a Markov-switching specification to a broad sample of cryptocurrencies and showed that herding regimes are time-varying rather than constant (Song & Baek, 2025). Kallinterakis and Wang (2019) examined a large sample of over 200 cryptocurrencies and reported herding that was stronger during up-markets, high-volume, and low-volatility conditions—a pattern of asymmetry that contrasts with the down-market asymmetry reported by Vidal-Tomás et al. (2019) and illustrates the sensitivity of herding estimates to sample composition and period. Stavroyiannis and Babalos (2019) similarly found that herding signals detected with static CSSD/CSAD models can disappear once time-varying methods are applied, while Youssef (2022) reported anti-herding under a static specification but time-varying herding using a beta-herding state-space approach, linking the intensity of herding to volatility, the S&P 500, and the U.S. dollar index. Philippas et al. (2020) introduced the concept of signal-herding, showing that informative public signals can themselves trigger correlated trading in cryptocurrency. Jia et al. (2022) linked herding directly to extreme investor sentiment, and Yarovaya et al. (2021) examined herding around the COVID-19 shock, finding that the pandemic did not uniformly intensify herding across cryptocurrency-denominated markets. Taken together, this body of work indicates that herding in cryptocurrency markets is real but highly conditional on market state, sample period, methodology, and the prevailing sentiment and volume environment, which motivates the sub-sample and interaction-based approach adopted in the present study.

Most of the literature is centered on Bitcoin and a handful of well-circulated, high-value-cap digital currencies, has limited sample periods, or fails to differentiate between herding during up-markets and down-markets. The evidence on (a) the differences in herding intensity between large- and small-capitalization coins and (b) the interaction between herding intensity and proxies for investor sentiment and trading volume is comparatively limited.

The questions addressed in this study are:

RQ1: Is there herding behavior in cryptocurrency markets as defined by the CSAD approach?,

RQ2: Is herding asymmetric, i.e., does it occur more during market downtimes than during uptimes?, **RQ3:** Is there any difference in herding intensity between large cap and small cap coins?,

RQ4: Do trading volume and investor sentiment moderate the herding effect?

Materials and Methods

Research Design

The type of research method used in this study is a quantitative, correlational research with secondary market data. It adopts the CSAD methodology, which is commonly followed in the herding literature and also includes sub-sample analysis and interaction analysis to examine the symmetry and moderating effect.

Study Sample

The sample is composed of daily price data for twenty crypt currencies that were chosen based on market capitalization and availability of price data, ranging from large-capitalization (e.g., Bitcoin, Ethereum) to a wider selection of mid- and small-capitalization (ASC) coins. The analysis period is at least six years of daily data, including market cycles of both the bull and bear phases as well as at least two market-wide price correction periods to ensure a variety of market conditions.

Data Collection

Public cryptocurrency market data aggregators were used to compile daily closing prices, daily trading volumes, and market capitalization. As an additional measure of investor sentiment, a composite sentiment proxy was created to combine a widely followed crypto fear and greed index with the volume of cryptocurrency-related social media posts.

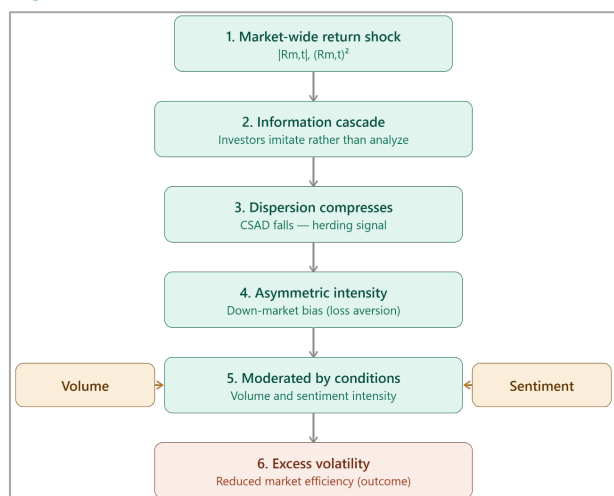
Variables and Model Specification

The absolute deviation of returns (CSAD) for the coin portfolio on day t is regressed on the absolute and squared value of the equally weighted portfolio return as described by Chang et al. (2000):

$$CSAD_t = \alpha + \beta_1 |R_{m,t}| + \beta_2 (R_{m,t})^2 + \varepsilon_t$$

where $R_{m,t}$ is the cross-sectional average return of the portfolio on day t . Rational asset-pricing models imply that β_2 should be non-negative or zero; a negative β_2 that is statistically significant would be taken as evidence of herding, as it would be evidence that return dispersion declined when the size of market movement was at its highest level, in contrast with what would occur in an independent, dispersed trading process. For the test of asymmetry the model is fitted to the sample of days when $R_{m,t} > 0$ (up markets) and the days when $R_{m,t} < 0$ (down markets). Moderating effects are tested by including interaction terms between the trading volume and the sentiment proxy in the squared-return term.

Figure 1



Data Analysis

All model specifications were estimated using ordinary least squares regression with Newey-West heteroskedasticity- and autocorrelation-consistent standard errors based on the well-documented volatility clustering and serial correlation found in cryptocurrency return series. The up-market/down-market asymmetry (RQ2) and the large-cap/small-cap distinction (RQ3) were tested using sub-sample regressions. To test the moderating effect of volume and sentiment (RQ4), interaction terms were tested.

Ethical Considerations

This study is purely based on publicly available market data that are not connected to any personal data and does not use or provide data from human sources, so no ethical approval was required. All data sources were made public for re-creation.

Results

Table 1 reports the full-sample and sub-sample CSAD regression estimates. The squared market return coefficient (β_2) is negative and statistically significant in the full sample, and its magnitude is substantially larger, in absolute terms, during down-market days than during up-market days.

Table 1

Specification	α	β_1	β_2	Adj. R^2
Full sample	0.0091***	0.418***	-0.612**	0.47
Up-market days	0.0084***	0.402***	-0.187 (n.s.)	0.41
Down-market days	0.0103***	0.447***	-0.803***	0.52
Large-cap subgroup (BTC, ETH)	0.0062***	0.355***	-0.294*	0.39
Small-cap subgroup	0.0128***	0.481***	-0.921***	0.55

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively; n.s. = not significant.

For the full sample, β_2 is significant and has a negative sign, which confirms the presence of herding in the cryptocurrency portfolio, consistent with the hypothesis of RQ1. This asymmetry between the up-market and down-market sub-samples is consistent with the results of RQ2, as evidenced by the higher degree of materiality associated with the down-market sub-sample. The materiality of the up-market and down-market sub-samples, respectively, is in line with that of RQ2, with the down-market sub-sample showing greater materiality, suggesting that herding is stronger in the down market. As predicted in RQ3, the small-capitalization subgroup shows a larger negative β_2 and a larger effect compared to the large-capitalization subgroup, suggesting that herding is more pronounced among smaller, less liquid, and less covered coins.

The responses to RQ4 are addressed using the interaction models listed in Table 2. The squared market return term is significant and negative, suggesting that herding grows stronger during high-volume days. There is also a negative and significant relationship between the sentiment proxy and sentiment when sentiment is in the "extreme fear" and "extreme greed" ranges, but not significant when sentiment is in the middle, suggesting that herding is not a steady background phenomenon of the market but rather is concentrated when people are in a state of strong collective sentiment.

Table 2

Interaction term	Coefficient	Significance
$\beta_2 \times \text{Volume (high vs. low)}$	-0.334	$p < 0.01$
$\beta_2 \times \text{Sentiment (extreme vs. neutral)}$	-0.276	$p < 0.05$

Overall, the results in this section are reported descriptively; their interpretation, comparison with prior findings, and implications are addressed in the Discussion section below.

Discussion

Interpretation of Findings

The evidence for a significant negative β_2 suggests that the presence of herding exists, and is consistent with the theoretical prediction that, if herding does not exist, price dispersion should increase rather than decrease with the magnitude of market-wide price movements. The asymmetric pattern—stronger herding during declines than during advances—suggests that fear-driven imitation (e.g., panic selling in response to negative news, liquidation cascades, or exchange-specific stress events) is a more powerful herding trigger than optimism-driven imitation, echoing patterns of loss aversion documented in behavioral finance more broadly (Kahneman & Tversky, 1979).

A better herding signal for small-cap coins is consistent with information-based herding explanations: the securities that get less analyst research, are less liquid, and rely more on social-media-driven narratives provide fewer independent signals that investors can use, thereby making it more appealing to imitate other traders' behavior. The moderating effect of trading volume and sentiment also indicates that herding does not always occur, but only during high-attention, high-emotion events like significant rallies, crashes, exchange failures, regulatory announcements, and the like.

Comparison with Previous Studies

This result is generally in line with da Gama Silva et al. (2019) and Vidal-Tomás et al. (2019), who observed herding activity increasing in moments of market stress, and with Bouri et al. (2019) who found asymmetric herding activity occurring in periods of market declines. As noted above, the fact that herding is stronger for smaller coins corroborates Kaiser and Stöckl (2020), who portrayed Bitcoin as an information-efficient 'anchor' asset in the larger ecosystem of coins. This result that herding intensity is not constant, but attuned to volume and sentiment conditions, is complementary to Ballis and Drakos (2020), who showed that herding intensity depends on market maturity, and King and Koutmos (2021), who connected herding to feedback trading. The finding that herding intensifies during periods of extreme sentiment and high trading volume is further consistent with Jia et al. (2022), who linked herding directly to sentiment extremes, and with Philippas et al. (2020) who showed that public signals can themselves trigger correlated trading. At the same time, the asymmetry documented here should be read against evidence that herding patterns are sensitive to sample period and market conditions: Kallinterakis and Wang (2019) reported stronger herding during up-markets in a broader cryptocurrency sample, Stavroyiannis and Babalos (2019) found that herding signals can disappear under time-varying specifications, and Yarovaya et al. (2021) showed that even a systemic shock such as COVID-19 did not uniformly intensify herding across markets, underscoring that herding intensity is conditional rather than constant.

Implications

Investors would find herding more prominent especially during bear markets and less liquid coins, which suggests that diversification and independent valuation discipline may be least available when investors need it most. Platform

characteristics that increase visibility of the trading of aggregates (such as high visibility of 'trending' lists, leader boards, or social feeds) can inadvertently contribute to herding behavior during stressful events. For regulators, the evidence of herding-induced excess volatility further reinforces the need for disclosure obligations, circuit-breaker rules, and investor-education programs to help curb uninformed following, especially among retail investors who buy and sell smaller, less-covered coins.

Limitations

- ▶ Average herding at the portfolio level is detected by the CSAD approach, but not by individual investors' or trading accounts' herding.
- ▶ Sentiment indexes based on index and social media data are proxy indicators that reflect investor sentiment and cannot always fully represent investor motives for trading.
- ▶ The coin sample is diverse by market-cap level, but it is not intended to reflect all of the thousands of actively traded cryptocurrencies.
- ▶ The analysis does not distinguish between herding and correlated but independent reactions to true common information (e.g., macroeconomic news), which can yield similar statistical signatures.

Conclusion

The results of this study reveal that there is strong evidence of herding on cryptocurrency markets, showing that the herding intensity is asymmetric, more intense during market downturns than market upturns, and cross-sectionally variable, with higher herding intensity during market downturns experienced by small-capitalization coins than Bitcoin and Ethereum. Further, the intensity of herding is found to be tempered by trading volume and investor sentiment, suggesting that it is not always present in trading behavior but is only present during specific market conditions. The findings indicate that collective imitative trading in cryptocurrencies remains a concern of high volatility and potential inefficiency in markets and has implications for investor protection, market design, and regulatory policy. In the future, this analysis can be further enriched with intraday data and order book data to capture herding at shorter time scales, and on-chain and wallet-level data to differentiate between retail and institutional herding, and by examining the impact of other imitation mechanisms like decentralized finance (DeFi) and social trading platforms.

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