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Herding and Investor Sentiment in Cryptocurrency Markets

1.) Introduction.

In recent years, the cryptocurrency market has gained popularity in the investment community from both tenured and new investors. The popularity has been spurred not only by the explosive growth and volatility of such currencies for speculative means but also "Digital currencies offer an alternative of mainstream currencies with substantial lower transaction costs" (Stavros, Vassillios, 2019, p. 1). Amidst this, understanding the factors driving the cryptocurrency market movements has become increasingly important.

Rationality concepts such as the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH) theorise that market prices clear at the individual stocks true intrinsic value where all information is instantaneously reflected in the price therefore making it impossible to "beat the market". This then begs the question what drives prices away from their intrinsic value and allows investors to gain profit.

One potential reason was argued by Banerjee (1992) who noted that herd behaviour occurs when individuals follow the actions of others, even when their private information suggests a different course of action, leading to a potential "lock-in" to a non-optimal equilibrium, sparking inefficiency. The condition of herding is therefore in complete disagreement with the EMH.

The aim of this project is to detect whether participants in the cryptocurrency markets are conducting their investment practices via herd behaviour, in contrast to rational practices.
The remainder of this paper is organised as follows. Section 2 will review the existing literature in the field of detecting herd behaviour in both traditional finance and decentralised finance markets. Section 3 will describe the data. Section 4 will describe the methodology of the analysis. Section 5 contains the findings of our analysis. Section 6 contains a conclusion.

2.) Literature Review.

Herd investing has been a well-known phenomenon in traditional finance for many years. Throughout history, events such as the Dutch "tulip bulb" bubble of 1636, the 1929 stock-market crash and the "dot-com bubble" have all been thought to be events driven by Herding behaviour that has dramatically affected movements in markets. Banerjee (1992) notes that in numerous social and economic situations our decision making is often swayed by others. Most famously Keynes (1936) 'Beauty contest' showed how individuals' decisions are based on the perceived preference of others and that this may be how investors in markets behave. Whilst extensive research has been undergone over the last four decades there has not been a unanimous consensus on the existence and severity of herding within financial markets.

Herding related studies (Christie and Huang (1995); Chang, Cheng, Khorana (2000); Caparrelli, D'Areangelis, Cassuto (2004)) have focused predominantly on traditional finance markets whereby only a handful of papers have explored Decentralized finance markets i.e. Cryptocurrency Markets.

The most notable method of verifying herding used on numerous occasions in papers was first presented by Christie and Huang (1995) who proposed a returns-based model. The foundation of this model is derived from the well-known Capital Asset Pricing Model (CAPM), which asserts a linear relationship between asset returns and market returns Stavros and Vassilios (2019). Christie and Huang (1995) stated that low dispersions from the linear relation between market returns and asset returns may indicate the presence of herd behaviour. Their research isolated the market into periods of stress i.e. Bull/Bear Markets and concluded that individual returns did not cluster around the market refuting the presence of herding.

Chang, Cheng, Khorana (2000) expanded on the principles of Christie and Huang (1995) by using a non-linear approach to examine the relation between equity return dispersions measured by the Cross-Sectional Absolute Deviation of returns (CSAD) and the overall market return in the US, Hong Kong, Japan, South Korea and Taiwan. Their results supported those of Christie and Huang (1995) in developed countries whilst also presenting Herding in emerging countries. They concluded that the differences in dispersion levels between countries may be a result of incomplete information disclosures in the emerging markets.

Following on from Chang et al, (2000) non-linear approach for herding, research boomed in the field with works from Caparrelli et al. (2004); Chiang and Zheng (2009); Ramadan (2015) and Wu et al. (2020) conducting analysis of Italy, Globally, Amman and China respectively.

Chiang and Zheng. (2009) applied the work of Chang et al. (2000) over advanced, Latin American and Asian markets. Their findings indicated a herding presence in advanced markets except for the US and in the Asian markets whilst no evidence was found in Latin America. Chiang et al. (2009) suggested that the evidence showed that herding activity is triggered in times and crises ultimately in the country of origin which then produces a contagion affect, spreading the crises to other neighbouring countries. The contagion aspect is crucial to the stability and efficiency of a market as observed by Chiang et al. (2000) supportive evidence showed that US and Latin American markets who prior to the crises showed no herding activity had herding formation.

Bouri, Gupta, Roubaud (2018) noted that unlike equities, there is no consensus on how to value cryptocurrency which ultimately leads to widely varying opinions dividing participants with some viewing it as the currency of the future and some as fraudulent. Research such as Cheah and Fry (2015) have taken an interesting approach into the valuation of Bitcoin. The paper concluded that Bitcoin prices are prone to speculative bubbles and that the intrinsic value of Bitcoin is zero. This is particularly crucial as Bitcoin has a Majority share of approximately 60% in total crypto market cap. Their research concluded that 'cryptocurrency markets share some stylised empirical facts with other markets-namely a vulnerability to speculative bubbles".

Vidal-Tomas, Ibanez, Farinos (2018) analyses the existence of herding in the cryptocurrency market through Cross Sectional standard (absolute) deviation of returns. Building on the work of Bouri et al. (2018) they analysed the asymmetric herding behaviour of 65 cryptocurrencies. Their analysis employed a rolling window to shed light on the existence of herding in a market of 14 cryptocurrencies and further analysed asymmetric herding behaviour of 65 cryptocurrencies through CSSD and CSAD methods. The results of Vidal-Tomas et al. (2018) fell in agreement with the work of Bouri et al. (2018) since at a static observation herding was not observed but highlighted the relevance of the asymmetric herding behaviour. They ultimately concluded that extreme dispersion of returns is explained by rational asset pricing models although it is possible to observe herding behaviour during bear markets highlighting the inefficiency and risk of cryptocurrencies. In addition, the smallest currencies herded with the biggest concluding that market participants based omitted their own beliefs to base their decisions on the performance of the main cryptocurrencies Vidal-Tomas et al. (2018) Stavros, Vassilios (2019) utilised a more sophisticated time-varying estimation approach to allow for a more efficient estimation. Furthermore, they examined the market prices of the largest cryptocurrencies for a period of extending from 2015 to 2018. Their results concluded that through using ordinary least squares the existence of herding within the cryptocurrency markets was observed. This was further corroborated when applying a quantile regression accounting for the asymmetric nature of the cryptocurrency returns. In contrast however, when applying a time-varying regression model herding behaviour was no longer present.

3.) Data.

As considered in Vidal-Tomas et al. (2018) the behaviour of cryptocurrency markets is driven by the largest currencies. The data used in this paper focuses on 57 leading cryptocurrencies by Market-Cap as dated from 1st January 2025. This selection however excludes stable-coins. Daily market returns of the cryptocurrencies are computed for the period running from the 1st of January 2021 to the 1st of January 2025 for a total of 1459 observations**.** The selection of the time-period and the number of cryptocurrencies included in the analysis was chosen to capture different market stages. In particular the selection of the cryptocurrencies was devised so that the initial offering of the cryptocurrency was dated before the 1st of January 2021 as to gain a static market, omit any chance of an NA Value in the data and guarantee consistency in the weighting of each cryptocurrency in the calculation of the market return.

The Closing prices of the 57 cryptocurrencies were gathered from https://uk.finance.yahoo.com/ and individual returns were calculated using the logarithmic differences of the closing prices. Testing for herding towards the market requires the returns of a market portfolio. To this end following a series of previous studies Chiang et al. (2010); Vidal-Tomas et al. (2018) We have computed market return as an equally weighted portfolio of the individual cryptocurrencies' daily returns,

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

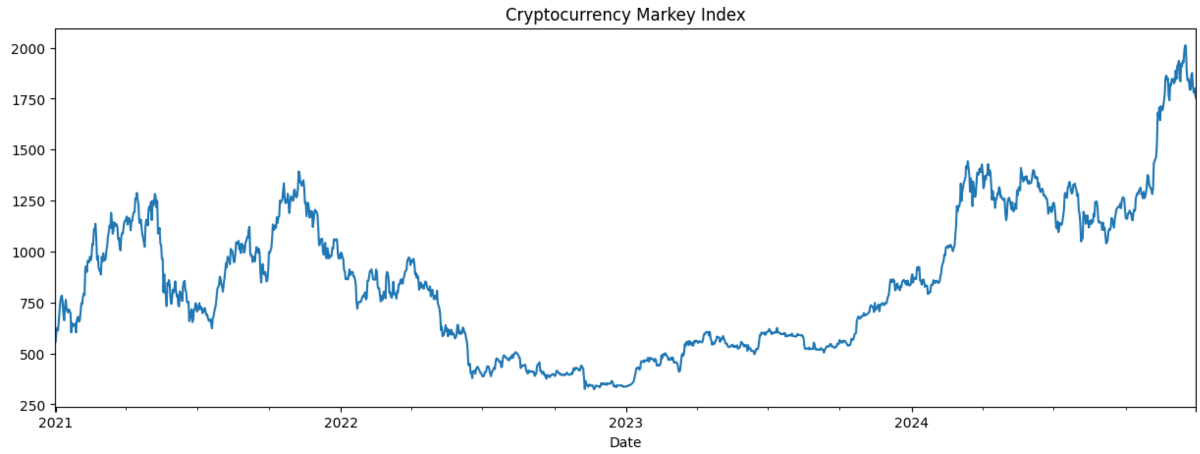
Where N is the number of cryptocurrencies, $r_{m,t}$ represents the market return at time (t). $r_{i,t}$ is the individual (i) cryptocurrency at time (t). Table 1 shows the descriptive statistics, in which we can observe a positive performance of the market over the period with a mean equal to 0.001336.

Table 1.
Descriptives of the market.

	Market Return
count	1459.000000
mean	0.001336
std	0.032728
min	-0.171353
25%	-0.013413
50%	0.000377
75%	0.016747
max	0.169678

The time behaviour of the market is depicted in Fig.1. it is clear to see that the portfolio of cryptocurrencies chosen for analysis experienced a decline in the second half of 2022 through to mid-2023 where the decline seemed to plateau. Just before the last quarter of 2023 we can see an explosive behaviour starting. This behaviour suggests a suitable context for the emergence of herding behaviour.

Figure 1.)



In addition to the 57 cryptocurrencies portfolio, we utilise the Fear and Greed index to capture investor sentiment over the course of the analysis. The data has been sourced through https://Alternative.me/crypto/fear-and-greed-index/. The index attempts to capture overall investor emotions and sentiments through different sources and reduce them to a number ranging from 0 representing 'Extreme Fear' to 100 representing 'Extreme Greed'. Extreme Fear is rationalised to represent investor worry and therefore a downturn in the market i.e. bear market. Whilst Extreme Greed is rationalised to be overconfidence in investors and therefore a bull market.

4.) Methodology.

In terms of the methodology for detecting herding activity in the cryptocurrency market we will use the model first posed by Chang et al. (2000) which is based on the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion.

$$Equation\ 1.)\ CSAD_{m,t} = \frac{\sum_{i=1}^{N} |r_{i,t} - r_{m,t}|}{N}$$

The CSAD also known as the average absolute value of the deviation, demonstrates that the rational asset pricing model predicts that equity return dispersions are an increasing function of the market return and that it is also linear Chang et al. (2000). The model is built on the intuition that when market participants follow aggregate market behaviour, ignoring their own beliefs in periods of large average price movements then the increasing linear relationship between dispersion and market return can become non-linear increasing or decreasing Chang et al. (2000).

Regressing the CSAD of returns with respect to market returns gives the generalised form below,

$$Equation\ 2.)\ CSAD_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 |r_{m,t}| + \beta_3 r_{m,t}^2 + \varepsilon_t$$

Where $|r_{m,t}|$ is the absolute term of market returns and $r_{m,t}^2$ denotes the squared returns of the market. More importantly a negative coefficient of β_3 will indicate the existence of herding, whilst a positive coefficient β_3 is predicted by rational asset pricing models. To further this model, we then include Market Trading Volume (Vt) as a control variable calculated as,

$$Equation\ 3.)\ V_{m,t} = \frac{\sum_{i=1}^{N} V_{i,t}}{N}$$

Where $V_{m,t}$ denotes the average market trading volume and $V_{i,t}$ denotes each cryptocurrency daily trading volume.

We Loosely follow the work of Chiang et al. (2010) and Vidal-Tomas (2018) who when testing for herding in global stock markets and cryptocurrencies respectfully, divided market returns into two sub-markets to distinguish asymmetric herding when the market is up or down by isolating the study in the lower and upper tails of the market distribution. Instead of dividing the market in this way we instead employ the Fear and Greed index as a measure of investor sentiment to distinguish the markets between extreme fear and extreme greed giving the following empirical specification

$$Equation\ 4.)\ CSAD_{m,t}^F = \alpha^F + \beta_1^F r_{m,t}^F + \beta_2^F |r_{m,t}^F| + \beta_3^F (r_{m,t}^F)^2 + \beta_4^F V_{m,t}^F + \varepsilon_t$$

$$Equation\ 5.)\ CSAD_{m,t}^G = \alpha^G + \beta_1^G r_{m,t}^G + \beta_2^G |r_{m,t}^G| + \beta_3^G (r_{m,t}^G)^2 + \beta_4^G V_{m,t}^G + \varepsilon_t$$

Where extreme fear at time (t) is indicated when the fear and greed index has a value that is equal or less than XX and extreme greed at time (t) is indicated when the fear and greed index has a value that is equal or greater than YY.

We can therefore test for the presence of herding through the following hypothesis:

H0: In the absence of herding, we expect $\alpha > 0\ and\ \beta_3 = 0.$

H1: in the presence of herding, we expect $\beta_3 < 0.$

H2: in the presence of anti-herding, we expect $\beta_3 > 0.$

5.) Results.

Table 2 and 3 report the results of the regression. Table 2 shows the estimated coefficients for the CSAD of returns, when the Fear and Greed index is in a period of Fear therefore investor sentiment is negative and therefore represents equation 4.

Table 2.

Market (Fear)	α^F	β_1^F	β_2^F	β_3^F	β_4^F
2021 - 2025	0.0298***	0.3341**	0.0162	4.1002***	0.0182*
	(0.000)	(0.031)	(0.948)	(0.000)	(0.080)

*** significance at the 1% level; ** significance at the 5% level; * significance at the 1% level.

The result of the analysis shows that the value of β_3 in equation 4 is highly positive with a value of 4.1002 that differs from zero at a significance level of 1%. This means that during the period of 01/01/2021 – 01/01/2025, investors in the cryptocurrency market during periods of Fear were not forgoing their own beliefs and information when participating in the market. In other words, the price movements during periods in time where investors are facing negative sentiment is not explained by herding.

Therefore, we can reject hypotheses H0 and H1 and conclude that in Fear markets there is the presence of anti-herding.

Table 3 shows the estimated coefficients for the CSAD of returns when the market is in a period of Greed and therefore investor sentiment is positive. This is represented by equation 5.

Table 3.

Market (Greed)	α^G	β_1^G	β_2^G	β_3^G	β_4^G
2021 - 2025	0.0310***	0.3876***	0.1750*	4.3201***	-0.0010
	(0.000)	(0.000)	(0.071)	(0.000)	(0.847)

*** significance at the 1% level; ** significance at the 5% level; * significance at the 1% level.

The result of the analysis shows that the value of β_3 in equation 5 is again highly positive with a value of 4.3201 that differs from zero at a significance level of 1%. This means that during the period of this analysis investors in the cryptocurrency market during periods of Greed were not forgoing their own beliefs and information when participating in the market. Again, it can be said that in times where investor sentiment is highly positive price movements are not explained by herding.

Therefore, we can reject hypotheses H0 and H1 and conclude that in Greed markets there is the presence of anti-herding.

6.) Conclusion.

This study delves into the potential presence of herding behaviour in the cryptocurrency marker by evaluating the relationship between return dispersions and market conditions under differing investor sentiment. Having employed the CSAD model first introduced by Chang et al. (2000) and utilising the Fear and Greed Index as a representation of marker sentiment, we assessed whether cryptocurrency market participants tend to forsake their private information in favour of market consensus.

Our findings reveal that, contrary to the traditional herding behaviour observed in other financial markets, the cryptocurrency market exhibits anti-herding tendencies in both extreme fear and extreme greed conditions. The notably positive coefficients of β_3 in both market sentiment conditions indicate that return dispersions expand rather than contract when market movements intensify. This reinforces the belief that participants in the cryptocurrency market make independent investment decisions based on their available information rather than blindly follow market trends even during periods of extreme sentiment.

The implications of these results challenge the conventional notion that cryptocurrencies markets are high susceptible to irrational behaviour and speculative bubba as was suggested by Cheah and Fry (2015). This portrays a market that is driven by rationale assessments of value rather than collective irrationality. The deviation from the herding behaviour which is observed in traditional financial markets may be attributed to the decentralised nature of cryptocurrencies, meaning the lack of a universally accepted valuation model, and the diverse nature of market participants.

Future research could probe deeper into the aspects of investor behaviour, examining the role of institutional versus retail investors and macroeconomic influences on cryptocurrency dynamics. Additionally, incorporating alternative sentiment measures or high-frequency data could offer more in-depth insights into the short-term behavioural patterns of participants.

In conclusion, this paper provides evidence that, contrary to the common perception of cryptocurrencies as speculative assets susceptible to herd-drive bubbles, market participants exhibit independent decision-making behaviours. This anti-herding tendency may contribute to the ongoing debate on the efficiency and maturity of cryptocurrency markets and their potential integration into the broader financial system.

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