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Herding and investor sentiment after the cryptocurrency crash: evidence from Twitter and natural language processing

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Abstract

Although the 2022 cryptocurrency market crash prompted despair among investors, the rallying cry, "wagmi" (We're all gonna make it.) emerged among cryptocurrency enthusiasts in the aftermath. Did cryptocurrency enthusiasts respond to this crash differently compared to traditional investors? Using natural language processing techniques applied to Twitter data, this study employed a difference-in-differences method to determine whether the cryptocurrency market crash had a differential effect on investor sentiment toward cryptocurrency enthusiasts relative to more traditional investors. The results indicate that the crash affected investor sentiment among cryptocurrency enthusiastic investors differently from traditional investors. In particular, cryptocurrency enthusiasts' tweets became more neutral and, surprisingly, less negative. This result appears to be primarily driven by a deliberate, collectivist effort to promote positivity within the cryptocurrency community ("wagmi"). Considering the more nuanced emotional content of tweets, it appears that cryptocurrency enthusiasts expressed less joy and surprise in the aftermath of the cryptocurrency crash than traditional investors. Moreover, cryptocurrency enthusiasts tweeted more frequently after the cryptocurrency crash, with a relative increase in tweet frequency of approximately one tweet per day. An analysis of the specific textual content of tweets provides evidence of herding behavior among cryptocurrency enthusiasts.

Keywords: Bitcoin, Cryptocurrency, Herding, Investor sentiment, Natural language processing, Sentiment analysis, Twitter

JEL classification: G41, G53

Introduction

Cryptocurrencies have grown rapidly in popularity, especially among non-traditional investors (Mattke et al. 2021). Consequently, the motivations underlying the decisions of many cryptocurrency investors are not always purely financial, with investors exhibiting substantial levels of herding behavior with respect to cryptocurrencies (Ooi et al. 2021). In fact, the culture developing around cryptocurrency enthusiasts engaging in herding behavior is rich and complex (Dodd 2018). The volatility of cryptocurrencies can vary substantially, and smaller cryptocurrencies (e.g., Dogecoin) are especially influenced by the decisions of herding-type investors (Cary 2021).

Because cryptocurrency investors are known to hold on to cryptocurrencies for ideological and cultural reasons, even when the return on cryptocurrency investments is negative (Mattke et al. 2021), the cryptocurrency crash of 2022 has the potential to drastically affect investor sentiment, especially among those who exhibit loyalty to cryptocurrencies despite negative wealth consequences. Magnifying this concern, Vidal-Tomás et al. (2019) showed that herding behavior among cryptocurrency investors is particularly strong in down markets.

The May 2022 cryptocurrency crash was one of the largest crashes in the history of cryptocurrency. Sparked by the collapse of the stablecoin Terra, the entire cryptocurrency market crashed (De Blasis et al. 2023). Before the crash, Terra was the third-largest cryptocurrency ecosystem after Bitcoin and Ethereum (Liu et al. 2023). Terra and its tethered floating-rate cryptocurrency (i.e., Luna) became valueless in only three days, representing the first major run on a cryptocurrency (Liu et al. 2023). The spillover effects on other cryptocurrencies have been widespread, with the Terra crash affecting the connectedness of the entire cryptocurrency market (Lee et al. 2023). Although an attempt to stabilize the stablecoin was made, the creator was ultimately charged and arrested for securities fraud (Judge 2023). While this was the first dissolution of a stablecoin cryptocurrency, it is worth mentioning that scholars have shown that pre-crypto stablecoins have existed, and failed (e.g., the Bank of Amsterdam from the 17th through the early 19th centuries, which tied its currency to silver and gold coins (Frost et al. 2020)). The cryptocurrency community has much to learn from the history of currency; in many cases, its ideas and attitudes are far from novel.

The consequences of an unregulated cryptocurrency market were not constrained by the cryptocurrency crashes examined in this study. Only months after the cryptocurrency crash of May 2022, the FTX collapsed (i.e., the Futures Exchange, formerly the world's third largest cryptocurrency exchange and hedge fund). This led to a bank run and, ultimately, multiple internationally renowned figures in the cryptocurrency community being imprisoned for fraud[1] These failures cost tax payers billions of dollars in the form of bailouts for cryptocurrency investors. These are not the only costs society faces due to cryptocurrency; cryptocurrency is also the medium of exchange for $76 billion of illegal activity, with approximately 46% of Bitcoin transactions representing illegal transactions (Foley et al. 2019).

To date, research on this crash has primarily focused on spillovers among different cryptocurrencies or certain commodities. While some research on investor-level sentiment has been published, studies have not explicitly tested the differences in responses between hardcore cryptocurrency enthusiasts and traditional investors who may have held some cryptocurrencies in their portfolios. Thus, given the severity, significance, and recency of this crash in the cryptocurrency market, it is critical to ascertain whether cryptocurrency enthusiasts behave in a fundamentally differently manner than traditional investors, especially in the context of a negative shock. If so, this could potentially

[1] Sam Bankman-Fried and Do Kwon are the two most notable, but many other fraud schemes have been caught across the world.

lead to greater volatility and is a further reason for regulating the cryptocurrency market. Accordingly, this study seeks to fill the gap in the literature by providing evidence that the May 2022 cryptocurrency crash disproportionately affected herding-type cryptocurrency enthusiasts (relative to traditional investors) as measured by its impact on the sentiment of tweets. This is accomplished by applying natural language processing techniques to harvested Twitter data to quantify the text of tweets, classifying Twitter users into cryptocurrency enthusiasts and a control group, and then feeding this data into a difference-in-differences (DID) model to estimate the potential differential effect of cryptocurrency crashes on herding-type cryptocurrency investors relative to traditional investors. Additionally, this paper analyzes the specific textual content of the tweets in each group to further assess the presence of herding behavior. Such an analysis is important because the presence of herding generates further cause for regulating cryptocurrency markets as herding is known to lead to bubbles (Haykir and Yagli 2022).

The results of the DID regressions confirm that the sentiment of tweets from these herding-type cryptocurrency investors became relatively more negative after the cryptocurrency crash, providing evidence of a decline in investor sentiment among herding-type cryptocurrency investors relative to that of traditional investors. The DID estimators estimated in this study are best interpreted as the magnitude of the differential response to the cryptocurrency crash between cryptocurrency enthusiasts and traditional investors. Critically, the significant effect estimated here indicates that these two groups behaved in fundamentally different ways, confirming that they are indeed distinct.

Additionally, the results show that cryptocurrency enthusiasts began to tweet relatively more often after the cryptocurrency crash, suggesting that multiple behavioral changes occurred as a consequence of the crash. This provides further evidence that cryptocurrency enthusiasts and traditional investors are fundamentally different groups, with distinct responses to similar stimuli. Evidentiary, a classification of the specific textual content of tweets in each group, reveals evidence of herding behavior among cryptocurrency enthusiasts but not among traditional investors. Furthermore, a large portion of this herding behavior exhibited by cryptocurrency enthusiasts is centered on related cultural artifacts such as non-fungible tokens (NFTs).

Literature review

Despite the fact that many cryptocurrencies (e.g., Bitcoin) have a history of bubbles (Chaim and Laurini 2019), many cryptocurrency enthusiasts routinely invest excessively in them. This seemingly irrational behavior can lead to people tying a large proportion of their financial well-being to cryptocurrency. Because financial distress can lead to deteriorated mental health (Starkey et al. 2013) and, by extension, more negative sentiment among investors, the cryptocurrency crash of May 2022 presents a major concern regarding the well-being of herding-type cryptocurrency investors.

The community of investors in cryptocurrencies is diverse, especially among more established cryptocurrencies such as Bitcoin (Dodd 2018). However, cryptocurrencies in general, and many smaller, less-established cryptocurrencies in particular, have a core group of ideologues that form the basis of the community (Ooi et al. 2021). These ideologically motivated communities are typically very libertarian (Obreja 2022), with many members more concerned with belonging to the community and holding cryptocurrency than maximizing the return on their investment (Mattke et al. 2021). Understanding the nature of the communities around cryptocurrencies is important because these communities are critical predictors of the growth and popularity of cryptocurrency in terms of both investing and mining (Al Shehhi et al. 2014).

The libertarian nature of the cryptocurrency community is particularly relevant given the prevalence of confirmation bias, political and information silos, and the growing number of calls to regulate cryptocurrencies. The strong role of confirmation bias among cryptocurrency investors has been documented (Zhang et al. 2019). While regulations may help increase public trust in cryptocurrencies and protect investors and members of this community are among the most likely to benefit from them, (Giudici et al. 2020) the cryptocurrency community is largely ideologically opposed to any regulation.

Collectivist behavior exhibits itself in the cryptocurrency community in other ways. Although perhaps unprincipled, herding behavior among cryptocurrency investors is a well-documented phenomenon (Kallinterakis and Wang 2019). According to Haykir and Yagli (2022), herding behavior in cryptocurrency was prominent during the global COVID-19 pandemic. A study of 50 cryptocurrencies also revealed evidence of herding behavior among investors (da Gama Silva et al. 2019). Specific events have been found to increase herding behavior among cryptocurrency investors, including the expiration date of Bitcoin futures on the Chicago Mercantile Exchange (Blasco et al. 2022). Generally, herding behavior tends to be at its highest when uncertainty is high (Bouri et al. 2019). Combining this with the result from Vidal-Tomás et al. (2019) that herding is strongest when markets are down, we can see that the cryptocurrency crash of 2022 is an important event that can be used to study the behavior of cryptocurrency investors.

Social media is one of the richest sources of data for studying investor behavior. Researchers can study investors' behavior and motivations by collecting social media data and using natural language processing (NLP) techniques (Zhou 2018). The most commonly used NLP technique is sentiment analysis (Liu 2010). A prominent example of the use of sentiment analysis in the finance literature comes from Gao et al. (2022), who used the announcement of the Chinese "dual carbon" target to study the impacts of investor sentiment on the volatility of (green) stock returns.

Several studies generally consider the role of investor sentiment in stocks (Baker and Wurgler 2006, 2007; Baker et al. 2012; Da et al. 2015). In addition, Seok et al. (2019) and Xu and Zhou (2018) examined the role of investor sentiment in Korean and Chinese stocks, respectively. However, the application of sentiment analysis to financing does not end with the stock market. Using data on bettor sentiment, Avery and Chevalier (1999) showed that bettor sentiment affects the point spread in football games.

Other important papers related to this one include Kou et al. (2023) which demonstrates how fuzzy methods of studying facial expressions are relevant to making sustainable financial decisions. Kou et al. (2024) used fuzzy methods to impute expert financial decisions that are "based on the golden ratio". Another paper by Kou et al. (2021) used fuzzy methods to study fintech investments in the context of European banks. Leaving the realm of fuzzy methodologies, Kou et al. (2021) developed a model to predict bankruptcies among small and medium sized businesses.[2]

Turning to the effects of investor sentiment on cryptocurrencies, the literature remains plentiful. Cryptocurrencies do not always respond to new information in the same manner as traditional investments Rognone et al. (2020). This is particularly important because the sentiment analysis of both news (Lamon et al. 2017) and social media (Philippas et al. 2019) has been linked to changes in cryptocurrency prices. Mai et al. (2018) built on these results by showing that not only did social media sentiment affect cryptocurrency markets but also that such effects were driven by the sentiment of low-frequency posters, not high-frequency posters. Furthermore, relevant sentiment data from social media have been shown to affect the volatility of cryptocurrency markets (Ahn and Kim 2021) and liquidity (Yue et al. 2021) and can predict bubbles in cryptocurrency markets (Phillips and Gorse 2017). Several studies have considered the effects of the sentiment of (or pertaining to) influential figures on cryptocurrency prices, most notably Ante (2023) and Cary (2021).

In the case of Cary (2021), there was a severe negative impact on the price of Dogecoin attributable to the action of the crypto-tastemaker, who affixed their celebrity to the cryptocurrency. This raises an important, more general concern: given that Anastasiou et al. (2021) showed that sentiment correlates with the risk of a crash in the cryptocurrency market, what happens when there is a major drop in the market?

The May 2022 crash was not the first to occur in cryptocurrency markets. For instance, crashes occurred during 2017–2018 (Cross et al. 2021) and 2013–2014 (Bouri et al. 2017).

Herding behavior among investors is common in cryptocurrency crashes (Li et al. 2023). Examples of observed herding in cryptocurrency markets include a study by Vidal-Tomás et al. (2019), who presented evidence of herding in the lead up to the 2017–2018 cryptocurrency crash. Similarly, Shu et al. (2021) found proof that herding caused a bubble in Bitcoin in 2021. Bouri et al. (2019) studied herding over a longer period of time, finding it to be a persistent feature of cryptocurrency markets that ebbed and flowed over time. Raimundo et al. (2022) found that herding behavior was particularly prominent in cryptocurrency markets during periods of market stress. A typical approach to measuring sentiment throughout the literature is to find a source of relevant text, typically from social media, perform sentiment analysis on the text, and relate the results from the sentiment analysis to the price of a cryptocurrency (Abraham et al. 2018).

Although there are abundant studies on herding, not all such papers can be cited reasonably in this literature review. For example, although they did not study cryptocurrency specifically, Yousaf et al. (2018) found that Ramadan does not lead to herding behavior in the Pakistani stock market. Similarly, Yousaf and Ali (2020b) studied spillovers between Bitcoin, Ethereum, and Litecoin before and during the COVID-19 pandemic by comparing spillovers during the periods October 3, 2018 to December 31, 2019, and January 1, 2020 to April 1, 2020 using a vector autoregressive asymmetric

[2] I'd like to thank a particularly dedicated reviewer for suggesting these four papers.

generalized autoregressive conditional heteroskedasticity (VAR-AGARCH) framework. Building on this, Yousaf and Ali (2020a) also studied spillovers between Bitcoin, Ethereum, and Litecoin before and during the COVID-19 pandemic by comparing spillovers during the periods January 1, 2019 to December 31, 2019 and January 1, 2020 to April 22, 2020, using a VAR-DCC-GARCH framework. Building on this line of research, Yousaf and Ali (2021) examined spillovers between Bitcoin, Ethereum, and Litecoin, as well as the S &P 500, before and during the COVID-19 pandemic by comparing spillovers from May 21, 2019 to December 31, 2019 and from January 1, 2020 to May 21, 2020 using a BEKK-AGARCH framework. All three studies on cryptocurrency spillovers and COVID-19 have consistent results and, as of April 1, 2020, report a combined market cap of 76% for these three cryptocurrencies. The author of this paper highly recommends that the reader look at these three papers.[3]

While much literature exists on how herding and sentiment affect prices, the literature on the opposite direction is sparse and considerable progress remains to be made regarding the effects of returns on sentiment. This study builds on the existing literature by providing empirical evidence that returns on financial investments affect investor sentiment, but, in the case of cryptocurrencies, in a non-homogeneous manner across different types of investors. Furthermore, this difference in behavior is tantamount to herding.

Theoretical motivation

Before presenting the data and methodology, it is important to explain why we should expect to see behavioral differences between cryptocurrency enthusiasts and traditional investors. While other assumptions are possible, the model presented here specifically assumes expected utility theory (Mas-Colell et al. 1995). This framework is ideal because it allows for a straightforward economic interpretation of behavioral expectations derived from the model, which helps build a simple intuition for why we should expect to see the empirical results that we do indeed observe, considering the following setup with two types of agents: type θ_E represents cryptocurrency enthusiasts and type θ_I represents traditional investors. All agents are utility maximizers that maximize the following intertemporal utility function in Eq. 1, where agents derive utility from their wealth (W_t) and consumption (C_t), which is proportional to wealth (i.e., $C_t = \rho W_t$, where $0 < \rho < 1$ to ensure that some consumption and savings occur), and from investments in Bitcoin (B_t). The parameters $\alpha_B > 0$, $\alpha_W > 0$, and $\alpha_C > 0$ describe the relative contributions of held Bitcoin, wealth, and consumption, respectively, to an individual's total utility. The key assumption of the model is that the function $f(\theta)$ is equal to α_B for the cryptocurrency enthusiast type $\theta = \theta_E$; however, for the traditional investor type $\theta = \theta_I$, the value of $f(\theta)$ is zero. This finding implies that traditional investors gain utility from cryptocurrencies as their wealth increases. Thus, the parameter α_B describes the additional value (cultural or otherwise) ascribed to Bitcoin held by cryptocurrency enthusiast type agents. Importantly, this study assumes that $\alpha_B \leq \alpha_W$, such that θ_E-type agents still aspire to grow their wealth.

[3] I'd like to thank another particularly dedicated reviewer for suggesting these four papers and bringing my attention to all that they imply.

$$U_t(\theta) = f(\theta)\ln(B_t) + \alpha_w \ln(W_t) + \alpha_c \ln(C_t) \tag{1}$$

Next, we describe the evolution of wealth by using Eq. 2. Here, $I_t = W_t - B_t$ represents traditional (non-cryptocurrency) investments. The parameters r_I and r_B denote the rates of return on traditional investments and Bitcoin, respectively. Importantly, this study assumes that the rate of return r_I is equal to the highest rate of return available to investors; if Bitcoin has the highest rate of return available to a traditional investor, $r_I = r_B$. However, because this study focuses on investor behavior during the aftermath of the cryptocurrency crash of 2022, we assume that $r_i > r_B$ for the remainder of this analysis.

$$\dot{W} = W_t - W_{t-1} = (1 + r_I)I_t + (1 + r_B)B_t - C_t \tag{2}$$

By simply rearranging the terms and using the definitions of I_t and C_t, we obtain the following description of the change in investor wealth over time (Eq. 3):

$$\dot{W} = r_I W_{t-1} + (r_B - r_I)B_t - \rho W_t \tag{3}$$

Given this simple model, the natural questions are as follows: (1) How much wealth will be invested in Bitcoin by θ_E-type investors? (2) How does the evolution of wealth differ between the two investor types?

To answer the first question, we set equal partial derivatives of utility with respect to wealth and Bitcoin (Eq. 4).

$$\frac{\alpha_W}{W} = \frac{f(\theta)}{B} \tag{4}$$

Rearranging the terms and using the definition of $f(\theta)$ gives us the ratio of wealth invested in Bitcoin over time for each investor type:

$$\frac{B}{W} = \begin{cases} \frac{\alpha_B}{\alpha_W} & \text{if } \theta = \theta_\mathrm{E} \\ 0 & \text{if } \theta = \theta_\mathrm{I} \end{cases} \tag{5}$$

As can be seen from Eq. 5, the optimal proportion of Bitcoin holdings is equal to the relative utility a θ_E-type investor obtains from holding Bitcoin compared to their utility from wealth in general.

Turning our attention to the second question, the goal is to describe the difference in $\frac{\dot{W}}{W}$ between the two investor types. Equation 6 states the evolution of wealth for θ_I-type investors, and 7 states the evolution of wealth for θ_E-type investors. The "Appendix" provides the derivation of these results.

$$\frac{\dot{W}}{W} = (1 + \rho)\left(\frac{r_I}{1 + r_I}\right) - \rho \tag{6}$$

$$\frac{\dot{W}}{W} = (1 + \rho)\left(\frac{r_I W + (r_B - r_I)B}{(1 + r_I)W + (r_B - r_I)B}\right) - \rho \tag{7}$$

Taking the difference between these two equations, we find that traditional investors' wealth grows at a faster rate than in (Eq. 8; derivation in the "Appendix").

Table 1 Summary statistics for the data

Category	Variable Name	Mean	SD	Min	Median	Max
Sentiment	Compound	0.048	0.133	0.000	0.000	1.000
	Positive	0.775	0.311	0.000	1.000	1.000
	Negative	0.120	0.221	0.000	0.000	1.000
	Neutral	0.085	0.318	-0.986	0.000	0.998
Emotions	Anger	0.021	0.075	0.000	0.000	1.000
	Disgust	0.013	0.060	0.000	0.000	1.000
	Negative	0.064	0.165	0.000	0.000	1.000
	Joy	0.036	0.090	0.000	0.000	1.000
	Positive	0.126	0.240	0.000	0.000	1.000
	Fear	0.027	0.090	0.000	0.000	1.000
	Sadness	0.021	0.076	0.000	0.000	1.000
	Trust	0.078	0.183	0.000	0.000	1.000
	Surprise	0.021	0.076	0.000	0.000	1.000
$BTC	Bitcoin	22,308.496	4104.924	19,017.640	21,398.910	47,686.810
	Change in bitcoin	− 271.547	774.296	− 4275.260	− 133.070	5483.450

$$\frac{\dot{W}_I}{W_I} - \frac{\dot{W}_E}{W_E} = \frac{(1+\rho)\left(\frac{\alpha_B}{\alpha_W}\right)(r_I - r_B)}{(1+r_I)\left(1 + r_I + \left(\frac{\alpha_B}{\alpha_W}\right)(r_B - r_I)\right)} > 0 \tag{8}$$

Thus, using a simple model, we show that cryptocurrency enthusiasts will experience a lower growth rate for wealth as a consequence of the utility they gain from holding Bitcoin. Given that changes in wealth can be reasonably expected to affect the sentiment embedded in relevant tweets, this derivation provides a formal justification for why we should expect to see changes in the sentiment of tweets among cryptocurrency enthusiasts in the aftermath of the cryptocurrency crash of 2022.

It is important to acknowledge that an expected utility framework is not the only way to motivate the empirical analysis in this study. The prospect theory is another means of framing this study. However, there is extensive value in establishing and deriving this expected utility model. Specifically, this study shows how non-financial factors, such as belonging to a community, can affect the utility-maximizing behavior of cryptocurrency enthusiasts. Essentially, while the cryptocurrency enthusiast's position of holding crypto assets during a crash is not what a traditional investor would consider rational, it is rational from the perspective of a cryptocurrency enthusiast. This is important for policymakers when designing regulations for cryptocurrency markets.

Data and identification strategy

Data

The data used in this study were obtained from Twitter. To identify a differential effect linking the cryptocurrency crash to changes in the sentiment of cryptocurrency enthusiasts relative to traditional investors, we ultimately need to quantify the relevant aspects of tweets using sentiment analysis. These relevant aspects of tweets are referred to as affective states in the sentiment analysis literature (Xie et al. 2021) as a "positive," "negative," "neutral," and an aggregate or "compound" score. Once all tweets are assigned scores for each affective state, all tweets by a given user during each of the two time periods (before and after the cryptocurrency market crash) the scores are combined and averaged to give a mean score for each user and affective state pair. This dataset also contains the frequency of tweets made by each user before and after the cryptocurrency crash. Because the state of the cryptocurrency market itself is likely to affect investor sentiment, the price of Bitcoin is also included. Table 1 presents the summary statistics, and the process for generating these data is described below.

The data were generated using a four-step process. The first step was to curate a list of Twitter users for the potential treatment and control groups. This was done by searching for and collecting tweets containing at least one of a series of finance related terms including cryptocurrency specific terms such as "wagmi." (An acronym for "We are all gonna make it," "wagmi" is a rallying cry among herding-type cryptocurrency enthusiasts). This approach was chosen over other sample selection methods (e.g., the seed-based method proposed by Yang et al. (2015)) because it allows for a straightforward classification of users. While many different clustering methods could have been used to (bi)partition the users, such methods rely on the full sample of users having already been determined and, therefore, are not appropriate for use here (Li et al. 2021).[4] Twitter was selected as a data source for several reasons. First, when the data for the study were collected, the Twitter API was freely accessible to researchers. Second, Twitter users tend to post frequently, with short yet expressive posts, which is an ideal combination for this study. Third, a body of literature exists on extracting a representative sample of users from Twitter for a given research purpose (Vicente 2023; Mislove et al. 2011).

Once the tweets were collected, the second step was to partition the users into the treated and control groups for the DID regression. The treated group; that is, herding-type cryptocurrency enthusiasts, was defined via the existence of herding-type cryptocurrency enthusiast-specific keywords in tweets. If a herding-type cryptocurrency enthusiast-specific keyword was present in any of a user's tweets, the user was classified as "treated." The remaining users were classified as "controls" and may be thought of as more traditional investors (i.e., investors who did not exhibit outward evidence of herding-type behavior in the cryptocurrency market prior to the cryptocurrency crash of May 2022). It is important to note that these users may still invest in cryptocurrencies; however, such investment decisions are no different from any other investment decision.

With a large number of tweets (614,116) collected and users classified into treated and control groups, the third step was to define the time periods for "pre" and "post" event (pre = January 1–April 30; post = June 1–August 31), representing before and after the initial cryptocurrency crash in May 2022. All of the tweets were classified accordingly, and tweets between these two periods were omitted from the study. This choice of period allows us to look at persistent changes in investor sentiment, as opposed to the more transient changes that may have been observed during the omitted intermediate period.

Finally, the various affective states considered in the study were quantified as "positive," "neutral," "negative," and an aggregate measure. This was achieved by performing

[4] This paper was also suggested by one of the afore-thanked reviewers.

sentiment analysis of the tweets using the Sentiment Intensity Analyzer tool from the Natural Language Toolkit (NLTK) module in Python. Individual tweets were tokenized, lemmatized, and stemmed, and all usernames were removed from the tweets. The output of the Sentiment Intensity Analyzer tool consists of four scores that quantify the presence of specific affective states in tweets: "positive," "neutral," "negative," and "compound" (an aggregate measure). The scores assigned to each affective state come from the unit interval [0, 1], with the exception of neutral sentiment, which is mapped to the interval $[-1, 1]$. For more details on performing sentiment analysis, please see Feldman (2013). For replicability, all code pertaining to this study is available from https://github.com/cat-astrophic/cryptocrash.

Relating these affective states to investor sentiment, if the cryptocurrency crash had negatively impacted investor sentiment, one consequence we might expect to observe would be relatively less positive sentiment expressed in tweets, meaning a greater prevalence of negative and neutral tweets in the post-crash period. This is because typically positive herding-type cryptocurrency enthusiasts may have either a higher sentiment baseline or employ a more positively measured diction relative to other users, including other herding-type cryptocurrency enthusiasts. Tweets by these users may become more "neutral," meaning that although they no longer express explicitly positive sentiment on Twitter, they do not necessarily express explicitly negative sentiment. A practical example of this would be unimpassioned appeals within the herding-type investor community to hold a course that does not explicitly express dismay at the current state of the cryptocurrency market.

In addition to these four broad affective states, more nuanced emotion-specific variables were created in the same manner as the data for the four broad affective states, namely "anger," "disgust," "fear," "sadness," "negativity," "surprise," 'trust," "joy," and "positivity." As was the case for the broader affective states discussed above, these emotions were calculated using the NLTK module in Python and followed the data preprocessing methods outlined above.

Finally, we acquired data on the number of tweets that each user tweeted during each period. These data are included because significant results indicate that cryptocurrency enthusiasts changed not only their sentiment but also their behavior regarding Twitter usage.

Identification strategy

Given the nature of the research question and the data, two sets of ID models were used to determine whether cryptocurrency enthusiasts behaved fundamentally differently from traditional investors. The standard interpretation of the DID estimator is the average treatment effect of the treated units (ATT). However, in the context of this study, where the treated units are cryptocurrency enthusiasts and the control units are traditional investors, this tells us whether there is a differential response to the cryptocurrency crash between the two groups. If so, these two groups behave fundamentally differently from one another and thus represent two distinct types of investors.

In the first model in each set, we estimated the effect of cryptocurrency crashes on the mean tweet sentiment across all Twitter users in the sample. Here, the model is specified as shown in Eq. 9, where $Y^{s}_{x,i,t}$ is the mean score for affective state s for tweet x by user

i in period t, $Treated_x$ is a dichotomous variable indicating whether tweet x was written by a herding-type cryptocurrency enthusiast, $Post_t$ is a dichotomous variable indicating whether the day t of tweet x was before or after the cryptocurrency crash, δ_i is a user-specific fixed effect, $\epsilon_{i,t}$ is the error term, and β is the parameter of interest. Separate regressions were run for each affective state, and this approach was used for both the sentiment and emotion analyses.

$$Y^s_{x,i,t} = \beta \cdot (Treated_x \times Post_t) + \rho \cdot Treated_x + \tau \cdot Post_t + \gamma \cdot \Delta BTC_t + \delta_i + \epsilon_{x,i,t} \tag{9}$$

To provide additional support for these regressions, we estimate the regression shown in Eq. 10, where we examine the user-level average values for each affective state in each of the two time periods. β remains the parameter of interest.

$$Y^s_{i,t} = \beta \cdot (Treated_i \times Post_t) + \rho \cdot Treated_i + \tau \cdot Post_t + \gamma \cdot \Delta BTC_t + \delta_i + \epsilon_{i,t} \tag{10}$$

To test for another potential change in behavior among herding-type cryptocurrency enthusiasts, another DID model was specified, as shown in Eq. 11. Here, $Tweets_{i,t}$ becomes the dependent variable; otherwise, we follow the specification from Eq. 10 and are again interested in estimating the parameter β. Changes in the frequency at which a tweet can be an additional indicator of sentiment have not been previously considered in the literature.

$$Tweets_{i,t} = \beta \cdot (Treated_i \times Post_t) + \rho \cdot Treated_i + \tau \cdot Post_t + \gamma \cdot \Delta BTC_t + \delta_i + \epsilon_{i,t} \tag{11}$$

Finally, these models cannot be presented without a discussion of endogeneity. When running a DID model, a key assumption for causality is that there can be no self-selection in the treatment. In this study, individual investors can choose whether they are willing to participate in a broader cryptocurrency culture (type θ_E investors in the theoretical model). However, we do not estimate the causal effect of a policy but rather exploit an exogenous market shock to directly observe the differential responses of two distinct groups of investors to this shock. Therefore, the only potential endogeneity concern in this paper lies in potential correlations between the use of the term "wagmi" in tweets and the sentiment of the words surrounding "wagmi" in the tweet. However, as will be shown in the following section, if anything, this study *underestimates* the magnitude of the differential response to the May 2022 cryptocurrency crash between cryptocurrency traders and traditional investors.

Results

This section presents and discusses the regression results and textual evidence suggestive of herding behavior. First, we focus on the results of the tweet- and user-level regressions for broad affective states (i.e., compound, positive, negative, and neutral). The results are presented in Tables 2 and 3, respectively. Next, we take a more nuanced look at these affective states using the results from the tweet- and user-level regressions for the presence of specific emotions in the tweets. The results are presented in Tables 4 and 5, respectively. Third, we address the results of the regressions on the frequency at which users tweet (see Table 6). Finally, we analyze the specific textual content of the

Table 2 Results for the tweet-level regressions for change in tweet sentiment

	Sentiment			
	Compound	**Positive**	**Negative**	**Neutral**
Treated×Post	− 0.004	− 0.001	−0.005**	0.041***
	(0.006)	(0.004)	(0.003)	(0.006)
Treated	0.057	0.057	− 0.030	− 0.111
	(0.077)	(0.053)	(0.032)	(0.072)
Post	0.007	− 0.001	− 0.0005	0.0001
	(0.004)	(0.003)	(0.002)	(0.004)
Δ$BTC	0.000	0.000	0.000	− 0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.158***	0.126***	0.045***	0.831***
	(0.034)	(0.024)	(0.014)	(0.032)
Observations	614,116	614,116	614,116	614,116
Adjusted R^2	0.079	0.084	0.068	0.153

Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are provided in parentheses

Table 3 Results for the user-level regressions for change in tweet sentiment

	Sentiment			
	Compound	**Positive**	**Negative**	**Neutral**
Treated×Post	− 0.010	− 0.005	− 0.002	0.048***
	(0.009)	(0.006)	(0.003)	(0.010)
Treated	0.063***	0.061***	−0.034***	−0.118***
	(0.009)	(0.006)	(0.003)	(0.010)
Post	0.012	0.005	− 0.003	− 0.012
	(0.010)	(0.006)	(0.003)	(0.008)
Δ$BTC	0.000	0.000	− 0.000	−0.00002*
	(0.000)	(0.000)	(0.000)	(0.00001)
Constant	0.153***	0.121***	0.046***	0.837***
	(0.008)	(0.005)	(0.002)	(0.006)
Observations	4479	4479	4479	4479
Adjusted R^2	0.410	0.117	0.439	0.374

Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are provided in parentheses

tweets and provide evidence of herding among herding-type investors but not among traditional investors.

Broad affective states

Beginning with the regressions for the four broad affective states (Tables 2 and 3), cryptocurrency enthusiasts saw a decrease and increase in negative sentiments and neutral sentiments in their tweets, respectively. The increase in neutral sentiment should not be surprising as it can be explained by a more subdued discourse among cryptocurrency enthusiasts that contains both increases in negative sentiment attributable to the cryptocurrency crash and the deliberately positive, collectivist, and perhaps even dogmatic, "wagmi" mantra. Conversely, the decrease in negative sentiment

Table 4 Results for the tweet-level regressions for change in tweet emotion content

	Emotion								
	Anger	**Disgust**	**Fear**	**Sadness**	**Negative**	**Surprise**	**Trust**	**Joy**	**Positive**
Treated × post	0.00003	− 0.001	0.001	− 0.00003	0.0005	− 0.002	− 0.003	−0.004**	− 0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.0002)	(0.004)
Treated	− 0.028	− 0.014	− 0.017	0.033*	0.060	− 0.027	−0.090**	− 0.032	− 0.149
	(0.018)	(0.015)	(0.022)	(0.019)	(0.040)	(0.019)	(0.041)	(0.022)	(0.057)
Post	−0.003***	−0.001*	− 0.001	− 0.001	− 0.004	0.001	0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)
Δ$BTC	0.000	−0.000***	0.000	0.000	− 0.000	− 0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.031***	0.016**	0.033***	0.008**	0.068***	0.028***	0.124***	0.080***	0.210***
	(0.008)	(0.007)	(0.010)	(0.008)	(0.018)	(0.008)	(0.018)	(0.010)	(0.026)
Observations	614,116	614,116	614,116	614,116	614,116	614,116	614,116	614,116	
Adjusted R^2	0.044	0.032	0.052	0.046	0.059	0.040	0.198	0.061	0.104

Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are provided in parentheses

might be surprising given the negative nature of the cryptocurrency crash and its impact on cryptocurrency enthusiasts. Given that the cryptocurrency enthusiast community made a deliberate, collective effort to stay positive ("wagmi"), a decrease in negative sentiment makes sense. Since "wagmi" is a deliberate positive rallying cry, its use appears to have offset a decline in positive sentiment, leading to statistically insignificant results for both positive sentiment and the compound score. This is particularly important because the decrease in the price of Bitcoin (assuming it is correlated with investor sentiment), may have been partially offset by the collective effort to hold Bitcoin, despite the financial implications of the herding-type cryptocurrency enthusiasts, thus validating the model presented in Sect. "Theoretical Motivation".

These results suggest that cryptocurrency enthusiasts behave in a fundamentally different manner compared to traditional investors. From an economic policy standpoint, this is particularly important because it suggests the potential for herding. (The next section of this paper explores herding further.) A market flooded with participants who engage in herding behavior is more likely to have bubbles and eventually runs. As the cryptocurrency market is still largely unregulated, there is a need for regulations to prevent runs. While this would seem a dramatic claim in other contexts, a run in the cryptocurrency market occurred between the beginning of this study and its publication.[5]

In the user-level regressions (Table 3), we can see that cryptocurrency enthusiasts are overall more positive, less negative, and less neutral and have higher compound scores than traditional investors. The statistical insignificance of the treated indicator in the tweet-level regressions suggests that user-level fixed effects account for the differences between the two user types. We also find that the change in the price of the Bitcoin variable was statistically significant and negative for neutral sentiment. This suggests that increased emotionality was present among finance-oriented Twitter users when Bitcoin prices went up.

[5] This is a reference to the FTX collapse and ensuing run.

Table 5 Results for the user-level regressions for change in tweet emotion content

	Emotion								
	Anger	**Disgust**	**Fear**	**Sadness**	**Negative**	**Surprise**	**Trust**	**Joy**	**Positive**
Treated × post	0.001	− 0.001	− 0.0005	0.001	0.002	−0.003**	− 0.008	−0.005**	0.006
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.006)	(0.003)	(0.006)
Treated	−0.030***	−0.014***	−0.015***	0.032***	0.059***	−0.025***	−0.085***	−0.031***	−0.158***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.006)	(0.003)	(0.006)
Post	−0.003**	− 0.001	−0.005**	− 0.002	0.001	0.003*	0.013*	0.001	0.007
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.007)	(0.003)	(0.006)
Δ$BTC	− 0.00000	0.000	−0.00001***	− 0.00000	0.00000	0.00000	0.00001	0.00000	0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00001)
Constant	0.031***	0.015***	0.034***	0.019***	0.064***	0.027***	0.116***	0.080***	0.207***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.006)	(0.002)	(0.005)
Observations	4479	4479	4479	4479	4479	4479	4479	4479	
Adjusted R^2	0.396	0.336	0.462	0.398	0.386	0.223	0.140	0.160	0.547

Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are provided in parentheses

Table 6 Results for the regressions for the volume of tweets by users

	Volume of tweets					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × post	103.296***	103.561***	103.047***	103.057***	104.310***	105.645***
	(27.928)	(27.970)	(27.960)	(27.956)	(28.264)	(28.370)
Treated	− 162.966	− 164.597	− 160.131	− 167.177	− 165.473	− 166.107
	(325.875)	(326.212)	(326.246)	(326.290)	(326.324)	(327.320)
Post	65.419***	65.119**	65.649***	65.050**	65.164**	64.477**
	(25.170)	(25.216)	(25.200)	(25.206)	(25.214)	(25.296)
Δ$BTC	− 0.015	− 0.015	− 0.015	− 0.016	− 0.016	− 0.016
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Compound		25.820				85.128
		(95.733)				(160.754)
Positive			− 46.140			− 159.101
			(134.147)			(210.093)
Negative				− 125.215		− 46.149
				(306.534)		(386.170)
Neutral					− 21.281	− 50.811
					(87.880)	(98.962)
Constant	9.317	5.363	14.908	15.082	27.138	60.235
	(230.542)	(231.205)	(231.302)	(231.151)	(242.195)	(251.095)
Observations	4479	4479	4479	4479	4479	4479
Adjusted R^2	0.516	0.515	0.515	0.515	0.515	0.513

Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are provided in parentheses

These results confirm and build on the findings of previous studies (e.g., (Baker and Wurgler 2007)) that link investor sentiment to market conditions. In particular, these results expand the literature by showing that investor sentiment responds to market conditions and that there is profound heterogeneity in responses to changes in market conditions across different types of investors.

Emotions

Next, we focus on the emotion-specific regression results (Tables 4 and 5), which indicate that cryptocurrency enthusiasts experienced significant changes in their expression of two specific emotions: surprise and joy. Specifically, cryptocurrency enthusiasts expressed less surprise and joy in their tweets than more traditional investors. These results, especially the decrease in the expression of joy, suggest that there is indeed some fundamental difference between how cryptocurrency entrants and traditional investors invest in, utilize, and experience cryptocurrencies such as Bitcoin. The decrease in the expression of surprise is interesting because it suggests that cryptocurrency enthusiasts may have begun to anticipate the persistence of cryptocurrency crashes. This implies that cryptocurrency enthusiasts possibly held Bitcoin despite poor expectations of its future performance. These results strongly support the model provided in Sect. "Theoretical Motivation" in which cryptocurrency enthusiasts derive extra utility simply from holding cryptocurrency assets.

Similar to the regressions for the four broad affective states, the user-level regressions suggest stark differences in how the two groups communicate. Cryptocurrency opportunists appear to express less anger, disgust, fear, surprise, trust, joy, and positivity and tend to express more sadness and negativity. Finally, changes in the price of Bitcoin lead to a decrease in disgust and fear, which, in turn, results in an increase in trust. These results confirm the existing literature on the psychology of cryptocurrency enthusiasts.

As in the previous subsection, these results confirm and build on the literature that links investor sentiment and market conditions. In particular, we find that (1) the cryptocurrency crash caused a decrease in the expression of surprise and joy among herding-type cryptocurrency enthusiasts and (2) herding-type cryptocurrency enthusiasts have a distinct emotional profile compared to traditional investors. Cryptocurrency enthusiasts are prone to express themselves in sadder and more negative ways, with less trust, joy, anger, disgust, fear, and surprise than traditional investors. This suggests that a certain type of person (i.e., a certain set of personality traits) self-selects into a herding-type cryptocurrency group.

Tweet frequency

The final set of regressions examines the actual tweet behavior of users by studying the frequency of their tweets. Here, we see that cryptocurrency enthusiasts increased the frequency with which they tweet by over 100 tweets during the post-cryptocurrency crash period compared to the control group, which translates to an increase of more than one tweet per day relative to that of traditional investors. As shown in Table 6, these results are highly consistent across the specifications, demonstrating their robustness to the sentiments contained in the tweets. Moreover, they suggest that behavioral changes in cryptocurrency enthusiasts may be numerous and correlated as we found changes in both sentiment/emotionality and tweet frequency attributed to the same event. This builds on the existing literature by providing the first evidence that market conditions differentially affect investors' use of social media when discussing investment-related topics.

Textual evidence of herding

In this section, we present evidence suggesting the presence of herding among cryptocurrency enthusiasts by analyzing the specific textual content of tweets. To this end, we apply a manually augmented hierarchical clustering method to the most frequent terms found in the tweets using the following process.

First, after following the same data preprocessing steps outlined in the methodology for performing sentiment analysis; that is, tokenization, lemmatization, and stemming, a bag of (unique) words was created for each group. Once the unique words were identified, the frequency with which they appeared in the tweets was computed, and words appearing in at least 1/1000 tweets were identified. In total, 19 words are associated with traditional investors, whereas 57 are associated with cryptocurrency enthusiasts.

Table 7 Final term classes from the herding analysis

Cryptocurrency enthusiasts				**Traditional investors**
Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 1**
(Cryptocurrency)	**(NFT)**	**(wagmi)**	**(misc)**	**(All)**
15min	art	always	check	also
analytic	collect	amaze	collect	better
avg	mint	awesome	done	business
buy	**nft**	bro	morn(ing)	but
crypto	piece	commun(ity)	wait	could
eth	project	congrat(ulations)		do
gt	purchase	eden		game
lfg	sale	<eyes emoji>		he
link	unique	fam		help
<money emoji>		feel		how
price		<fire emoji>		invest
realtime		fren		job
sol(ana)		follow		life
sold		gm		money
trade		gn		quote
		guy		start
		happy		they
		<heart emoji>		would
		hope		year
		join		
		lol		
		magic		
		nice		
		<rocket emoji>		
		ser		
		space		
		wagmi		

Terms are roots and may reflect several possible extensions, e.g., commun may include community, communities, communal, etc. Common extensions are presented in parentheses at the end of a root on occasion to help provide clarity and intuition

The bold terms are simply the terms around which each category is based, if one exists

To provide evidence of herding, these frequent terms were classified using a hierarchical clustering method from SciPy in Python (scipy.cluster.hierarchy). This algorithm clusters terms based on their co-occurrence in tweets. The results (classes) of this algorithm were then manually updated to the final classes listed in Table 7.

These classifications support the notion of herding for two primary reasons. First, the disjoint nature of terms between the two groups of investors suggests that cryptocurrency enthusiasts represent their own "clique" within the online investing community. Second, across the classes for the terms commonly used by cryptocurrency enthusiasts, clear themes emerge as the dominating discourse. Class 1, a class of terms related to cryptocurrencies, is not surprising and does not necessarily imply the existence of herding behavior. However, Classes 2 and 3 suggest otherwise. Regarding Class 2, the fact that the NFT bubble was not observed as a common topic of discourse among traditional investors but was important enough to constitute its own class among cryptocurrency enthusiasts is qualitative evidence suggesting that cryptocurrency enthusiasts engage in herding behavior, at least regarding NFTs. Class 3 (i.e., the ("wagmi" class) suggests that this behavior extends to cryptocurrencies as well since it is, by definition, representative of the discourse related to holding cryptocurrency despite the nature of the market at that time. This is direct evidence of herding behavior among cryptocurrency enthusiasts but not traditional investors in the cryptocurrency market in the aftermath of the cryptocurrency crash in May 2022.

Finally, other important trends became apparent during the analysis. First, cryptocurrency enthusiasts use more current Internet vocabulary than traditional investors do. Examples include the use of emojis; no emojis were among the most frequent terms used by traditional investors, while five emojis appeared among the most common terms used by cryptocurrency enthusiasts. While this certainly reflects a significant cultural difference between the two groups, it could also reflect meaningful demographic differences. These differences and the elevated risk-seeking behavior observed among cryptocurrency enthusiasts fits the social identity model of risk-taking (Cruwys et al. 2021).

The second theme that emerged is the gendered nature of online investment communities. "He," "bro," "guy," "ser," "fam," and "they," were all among the most commonly used words used by the two groups in this study, yet no female-gendered words (e.g., "she") appeared among the most common words. This suggests that online investment communities are largely male-dominated.

The last trend that emerged was within the community of cryptocurrency enthusiasts, concerns the use of the term "ser." This term is used as a synonym for "sir," but it also has a racist second meaning; it is used to mock Indian and East Asian cryptocurrency enthusiasts for their relatively more frequent use of "sir" in the online discourse (Limbu 2022). To emphasize the toxic nature of the online cryptocurrency enthusiast community, the source cited on the previous line, an article published on the popular cryptocurrency news site Blockchain.News, classified this behavior as "trolling," minimizing the iniquity.

Conclusion

In the aftermath of the cryptocurrency crash of 2022, investor sentiment among cryptocurrency generators has changed relative to that of traditional investors, specifically, an increase in neutral sentiment and, surprisingly, a decrease in negative sentiment. This is particularly significant as the deliberate, collectivist approach to publicly displaying positivity and holding Bitcoin ("wagmi") could have mitigated the magnitude of the crash to a small extent. These findings are also important as they provide further support that cryptocurrency enthusiasts will hold on to a cryptocurrency even when they could earn better returns by investing elsewhere. These results validate the model described in Sect. "Theoretical Motivation" of this paper. In summary, cryptocurrency enthusiasts and traditional investors exhibit visibly distinct behavioral patterns.

In addition to changes in investor sentiment, two other changes were observed in the behavior of cryptocurrency enthusiasts. First, there were changes in the specific emotional content of their tweets, specifically a decrease in surprise and joy. Second, the frequency at which these cryptocurrency enthusiasts tweet increased in the aftermath of the cryptocurrency crash of 2022, suggesting that public displays of loyalty to Bitcoin and/or the Bitcoin community are an important cultural practice that manifests itself in herding behavior. This reinforces the notion that herding and other collectivist behaviors are central to cryptocurrency community membership.

From a policy perspective, cryptocurrency markets must be regulated. The prevalence of herding behavior among cryptocurrency enthusiasts is not only present but also a core cultural component in this community. This could lead to the formation of bubbles and subsequent runs. As stated in the body of this paper, runs are not an abstract and unlikely concern but an observed consequence of this behavior. Given the gradually increasing role of cryptocurrencies in traditional portfolios, a failure to regulate the cryptocurrency market could lead to spillovers to other markets and negatively impact all investors. Only months after the cryptocurrency crash studied in this paper, the FTX Exchange collapsed, a bank run occurred, multiple leading global figures in the cryptocurrency market (as of May 2022) are now in prison, illicit activities have been financed, and taxpayers have lost billions of dollars bailing out cryptocurrency investors.

Another implication of this study is that we can identify potential herding-type cryptocurrency investors via social media. As researchers continue to study herding and other disconcerting phenomena in markets, this can be useful for various reasons, including targeting individuals for surveys or online experiments on social media. Additionally, the ability to identify herding investors on social media could allow targeted nudges designed to prevent herding in markets and increase market efficiency.

This study has two limitations. First, the herding results are largely, although not exclusively, qualitative. Causal analysis of herding behavior would be an excellent extension of this study. Second, the main results from the DID models may actually understate the true effects of the cryptocurrency crash on cryptocurrency enthusiasts as they deliberately emphasized positivity ("wagmi"), which could have impacted the sentiment scores assigned to tweets and users in this data set. An econometric consequence is a potential downward bias in the point estimates for negativity and a potential upward bias in the point estimates for positivity. If these biases are present, this further confirms the conclusions drawn in this study, and further analyses of this (and other related) phenomenon would be valuable extensions of this research. One possible way to expand the scope of this analysis is to collect data from a broader set of source materials.

So far, the importance of the results has been framed in the context of fundamental differences between traditional investors and cryptocurrency enthusiasts regarding their perceptions of, experiences with, and motivations for investing in cryptocurrencies and the consequential regulatory implications. While this consequence is incredibly important, there is another potential consequence of these results. While the literature is not conclusive regarding the sentiment of social media posts and mental health, if such a relationship exists, these results suggest that the mental health of cryptocurrency enthusiasts can be linked to the state of cryptocurrency markets. This is concerning for both financial and humanitarian reasons.

Appendix

Derivation of Eq. 6

$$\begin{aligned}
\frac{\dot{W}}{W} &= \frac{W_t - W_{t-1}}{W_t} \\
&= \frac{(1+r_I)W_{t-1} - C_t - W_{t-1}}{W_t} \\
&= \frac{r_I W_{t-1}}{W_t} - \frac{C_t}{W_t} \\
&= \frac{r_I W_{t-1}}{(1+r_I)W_{t-1} - \rho[(1+r_I)W_{t-1} - \rho W_t]} - \rho \\
&= \frac{r_I W_{t-1}}{(1-\rho+\rho^2 - \ldots)[(1+r_I)W_{t-1} - (1+r_I)W_{t-1}]} - \rho \\
&= (1+\rho)\left(\frac{r_I}{1+r_I}\right) - \rho
\end{aligned}$$

Derivation of Eq. 7

$$\begin{aligned}
\frac{\dot{W}}{W} &= \frac{W_t - W_{t-1}}{W_t} \\
&= \frac{(1+r_I)I_{t-1} + (1+r_B)B_{t-1} - C_t - W_{t-1}}{W_t} \\
&= \frac{(1+r_I)(W_{t-1} - B_{t-1}) + (1+r_B)B_{t-1} - W_{t-1}}{W_t} - \frac{C_t}{W_t} \\
&= \frac{r_I W_{t-1} + (r_B - r_I)B_{t-1}}{W_t} - \rho \\
&= \frac{r_I W_{t-1} + (r_B - r_I)B_{t-1}}{(1+r_I)(W_{t-1} - B_{t-1}) + (1+r_B)B_{t-1} - \rho W_t} - \rho \\
&= \frac{r_I W_{t-1} + (r_B - r_I)B_{t-1}}{(1+r_I)W_{t-1} + (r_B - r_I)B_{t-1} - \rho W_t} - \rho \\
&= \frac{r_I W_{t-1} + (r_B - r_I)B_{t-1}}{(1+r_I)W_{t-1} + (r_B - r_I)B_{t-1} - \rho W_t} - \rho \\
&= \frac{r_I W_{t-1} + (r_B - r_I)B_{t-1}}{(1-\rho+\rho^2 - \ldots)[(1+r_I)W_{t-1} + (r_B - r_I)B_{t-1}]} - \rho \\
&= (1+\rho)\left(\frac{r_I W_{t-1} + (r_B - r_I)B_{t-1}}{(1+r_I)W_{t-1} + (r_B - r_I)B_{t-1}}\right) - \rho \\
&= (1+\rho)\left(\frac{r_I W + (r_B - r_I)B}{(1+r_I)W + (r_B - r_I)B}\right) - \rho
\end{aligned}$$

Derivation of Eq. 8

First, we derive the difference between $\frac{\dot{W}_I}{W_I}$ and $\frac{\dot{W}_E}{W_E}$ as

$$
\begin{aligned}
\frac{\dot{W}_I}{W_I} - \frac{\dot{W}_E}{W_E} &= (1+\rho)\left(\frac{r_I}{1+r_I}\right) - \rho \\
&\quad - (1+\rho)\left(\frac{r_I W + (r_B - r_I)B}{(1+r_I)W + (r_B - r_I)B}\right) + \rho \\
&= (1+\rho)\left(\frac{r_I + r_I^2 + \left(\frac{\alpha_B}{\alpha_W}\right)r_B r_I - \left(\frac{\alpha_B}{\alpha_W}\right)r_I^2 - r_I - \left(\frac{\alpha_B}{\alpha_W}\right)r_B + \left(\frac{\alpha_B}{\alpha_W}\right)r_I - r_I^2 - \left(\frac{\alpha_B}{\alpha_W}\right)r_B r_I + \left(\frac{\alpha_B}{\alpha_W}\right)r_I^2}{(1+r_I)\left(1+r_I+\left(\frac{\alpha_B}{\alpha_W}\right)(r_B - r_I)\right)}\right) \\
&= \frac{(1+\rho)\left(\frac{\alpha_B}{\alpha_W}\right)(r_I - r_B)}{(1+r_I)\left(1+r_I+\left(\frac{\alpha_B}{\alpha_W}\right)(r_B - r_I)\right)}
\end{aligned}
$$

All that remains to be shown is that the difference is positive. First, we consider the numerator. As $\rho > 0$, the term $1+\rho$ is positive. Similarly, because $\alpha_B > 0$ and $\alpha_W > 0$, ratio $\frac{\alpha_B}{\alpha_W}$ is positive. Finally, assuming that $r_I > r_B$, the difference $r_I - r_B$ is positive. This means that the numerator is the product of three positive terms and is therefore positive.

Moving on to the denominator and following an argument similar to that showing that the numerator is positive, we must show that $1 + r_I > \left(\frac{\alpha_B}{\alpha_W}\right)(r_I - r_B)$. Since $0 < (r_I - r_B) < r_I$, and since $0 \leq \left(\frac{\alpha_B}{\alpha_W}\right) \leq 1$ it follows that $1 + r_I > r_I \geq \left(\frac{\alpha_B}{\alpha_W}\right)(r_I - r_B)$ and thus the claim that $\frac{\dot{W}_I}{W_I} - \frac{\dot{W}_E}{W_E} > 0$ is verified.

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