Social Learning and Sentiment Contagion in the Bitcoin Market

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Abstract

Using novel data on investors' social interactions, we document sentiment contagion as a direct consequence of social learning in the Bitcoin market. Our findings suggest that the social learning process is inefficient, as investors respond positively to social sentiment, but social sentiment does not positively predict returns. Echo chamber effect and selective interpretation of information may simultaneously contribute to such inefficiency. We further confirm that sentiment contagion is not a sideshow: at the individual level, sentiment contagion predicts the direction of trading conditional on its occurrence; at the Bitcoin market level, the aggregated sentiment contagion index positively predicts market trading volume and volatility. Moreover, we highlight the error-prone nature of social learning, wherein the socially constructed optimism predicts Bitcoin crashes. Finally, we establish a link between social learning and bubbles: the elevated propagation of optimism is highly correlated with the trading volume.

Keywords: Social Finance, Sentiment Contagion, Bubbles, Bitcoin

JEL Code: G11, G12, G41, G53

1 Introduction

“*Man is by nature a social animal*”- Aristotle

Like Aristotle, researchers have long realized the importance of social activities on economic outcomes. However, the role of social interactions has been largely absent in economics and finance until recent decades (Shiller et al. (1984); Shiller and Pound (1989); Shiller (2007); Hirshleifer (2020)). In his pioneering works, Robert Shiller argues that social learning, among other factors, plays a pivotal role in influencing investors' decisions as they update their beliefs through social interactions. Shiller further proposes a potential link between social learning and asset pricing dynamics. Despite its prominence in the literature, direct empirical evidence on social learning has been limited, possibly due to data constraints.

We provide novel insights into social learning by leveraging new data on investors' social activities in the Bitcoin market. We document direct evidence for social learning and shed light on whether social learning is fully rational. We further document the aggregate impact of social learning on market outcomes. The Bitcoin market is well-suited for our study due to its distinctive social characteristics. First, Bitcoin, as a product born in the internet era, has its origins and development closely tied to social networks. Right after the inception of Bitcoin, its founder, Satoshi Nakamoto, quickly established Bitcointalk, an online social platform designed to support Bitcoin operations and facilitate information sharing and communications among Bitcoin users. Over time, Bitcointalk has grown into the most influential social platform on Bitcoin. Second, as a novel asset class, investors have a limited understanding of Bitcoin, making its valuation relatively difficult to determine. Users often turn to social platforms to share information and views. Third, as suggested by recent studies (Cong et al. (2021)), the valuation of Bitcoin depends on the aggregate demand from the social network, which further relies on social adoption. Rational investors would engage in social interactions to gather information on such social demands. Moreover, mistaken beliefs can form and spread via social interactions among investors (e.g., Hirshleifer (2020), Han et al. (2022)). In fact, the Bitcoin market exhibits high volatility and frequently displays bubble-burst characteristics. This correspondence is unlikely coincidental, and instead consistent with the long-standing hypothesis on the role of social dynamics in fueling boom-bust cycles (Shiller et al. (1984), Burnside et al. (2016)).

We utilize Bitcointalk data in our study of social learning. Given its influence on Bitcoin investors, we view social learning on this forum as indicative of broader social learning trends within the Bitcoin market. Moreover, employing this social platform offers several other advantages. Firstly, Bitcointalk enables investors to share opinions and engage with one another through posting and replying to each other's posts. As a result, we are able to observe conversations among investors, which is one of the most direct forms of social interactions. By leveraging Natural Language Processing (NLP) techniques, we can determine the sentiment of each message in these conversations. Consequently, we can examine the overall sentiment of the conversation as well as the sentiment of investors before and after each interaction. This setting provides an ideal environment for studying social learning. Furthermore, a subset of Bitcoin investors on this platform voluntarily disclose their Bitcoin wallet addresses to enhance the security of their forum accounts. Therefore, we can observe their wallet-level trading records on the blockchain of Bitcoin. By linking the sentiment expressed in their posts to their transactions, we can draw unique conclusions about the impact of social learning on investor trading behavior and market outcomes.

We begin by examining whether and how investors learn via social interactions. The basic unit of observation in our analysis is a conversation segment that starts and ends with two posts (post[0] and post[1]) from the same investor. We use the term *social sentiment* to refer to the average sentiment of other investors' messages between post[0] and post[1]. The investors' social learning within the conversation is manifested by the way their sentiment changes in response to social sentiment. We find that investors' sentiment updates in the same direction as the social sentiment, suggesting that sentiment spreads via conversations on the social network. Specifically, investors become more bullish (bearish) after being exposed to positive (negative) sentiment by other posters. Our results are robust to controlling for known factors related to belief changes as well as time- and user-fixed effects. Therefore, our results indicate that social learning leads to sentiment contagion.

It is striking that individuals tend to significantly update their beliefs about Bitcoin price in the same direction as social sentiment, although social sentiment is largely misinformed. It negatively predicts future Bitcoin returns for most horizons. However, investors appear to treat the social signals as informative. This suggests inefficiencies in the process of social learning. Further, we find that social learning is unrelated to the arrival of Bitcoin-related news in traditional media as reported by the RavenPack database. It intensifies on days with greater Bitcoin volatility or higher dispersion in the RavenPack Bitcoin news sentiment, suggesting a greater reliance on social signals during periods of high uncertainty.

Our research uncovers two patterns of inefficiency in social learning related to confirmation bias. Firstly, users selectively participate in conversations that are consistent with their priors, resulting in an echo chamber effect. For instance, users with positive prior sentiments are, on average, 6.738% more likely to engage in a thread initiated by a post with positive sentiment, compared to users with non-positive priors. To provide context, the unconditional probability of participating in a conversation that indicates a positive sentiment is 37.310%. Secondly, users selectively interpret information, responding more assertively to the social sentiment that aligns with their own prior sentiments.

To the extent that social learning is non-fully rational, we expect that sophisticated and informed investors are less affected by biased social learning. Consistent with this hypothesis, we find that investors who are less sophisticated, less socially connected, and less informed are more susceptible to social sentiment. For example, inexperienced users exhibit, on average, an additional sentiment adjustment of 3.585% after being exposed to a conversation with a social sentiment score of 1. Less informed users, compared to informed users, tend to update their sentiment by an additional 2.664% after participating in a conversation with a social sentiment score of 1. Furthermore, we consider users within a network structure and treat two users as connected if they have participated in at least one common conversation. We find that investors who have more connections are less responsive to social sentiment.

Taking a step further, we examine the impact of social learning on investors' trading decisions. We establish a clear link between the social sentiment encountered by investors and their subsequent net buying decisions using detailed trading records for a subsample of users on Bitcointalk. Our findings demonstrate that, in the presence of social interactions, social sentiment significantly predicts the direction of future trading decisions. If the encountered social sentiment increases by one unit, investors are 0.409% more likely to buy in the next day. The effect is economically significant, considering the average probability of buying is 0.934%. Furthermore, our results remain robust even after accounting for additional controls for news arrivals, market fluctuations, and overall sentiment on the Bitcointalk community. Overall, social learning is not merely a sideshow; instead, it strongly influences individuals' transactions. At a broad level, these results establish a micro-foundation for understanding the influence of social interactions on market outcomes.

We further document the aggregate impact of social learning on market dynamics. Specifically, we construct an index (SCI) to track the intensity of sentiment contagion in the market. We count the number of investors on Bitcointalk who change their sentiment in the same direction as the social sentiment in conversations and, after removing the time trend, use it as our proxy for the amount of social learning via conversations on Bitcointalk. As changes in investor sentiment are linked to individuals' future trading behaviors, we conjecture that SCI could also capture the aggregate demand for position changes in the future and, therefore, predict market dynamics such as trading volume. Consistent with our conjecture, we observe a strong predictive power of SCI for both Bitcoin trading volume and return volatility.

As sentiment spreads through the population via social interactions, more users become influenced by it. How do the accumulated belief changes via social interactions affect market outcomes? Given the documented inefficiencies in social interactions, we hypothesize that sentiment contagion may destabilize the market and contribute to the boom and bust in the Bitcoin market. We find confirmatory evidence for this hypothesis. First, we establish a link between social learning and bubbles. In our identified bubble episodes, we observe widespread optimism and a disproportionately high fraction of new investors engaging in these conversations. The contagion of optimism gets amplified in the bubble episodes and drives up the trading volume. We find that the correlation between the number of investors positively influenced by social interactions and the trading volume during bubbles can be as high as 0.669. Therefore, social learning offers a fresh perspective for comprehending the elevated trading volume during bubbles. Second, when the prevalence of optimistic views in the forum rises, the likelihood of a crash in Bitcoin returns substantially increases. This finding supports the error-prone nature of the impact of social interactions on aggregate outcomes proposed in David Hirshleifer's presidential address (Hirshleifer (2020)).

Our paper is connected to several strands of literature. First, there is a growing interest in how investment ideas are transmitted. Shiller et al. (1984) argues that investment in assets is a social activity and Shiller and Pound (1989) considers the role of social interaction in the transmission of financial information. Han et al. (2022) offers a model of social interactions to understand the transmission pattern of investment ideas. In line with these studies, our paper provides concrete evidence for the transmission of sentiment through social learning.

Our paper contributes to the growing literature on cryptocurrencies. Liu et al. (2022a) shares a similar spirit with our paper in terms of methodology and topic, as both studies adopt a machine-learning approach to address important questions about cryptocurrencies. Liu et al. (2022a) design machine learning methods to construct technology indexes from ICO whitepapers and investigate their role in cryptocurrency valuations. In comparison, we employ machine learning tools to measure sentiment in social media and examine social learning as well as its impact on trading decisions and market outcomes. Kogan et al. (2023) find that investors seem to form adaptive expectations about cryptocurrency prices while we highlight the role of peer sentiment on investor beliefs. Liu and Tsyvinski (2021) evaluates the risks and returns of cryptocurrencies, and Liu et al. (2022b) documents that three common risk factors—cryptocurrency market, size, and momentum—can capture the cross-sectional expected cryptocurrency returns. In contrast, we use the Bitcoin market as an ideal laboratory to study social learning and establish significant connections between social learning and Bitcoin market outcomes.

Our paper closely relates to an expanding body of literature that examines investor behavior on social networks. By leveraging data from an investor social network in the foreign exchange market, Simon and Heimer (2012) document that social interaction promotes active trading. Heimer (2016) further documents an increase in the level of the disposition effect after interacting with other investors. In the context of the investor social network StockTwits, Cookson et al. (2023) document that investors tend to selectively expose themselves to information aligning with their prior views, resulting in sustained disagreement. They also link this "echo chamber" effect to high trading volume in financial markets. In comparison, we highlight sentiment contagion as a direct consequence of social learning and document how social learning predicts individuals' trading decisions and aggregate market outcomes. Additionally, we utilize social learning to account for the significant trading volume during bubbles.

Our paper is related to studies that analyze the influence of peer actions. Hong et al. (2004) and Brown et al. (2008) provide evidence consistent with the notion that individuals are more likely to participate in the stock market when their geographically proximate peers participate. Hong et al. (2005) also shows that investors tend to buy stocks their local peers have been buying in the recent past. Huang et al. (2021) document the contagion of abnormal trading activity from "infected" investors to their neighboring investors by relying on stock-financed M&A as an exogenous shock. This paper highlights social learning as one plausible driver for the peer effect. Moreover, our data allows us to directly observe and measure social interactions, which further helps establish novel connections between social learning and individual-level trading decisions. Additionally, we establish links between social learning and aggregate market outcomes.

Do peer effects “wash out” in aggregate, or do they cause significant cyclical fluctuations in asset prices? Despite the significance of this question, there have been relatively few empirical studies conducted. One notable exception is Kuchler et al. (2022), who examine the Social Connected Index based on friendship links on Facebook. Their findings reveal that investors show a greater inclination to invest in companies located in socially connected regions, and firms in regions with stronger social ties tend to have higher valuations and liquidity. In contrast, our study focuses on direct evidence of social interactions and documents sentiment contagion as a consequence of social learning among Bitcoin investors. We document several important connections between social learning and market outcomes, including future market volume, volatility, and probability of crash.

The remainder of the paper is organized as follows: Section 2 describes the data and explains the main variables used in the analysis. Section 3 documents the social learning pattern. Section 4 studies the nature of social learning. Section **??** presents the impact of sentiment contagion on individuals’ trading decisions. Section 5 reports the impact of social learning on market outcomes. Section 6 concludes.

2 Data

2.1 Bitcointalk

Our study focuses on the Bitcoin market as it provides valuable opportunities to trace the full history of users’ social interactive activities since its inception in 2009. To gather data on social interactions, we primarily rely on Bitcointalk, an online forum that is considered to be the oldest and most influential community in the Bitcoin space, with over 54 million messages posted for over 1.2 million topics and more than 3.5 million registered users as of March 2023. The founder of Bitcointalk, Satoshi Nakamoto, is the presumed pseudonymous author (or authors) of the original Bitcoin white paper, which describes Bitcoin’s reference implementation. Bitcointalk holds significant influence on Bitcoin trading and the real world, serving as a hub for traders to discuss market trends, share trading strategies, and provide insights into the direction of the market. Its popularity has been widely covered by influential media outlets such as the Wall

Street Journal, Forbes, and Bloomberg. Considering its impact on Bitcoin investors, we perceive social interactions on this forum as a proxy for the general trend of social activities in the Bitcoin market.

In this paper, our research is centered around posts on Bitcointalk, which are timestamped messages containing sentences written by users. Generally, sentences within each post are concise in nature. These posts are organized within threads, which are collections of sequential posts that revolve around a common theme, allowing users to interact with each other. As an example in our sample, Figure 1 presents a thread titled “What does the future of bitcoin look like” joined by user DavidLuziz on May 31, 2018, with subsequent participations from other users sharing their opinions.

On Bitcointalk, threads are displayed under different “child boards”, which are subforums that gather discussions related to specific topics. Not all subforums are about topics related to the prospect of Bitcoin prices. For instance, the “Bitcoin Technical Support” child board is dedicated to addressing technical questions concerning Bitcoin Core, nodes, the Bitcoin network, transactions, and addresses. For our study, we specifically focus on the “Speculation” child board, where users predominantly discuss their views on Bitcoin’s prospects. Figure 2 presents the visual representation of the keywords mentioned in posts within this child board. The most frequent words include “Bitcoin”, “price”, “think”, and “know”. These keywords indicate that the topics are quite concentrated, and investors express their attitudes about Bitcoin prices in this subforum. The “Speculation” child board serves as an ideal field laboratory for our research, as we can examine how social interaction propagates users’ sentiment, and how sentiment contagion is linked to individual trading behavior and aggregate market outcomes.

There are multiple layers of user heterogeneity on this forum. For instance, we observe variations in the level of sophistication among users. Bitcointalk utilizes a merit system wherein users are awarded points for their contributions to the Bitcoin community. Based on their merits and activities, users are assigned different ranks on the Bitcointalk website, ranging from high ranks such as “Legendary” to lower ranks like “Newbie”. Typically, users with higher ranks demonstrate a greater understanding of Bitcoin. Moreover, a significant number of users voluntarily disclose their demographic information, including age, gender, and home country.

2.2 User Sentiment

2.2.1 Textual Analysis and User Sentiment

In this paper, “user sentiment” refers to users’ beliefs about future Bitcoin prices. We develop a methodology to extract user sentiment from posts collected on the Bitcointalk forum. Since our raw data consists of over 1 million posts, far beyond what we can manually interpret, we employ a textual analysis algorithm. Our algorithm is a two-step procedure based on a keyword dictionary and a natural language processing (NLP) algorithm developed by the Stanford University NLP group (Manning et al. (2014)).

In the first step, we randomly select 10,000 sentences from our dataset and manually label them into four categories: “positive”, “neutral”, “negative”, and “irrelevant”. This approach mainly follows the methods used in Baker et al. (2016) and Tetlock (2007). We then use these labeled sentences as our training set and construct a keyword dictionary for each category. For example, keywords for the “positive” category may include “buy”, “increase”, and “rise”, while keywords for the “negative” category may include “sell”, “decrease”, and “plunge”, and so on. The dictionary for the “neutral” category includes terms such as “hold”, “wait”, “unpredictable”, and others. If a sentence does not contain any of the keywords in the above three categories, we label it as “irrelevant”. For our analysis, we focus on relevant sentences.

One challenge we face in our labeling exercise is distinguishing between descriptive statements about past performance and beliefs about the future in certain posts. For instance, a sentence like “Bitcoin market really increased a lot in the past months” can be ambiguous in terms of an user’s opinion about future Bitcoin prices. To tackle this challenge, in the second step, we leverage the Stanford NLP algorithm to identify the tense of each sentence and detect backward-looking and forward-looking statements simultaneously. For example, if a sentence contains the keyword “increased”, the Stanford NLP would detect the past tense, and our algorithm would label it as “irrelevant”. Similarly, the Stanford NLP algorithm can identify future tense in sentences with phrases such as “will increase”. Furthermore, our definition of forward-looking statements aligns with the format recommended by the SEC for 10-K reports, including sentences with terms like “expects”, “anticipates”, and so on.

After applying labels from the aforementioned two steps, we are able to extract user sentiment from each sentence. Additionally, we process sentences containing negative particles like “not” and “couldn’t”. If a sentence with negative particles contains words that are classified as “positive”, we reverse our interpretation and label the sentence as “negative” instead of “positive”. We assign a value of 1 to sentences with a “positive” sentiment, -1 for “negative”, and 0 for all others. For example, a sentence like “Bitcoin price will roar” is assigned a value of 1, while “Bitcoin price is not going to fall” is also assigned a value of 1. Conversely, a sentence like “Bitcoin is doomed to fall” is assigned a value of -1, and a sentence like “Bitcoin price is really unpredictable” takes a value of 0. To calculate the overall sentiment of a post, we take the average of the sentiment values of all its sentences. As a result, the sentiment measurement for a post falls within a continuous range from -1 to 1. The out-of-sample accuracy of our algorithm is approximately 85%.

2.3 Transaction Data

We are able to link the sentiment of a subsample of users to their trading behaviors. This group of users voluntarily published their Bitcoin wallet addresses in a thread officially initiated by the forum organizer, as a protective measure for their Bitcointalk accounts against hacking.[1] Since Bitcoin transactions are publicly available on the Bitcoin Blockchain, we can trace their detailed transactions information such as trade size and trade timestamp using these published wallet addresses.

2.4 Other Data Sources

To proxy investor attention for the Bitcoin market, we utilize Google search volume data followingDa et al. (2011). Specifically, we define Google Search (Bitcoin) as the difference between the Google Search Volume Index and its past one-month mean, divided by the lagged one-month mean.

To systematically capture the impact of news events on the Bitcoin market, we obtain news related to Bitcoin from Ravenpack News Analytics, a reliable source that tracks news reports about Bitcoin and provides sentiment scores for them dating back to 2011. We refer to the general tone of news coverage on Bitcoin in the media as the news sentiment, and include it as a control variable in our analysis.

We gather Bitcoin market data, including returns and trading volume on an hourly basis from CoinAPI.

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[1] This is an official activity organized by the management team of the Bitcointalk forum. Users of Bitcointalk are recommended to disclose their public Bitcoin wallet address within this thread. When a user posts their public Bitcoin wallet address on Bitcointalk, they are creating a public record of their ownership of that wallet address. If their Bitcointalk account is later hacked, they can use their private key to create a digital signature that proves their ownership of the Bitcoin address they previously shared. This digital signature can then be used to authenticate the account holder’s identity and facilitate the recovery of their Bitcointalk account.

We also calculate daily return volatility. This data is also utilized in Griffin and Shams (2020). The transactions before May 2012 were relatively less frequent. Therefore, our focus is on transaction data starting from May 1st, 2012, and the sample period ends on July 30th, 2022.

2.5 Summary Statistics

To be consistent with the Bitcoin market data, our main dataset from Bitcointalk covers the period between May 1st, 2012, and July 30th, 2022. It comprises 666,006 posts in the ”Speculation” subforum, contributed by 44,356 users. Among these users, we successfully linked 2,550 individuals to their transaction records through their disclosed Bitcoin wallet addresses. In Panels A, B, and C, we present summary statistics for user sentiment at the user, daily, and thread levels, respectively. Panel D reports summary statistics for market information of Bitcoin, RavenPack news sentiment and Google Search Volume.

In Panel A of Table 1, we present the summary statistics for posting activities at the user level. For a representative user in our sample, the average sentiment score of the posts they published is 0.324, suggesting a general optimism towards Bitcoin among users. Such optimism is consistent with the existing literature on motivated beliefs (Bénabou and Tirole (2016)) and utility-based biases in beliefs (Brunnermeier and Parker (2005)). Furthermore, we observe a significant within-user standard deviation of sentiment at 0.608, indicating substantial variation in sentiment over time at the individual level. We require at least two posts for a given user to compute the standard deviation of post sentiment. The distribution of the number of posts is skewed, as evident from the difference between the median and mean number of posts per user.

Panel B of Table 1 describes post activities on a given day. On a representative trading day, about 120 users publish around 178 posts. The average post sentiment is 0.279, which is optimistic and consistent with the statistics at the user level.

Panel C reveals that posts within threads often exhibit dispersed sentiment, with an average within-thread standard deviation of 0.646. Furthermore, active user engagement is notable, with 25 users participating in a representative thread containinga total of 35 published posts. Overall, users seem to pay close attention to the posts, resulting in active exchanges within threads, with a median gap between consecutive posts within a thread of only 48 minutes.

Panel D provides summary statistics for variables at the aggregate market level. In the first row, the mean return (annualized) is 119.0% and the standard deviation is 16.166. When combined, the Sharpe ratio is approximately 0.074. The second row presents the within-day volatility of Bitcoin, calculated using hourly return data. On average, the volatility is approximately 3.7%. We present volume-related variables for Bitcoin, spanning from the third to the fifth row. On a typical trading day, there are 16,472 transactions involving 9,359 bitcoins being traded. The average daily trading volume totals 56.499 million dollars. Moving to the sixth row, we present summary statistics for the sentiment of RavenPack News. In its original form, the sentiment score for RavenPack News Database ranges from 0 to 100, but we have normalized it to the range of $[-1, 1]$. On average, the transformed sentiment of news within a single day is 0.041 with a standard deviation of 0.330. The daily correlation between RavenPack News sentiment and post sentiment is 0.262, indicating that while there is some overlap, these two data sources capture distinct dimensions of sentiment.

3 Social Learning and Sentiment Contagion

In this section, we investigate whether social learning propagates the spread of user sentiment, a pattern we refer to as *sentiment contagion*. Specifically, we examine how a user's sentiment may be influenced by the sentiment of others, as expressed through conversations on the forum.

3.1 Data Structure

Figure 1 illustrates an example conversation from the forum. User DavidLuziz published one post at 05:37:35 AM on May 31st, 2018 (post[0] at the top). Subsequently, several other users joined the conversation and shared their views about Bitcoin. At 07:50:10 AM on the same day, DavidLuziz published his second post in the same thread (post[1] at the bottom), becoming more optimistic about Bitcoin after interacting with other users.

We study consecutive posts from the same user, similar to the ones by DavidLuziz in Figure 1. We denote the first post published at timestamp t_0 as post[0], and the second post made at timestamp t_1 as post[1], as illustrated in Figure 3. We refer to the sentiment in post[0] and post[1] as the *prior sentiment* and the *ex-post sentiment*, respectively.

Between a consecutive pair of posts by a user, other users may publish posts, forming what we term as a *conversation*. To measure the views of peers in social interactions, we define *social sentiment* as the average sentiment of other users' posts within the conversation. One user's consecutive posts could be in two different threads.[2] In such cases, conversations refer to posts published between t_0 and t_1 in both threads to which post[0] and post[1] belong. Our results remain robust to restricting to a smaller sample with post[0] and post[1] in the same thread (see Appendix Table A4). In total, there are 296,291 pairs of posts by the same user (and correspondingly 296,291 conversations) from 16,535 users in our main test sample.

To understand how sentiment spreads via social interactions on Bitcointalk, we examine whether a user updates her belief about Bitcoin after being exposed to others' views on Bitcointalk. We achieve this by linking the social sentiment to the user's own sentiment change, defined as the revision from her prior sentiment to ex-post sentiment. We control for confounding factors that might affect sentiment change, such as Bitcoin return and volatility, the overall contemporaneous sentiment in other conversations on the forum and news arrivals documented in the RavenPack database.

3.2 Time Window for Consecutive Posts

Figure 3 illustrates the timeline of our analysis. There is a trade-off when determining the time window allowed between the consecutive pairs of posts. A shorter time window would reduce the confounding influence of unobservable factors for belief changes, but it would result in a smaller sample, thereby reducing the statistical power of our analysis. We strike a balance by choosing a window that is sufficiently short in order to cleanly capture belief changes caused by social interactions while avoiding excessive data loss. Figure 4 presents the cumulative distribution function of the time gap between consecutive posts by the same user in our sample. More than 50% of the pairs fall within a 24-hour window. Therefore, we select a 24-hour time window in our main analysis.[3]

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[2] After posting in one thread, the user will receive notifications from the forum if others publish follow-up posts in the same thread. Therefore, users will pay attention to subsequent posts in the thread to which post[0] belongs.

[3] Appendix Table A5 indicates that social learning is stronger for 48 hours or 72 hours time window than 24 hours window.

3.3 Evidence for Social Learning

To examine the effect of social learning, our main regression model is:

$$\begin{aligned} \text{Senti Change}_{i,j,t_0 \to t_1} &= \beta_1 \text{Social Sentiment}_{i,j,t_0 \to t_1} \\ &+ \gamma' \text{Control}_{i,t_0 \to t_1} + \text{Fixed Effects} + u_{i,t_1}, \end{aligned} \tag{1}$$

where Senti $\text{Change}_{i,j,t_0 \to t_1}$ is the revision in sentiment from post[0] to post[1] by user i in conversation j. As mentioned above, the timestamps for post[0] and post[1] are denoted as t_0 and t_1, respectively. Social $\text{Sentiment}_{i,j,t_0 \to t_1}$ is the social sentiment that user i has encountered in conversation j between time t_0 and t_1. $\text{Control}_{i,t_0 \to t_1}$ is a set of control variables, including Bitcoin return and volatility, activities in other conversations within the forum and news arrivals documented in the RavenPack database. We also include lagged news arrivals as controls to account for response delays. We control for user and day fixed effects, as well as a prior fixed effect to account for the direction of the prior sentiment. Standard errors are clustered at user and day levels.

We choose to use sentiment change as the primary dependent variable because we consider it a more direct measure of the social learning effect. This variable also aligns more coherently with our subsequent analysis of the impact of social learning on market outcomes. Another option for the dependent variable would be the ex-post sentiment. Appendix Table A1 verifies the robustness of our findings under this alternative setting. In fact, the magnitudes become larger when we use ex-post sentiment as the outcome variable, indicating that we provide a conservative estimation of the effect of social learning under the current setting using sentiment change. Moreover, our regression models incorporate fixed effects to account for the signs of the prior sentiment. This choice is motivated by the observation that users with a positive prior sentiment naturally have less room for increased optimism compared to those with a negative prior sentiment.

The social learning channel predicts a positive coefficient for social sentiment as evidence that forum users revise their sentiments in the direction of sentiments in the conversations, Table 2 confirms this hypothesis.[4] Column (1) studies the relationship between sentiment change and social sentiment controlling for the directions of prior sentiment. A one standard deviation increase in social sentiment is associated with an increase in changes in sentiment of 3.749% (calculated as $42.177\% \times 8.888\%$). In columns (2) and (3),

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[4] For ease of presentation, we scale up each coefficient by a factor of 100.

we further add user and day fixed effects, respectively to control for user characteristics[5] and day-specific confounding factors that might affect sentiment change. Even with both user fixed effect and day fixed effect included, the effect of social learning remains highly significant.

Column (4) adds additional controls to address alternative explanations for the effect of social learning. The first story concerns the common news shocks that arrive between post[0] and post[1], echoing the findings in Feng and Seasholes (2004). To account for this, we include the contemporaneous average news sentiment from Ravenpack News Database between the consecutive posts. We also include lagged Ravenpack news shocks up to 48 hours[6] before post[0] as additional controls to address the concern that investors might respond to news with a delay. Furthermore, we compute the contemporaneous Bitcoin return and volatility from hourly Bitcoin market data between t_0 and t_1, and include them as additional controls for contemporaneous information sources. We find that the regression coefficient of social sentiment remains unchanged. Finally, we construct the forum sentiment variable that measures the average sentiment of posts published between t_0 and t_1 in other conversations than the ones of post[0] or post[1]. Even controlling for all above confounding factors, the coefficient of social sentiment remains significantly positive.

In column (5), we test whether the effect of social learning is significant even within user-week. By adding user-week fixed effects, we solely rely on variation between different post pairs by the same user in the same week. Even in this stringent specification, the effect of social learning is still significantly positive, suggesting that our results are unlikely driven by time-varying user characteristics.

3.4 Propagation along the Network

We further investigate the propagation of sentiment through the social network. We consider two users as neighbors if they have interacted by participating in the same conversations. Our hypothesis posits that the sentiment of a neighbor's neighbor may affect a user's sentiment revision due to diffusion of sentiment. To test this hypothesis, we trace the conversations of these neighbors within a 24-hour window prior to the current conversation, excluding conversations in which the user herself has previously participated. We refer to these as neighboring conversations. We then calculate the average sentiment of the neighbors' neighbors

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[5] For example, see Barber and Odean (2001), D'Acunto et al. (2019), Grinblatt et al. (2011).

[6] In untabulated results, we also control for news arrivals in the past 7 days and our findings remain consistent.

in these indirectly connected conversations, which we term as indirect social sentiment. Table 3 shows that indirect social sentiment has a positive and significant effect on a user's sentiment, consistent with the hypothesis that a user' sentiment can propagate through a social network and affect other users without direct interactions.

3.5 Placebo Test

To further establish the significance of social learning in sentiment contagion, we conduct a placebo test. Specifically, we investigate whether sentiment changes are influenced by the average sentiment of randomly selected conversations in which the user does not participate. These conversations take place between the timestamps of post[0] and post[1]. The results are presented in Table 4. In columns (1) and (2), we randomly select one conversation and find that the average sentiment from this conversation does not significantly predict sentiment change. The coefficient magnitude is only 5% of that observed for social sentiment in Table 2. To demonstrate robustness, we also examine the effect of selecting multiple random conversations. For example, in columns (5) and (6), we randomly select ten conversations that occur between post[0] and post[1], in which the user does not participate. We find that the non-significant pattern remains robust.

4 Non-Fully Rational Learning: Suggestive Evidence

In this section, we evaluate the nature of social learning. The traditional view is that individuals update their beliefs in a rational manner by adhering to Bayes' theorem. However, recent evidence suggests non-fully rational learning. Individuals may assign disproportionate weight to information with certain features or selectively acquire and interpret information. They may also react to peer sentiment and update their beliefs based on messages from social media, even when social signals are not informative or not new. While our objective is not to exclude Bayesian learning, our analysis highlights the existence of non-fully rational components within the social learning process, which align more closely with a behavioral narrative.

4.1 Heterogeneity by User Features

To shed light on the nature of social learning, we start by investigating which types of users are more susceptible to it. In asset pricing models, investors are typically classified into two distinct groups based on their level of rationality: naïve investors, who are significantly influenced by psychological biases, and sophisticated investors, who exhibit more rational behavior and act as the counteracting force to market sentiment (De Long et al. (1990); Lee et al. (1991); Barber and Odean (2013)). Therefore, our initial focus is on examining how social learning differs between naïve users and sophisticated users. On Bitcointalk, users are classified into legendary and non-legendary categories based on their influence and contribution to the Bitcointalk community. We adopt this classification method and designate non-legendary users as naïve users, while treating legendary users as sophisticated users. Column (1) of Table 5 presents the heterogeneous effect of social learning among these two groups. The interaction term between the naïve user indicator and social sentiment is positive and significant, suggesting that naïve users are more responsive to social sentiment compared to sophisticated users. On average, when faced with a social sentiment of 1, a naïve user updates sentiment by 3.585% more than a sophisticated user. The same pattern shows up in column (2) where we incorporate the user-week interaction term.

Second, we compare users who are more central in the social network with less central users. Central users are those who are more connected to other users. We treat two users as connected if they have participated in at least one conversation together. Central users engage widely in conversations and are likely to be more experienced in social activities. Following an established algorithm in the network literature (Hagberg et al. (2008)), we calculate the centrality score for each user on a daily basis. Column (3) of Table 5 shows that in general, central users exhibit significantly lower response to social sentiment. A one-unit increase in the centrality score reduces the magnitude of sentiment contagion by 0.047%. The social learning effect is moderated for central users but it does not get eliminated. For instance, even for a user at the 75th percentile with a centrality score of 16.3, the effect of social learning remains at 3.320% (calculated as 4.086% - 0.047% * 16.3). Column (4) shows that our findings remain robust if we include the user-week interactive effect in the regression.

Third, we investigate whether users with distinct levels of informedness respond differently to social sentiment. On a rolling basis, we define less informed users as those whose sentiment exhibits a low correlation with future Bitcoin returns in 7 days (correlation $<$ 25th percentile). Column (5) of Table 5 presents evidence consistent with this hypothesis. The interaction term indicates that, compared to more informed users, less informed users update belief by 2.664% more after participating in a conversation with a social sentiment of 1. In column (6), we replace user and day fixed effects with the user-week interactive effect, and our results remain unaffected.

Overall, there is substantial heterogeneity regarding social learning. Less sophisticated, less experienced, and less informed investors—those who are likely less rational —are more responsive to social sentiment. These findings provide suggestive evidence for the existence of non-fully rational components in social learning.

4.2 Time-Varying Social Learning

Another perspective to further delve into the nature of social learning is how social learning varies over time. First, we investigate whether social learning is driven by information flow. We identify a day as informative if the total number of news arrivals in the RavenPack News database exceeds its sample median.[7] We expect to see a stronger effect of social learning on informative days if posts on Bitcointalk mainly serve to propagate news. Columns (1) and (2) of Table 6 indicate a statistically insignificant coefficient for the interaction term of social sentiment and the dummy for informative days, suggesting that social learning is not stronger when there is more new information. Therefore, social learning does not seem to be driven by the flow of information.

Second, we investigate whether social learning is influenced by the level of uncertainty in the Bitcoin market. Tversky and Kahneman (1974) established that availability heuristics influence judgments made under uncertainty. In our context, during periods of heightened uncertainty, availability heuristics may prompt individuals to be more inclined to conform to the social sentiment they encounter. Columns (3) to (4) of Table 6 show that social learning is significantly stronger when the standard deviation of news sentiment on Bitcoin from the RavenPack News database is higher than the sample median. In columns (5) and (6), we proxy for uncertainty using the standard deviation of hourly Bitcoin returns in a rolling 24-hour window and document a similar pattern. Overall, we provide consistent evidence for elevated social learning in uncertain periods.

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[7] In our untabulated analysis, we verify that our findings remain the same when we classify a day as informative if the total number of "novel" news labeled by RavenPack exceeds its sample median.

4.3 Informativeness of Social Sentiment

4.3.1 Social Sentiment and Future Returns

To further understand the rationality of social learning, we estimate the relationship between social sentiment and future returns by running the following regression:

$$\begin{aligned} \text{Cumulative Return}_{i,j,t_1+1\to t_1+k} &= \beta_1 \text{Social Sentiment}_{i,j,t_0\to t_1} \\ &+ \gamma \text{Control}_{t_0\to t_1} + \text{Fixed Effects} u_{i,t_1}, \end{aligned} \tag{2}$$

where the dependent variable, denoted as Cumulative Return$_{i,j,t_1+1\to t_1+k}$ represents the ex-post cumulative return in a forward-looking window from hour 1 to hour k after user i has participated in a conversation j that ends at timestamp t_1. We study five different time windows, 6, 24, 48, 72 and seven days after the conversation. The main explanatory variable, Social Sentiment$_{i,j,t_0\to t_1}$, represents the social sentiment encountered by user i in conversation j between timestamps t_0 and t_1. To address potential confounding factors, we further include a set of time-varying controls. We also include user and date fixed effects as well as a prior fixed effect. Standard errors are clustered by user and day, as recommended by Hodrick (1992).

This specification follows a well-established approach in the retail trading literature (Barber and Odean (2000)). The retail trading literature assesses the quality of decision-making by retail traders based on the timing of buys and sells relative to subsequent returns. Similarly, we evaluate the quality of information linked to social sentiment by analyzing its timing in relation to subsequent Bitcoin returns. In this context, a positive coefficient for β_1 would indicate that social sentiment is informative and enhances the quality of users' signals. Conversely, a negative coefficient indicates low informativeness, suggesting that social sentiment undermines the quality of users' signals. Table 7 shows that social sentiment is largely misinformed. Social sentiment negatively predicts future returns in most horizons. If users follow a trading strategy of buying bitcoin immediately after observing a social sentiment of 1 and hold for the next 24 hours, on average they would incur a loss of -0.094%. In comparison, Table 1 shows that a simple buy-and-hold strategy yields a daily return of 0.326% (calculated as 1.190/365).

4.3.2 Social Learning Through Informative Posts

While, on average, a higher social sentiment predicts lower returns, there may still be informative posts that positively forecast returns. Users may respond more to these informative posts. To explore this hypothesis, we analyze three user features discussed in Section 4.1 and Table 5: the level of sophistication represented by the legendary status, centrality, and post informativeness. For each highlighted feature, we separately measure the social sentiment by featured users and by non-featured users. Subsequently, we investigate whether each group's sentiment predicts future Bitcoin returns.

Panel A of Table 8 presents our findings. In columns (1) and (2), we compare the informativeness of social sentiment from legendary and naive users. Although social sentiment from naive users is slightly less informative than that from legendary users, both negatively predict future cumulative returns in the next 24 hours. Columns (3) and (4) demonstrate that the social sentiment of both central and non-central users negatively predicts returns. Somewhat surprisingly, social sentiment from central users more strongly predicts negative returns than social sentiment from non-central users. Columns (5) and (6) show that social sentiment by both informed and less informed users negatively predicts returns, although social sentiment by informed users seems relatively more precise.

In Panel B of Table 8, we investigate how users respond to social sentiment from users with different features. In columns (1) and (2), we find that users are twice as sensitive to social sentiment from naive users compared to social sentiment from legendary users. This finding is difficult to reconcile with a rational narrative, as social sentiment from both naive and legendary users negatively predicts future returns. As shown in columns (3) and (4), users strongly respond to the social sentiment from both central and non-central users. However, the social sentiment from both types of users negatively predicts future returns, as shown in columns (3) and (4) of Panel A. Columns (5) and (6) indicate that users respond positively to social sentiment from non-informed users and informed users, but this social sentiment also negatively predicts future returns. In untabulated tables, we include the user-week interactive fixed effect and find that our results remain similar. Overall, the findings from Panel A and B of Table 8 provide additional support for the behavioral narrative of social learning: different components of social sentiment are generally uninformative, but users actively learn from them and revise their sentiment accordingly.

4.4 Confirmation Bias

Why would users update their beliefs after being exposed to non-informative social signals? They might believe in wisdom of crowd, not realizing the lack of the information content of social sentiment. The psychology literature has extensively documented humans' cognitive limitations, which affect our perception, attention, memory, decision-making, and problem-solving abilities. One notable heuristic is confirmation bias (Nickerson (1998)), the tendency to search for, interpret, favor, and recall information in a way that confirms or supports one's prior beliefs or values. In this section, we study confirmation bias in social learning. We provide two pieces of evidence consistent with confirmation bias. First, users selectively participate in confirmatory conversations, a phenomenon also known as *echo chambers*. Second, they also selectively interpret the signals they encounter in conversations.[8]

4.4.1 Echo Chambers: Selective Participation of Conversations

Confirmation bias may cause users to selectively acquire signals. We examine users' decisions to participate in conversations that are confirmatory with their priors by estimating the following probit model:[9]

$$\begin{aligned} & Pr[\text{Participate Positive}_{i,t+k} = 1]_t \\ = \ & \Phi[\beta_0 + \beta_1 \text{Prior Sentiment}_{i,t} + \gamma_m \text{Control}_{i,t,m} + u_{t+k}], \end{aligned} \tag{3}$$

where Φ is the $c.d.f.$ of the standard normal distribution. The dependent variable Participate Positive is an indicator, taking a value of 1 if the subsequent conversation after post[0] has a positive sentiment and 0 otherwise. We employ two measures for whether the subsequent conversation has a positive sentiment. The first measure is based on the first post of the thread to which post[1] belongs since it garners the most attention when users browse through threads. The second measure takes a value of 1 if the social sentiment (i.e., the average sentiment of posts between post[0] and post[1]) is positive and 0 otherwise. The explanatory variable, Prior Sentiment$_{i,t}$, is an indicator for whether user i's sentiment is positive in her post[0] published at the timestamp of t. We also include a battery of control variables Control$_{i,t,m}$ to account for market and forum events that occur between the two consecutive timestamps t and $t+k$. The control variables are

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[8] By designing survey experiments, Faia et al. (2022) demonstrate how individuals selectively acquire and interpret information during the Covid-19 pandemic.

[9] The consecutive pairs of posts enable us to observe both users' prior beliefs and their subsequent participation decisions.

identical to those in Table 2.

Echo chambers predict that users with positive priors would more likely choose to participate in conversations signaling positive sentiment. We would therefore anticipate a positive coefficient for the Prior Sentiment$_{i,t}$ from estimating equation (3). The marginal effects reported in Table 9 corroborate the existence of echo chambers. For example, in column (1), the interpretation of the reported marginal effects is as follows: users with positive priors, on average, are 6.738% more likely to subsequently participate in a thread that starts with a post with positive sentiment, compared to users with non-positive priors. The unconditional probability of participating in a conversation that starts with a positive sentiment is 37.310%. Thus having a positive prior increases the probability of participating in a thread with a positive first post by 18.060% (6.738/37.310). The marginal effects of positive priors are robust to additional controls included in column (2). In columns (3) and (4), we estimate the regression with an alternative dependent variable that equals 1 when the social sentiment is positive and 0 otherwise. The marginal effects of positive priors remain significant at the 1% level.

4.4.2 Selective Interpretation of Information

Confirmation bias can lead users to interpret information in a way that confirms their priors. To examine this phenomenon, we investigate how users selectively interpret signals they encounter in conversations. Specifically, we create two new variables: social sentiment (-) and social sentiment(+). Social sentiment (-) is defined as the minimum value of social sentiment and zero. Social sentiment (+) is defined as the maximum value of social sentiment and zero. These two variables capture the linear relationship between sentiment contagion and social sentiment in the negative and positive regions, respectively. We then test for selective interpretation using two separate subsamples: one for users with positive priors and one for those with non-positive priors. Confirmation bias predicts that users with positive priors would respond more strongly to social sentiment (+), while users with negative priors would respond more aggressively to social sentiment (-).

Table 10 presents our findings. In column (1), we observe that users with positive priors adjust their sentiment towards the social sentiment, which supports the main message conveyed in Table 2. Column (2) shows that users with positive priors respond to both positive and negative social sentiment, but they are much more responsive to positive sentiment. Specifically, a one-unit increase in the positive social sentiment is associated with a 5.012% probability (statistically significant at 1% level) of a sentiment upward change. In contrast, a one-unit increase in social sentiment when it is negative is associated with only 2.687% probability (which is not significant at 10% level) of own sentiment change. In column (3), we find that users with negative priors also adjust their sentiment towards the social sentiment. Finally, in column (4), we observe that users with negative priors respond to both positive and negative social sentiment, but they are more responsive to negative social sentiment. In untabulated tables, we include the user-week interactive fixed effect and find that our results remain similar. Taken together, the results in Table 10 indicate a selective interpretation of information: investors respond more aggressively to the social sentiment that is consistent with their prior sentiment.

5 Social Learning and Market Outcomes

The link between social learning and trading decisions in section **??** provides a foundation for studying the effect of social learning at the aggregate level. This section connects social learning to market outcomes. To this end, we propose a daily Sentiment Contagion Intensity (SCI) index to measure the intensity of sentiment contagion at the aggregate level. As it is constructed from social interactions, it enables us to investigate market dynamics from a social perspective. We demonstrate that SCI contains novel information about future trading volume, volatility, bubbles and crashes in the Bitcoin market.

5.1 Sentiment Contagion Intensity Index

In contrast to existing sentiment indices (such as the one proposed in Baker and Wurgler (2006)), we construct the SCI index using a bottom-up approach. First, we identify users whose sentiment changes in the direction of social sentiment after participating in a conversation on Bitcointalk. The total number of such infected users within a given day can measure the intensity of social learning. To control for the growing number of participants on Bitcointalk, we remove the time trend and seasonality by regressing the number of infected users (in logarithm) against weekday and year-month indicators. The SCI index is obtained as the residual of this regression further normalized to have a mean of zero and a standard deviation of one.

Previous studies on investor sentiment using social media data typically focus on the average sentiment level (see, e.g., Antweiler and Frank (2004)). In contrast, our SCI indicator measures the spread intensity of sentiment, making it more pertinent to the dynamics of sentiment contagion among the population. Thus, we anticipate that SCI contains information beyond the average sentiment level. The contemporaneous correlation between SCI and the average sentiment level in the forum is only 0.6%, which is also statistically insignificant. We also find that the information content of SCI has little overlap with the average sentiment level in the news media computed from the RavenPack database of Bitcoin-related news each day. The correlation coefficient between SCI and RavenPack News sentiment is -0.3%, indicating that SCI contains distinct information that is not reflected in the news sentiment. This is perhaps not surprising, given that SCI is constructed from social media, a distinct source from news media, designed to capture the amount of sentiment propagation among investors, instead of the sentiment level.

We also examine how the SCI indicator relates to several proxies for investor attention. The first proxy of investor attention is Google search volume (as explained in section 2.4). It has a correlation of 23.8% with SCI. The second proxy is based on RavenPack news coverage, measured as the number of articles on Bitcoin on each day. It has a very low correlation with SCI at 0.4%. Overall, our SCI index appears to encompass unique and novel information when compared to existing indicators, such as proxies for investor sentiment and attention.

5.2 Social Learning and Future Volume

For individual investors, as previously demonstrated in section **??**, social learning plays a crucial role in predicting their trading decisions. Thus we expect a corresponding link at the aggregate level: the SCI index may serve as a predictor for trading volume in the Bitcoin market.

To examine our hypothesis, we conduct a regression analysis using the following equation:

$$\text{Ab Volume}_{t+N} = \beta_0 + \beta_1 SCI_{i,t} + \Sigma_m \gamma_m \text{Controls}_{t,m} + u_{t+k} \tag{4}$$

where Ab Volume$_{t+N}$ denotes the abnormal dollar trading volume of Bitcoin on the next N days. Specifically, we normalize the average dollar trading volume (in billions) over the next N days ($N = 1, 7$) by subtracting its average in the past 14 days. The key predictor is $SCI_{i,t}$. As for the control variables, Controls$_{t,m}$ encompass events occurring within the last m ($m = 14$) days. To proxy for news arrivals, we calculate the average sentiment levels in Ravenpack news during the previous 14 days. Additionally, we control for

Bitcoin volatility and the number of transactions by considering their cumulative sums within the past 14 days. To account for forum sentiment, we calculate the average sentiment of posts on the Bitcointalk forum published within the previous 14 days.

The findings presented in columns (1) and (2) of Table 12 strongly support our hypothesis. Overall, we observe a significant association between an increase in SCI and abnormal dollar trading volume in the subsequent days. For instance, in column (1), a one standard deviation increase in SCI leads, on average, to an additional \$4.47 million abnormal trading volume the following day. Importantly, even after controlling for news shocks, market fluctuations, and forum sentiment over the past 14 days, this relationship between SCI and abnormal trading volume remains unaffected. In column (2), we report the predictive power of SCI for the average abnormal trading volume over the next 7 days. We find that a one standard deviation increase in SCI results in an additional \$3.33 million abnormal trading volume per day over the next 7 days.

5.3 Social Learning and Future Volatility

Extensive research (Black (1986); De Long et al. (1990)) has long been devoted to examining the connection between user sentiment and asset price volatility. If users base their trading decisions on sentiment, then changes in sentiment lead to more noise trading and generate excessive volatility. Notably, recent studies (Da et al. (2014); Antweiler and Frank (2004)) have provided empirical evidence supporting this relationship, utilizing data from the U.S. stock market. However, few studies have emphasized this connection from a social perspective. Our SCI indicator naturally helps fill the gap. As highlighted in Section 4, there is a strong non-fully rational component in social learning, which results in the spread of sentiment. Consequently, as the SCI increases, social learning would trigger more subsequent noise trading and push up future volatility. Therefore, we hypothesize that the SCI index positively predicts future market volatility.

To examine this conjecture, we conduct the following regression analysis:

$$rv_{t+N} = \beta_0 + \beta_1 SCI_t + \Sigma_m \gamma_m \text{Control}_{t,m} + u_{t+N} \tag{5}$$

rv_{t+N} represents the average level of realized volatility within the next N ($N = 1, 7$) days. We compute the realized volatility by using the standard deviation of hourly returns within that day. The key explanatory variable of interest and the control variables are identical to those in equation (4).

The results of our study are presented in columns (3) and (4) of Table 12. We observe the SCI indicator positively predicts future volatility in the Bitcoin market. In column (3), a one standard deviation increase in SCI corresponds to a 0.530% increase in realized volatility over the next day. This increase amounts to 15.160% (calculated as 0.542%/3.496%) of the standard deviation of the realized volatility. In column (4), we examine how SCI predicts the average level of realized volatility over the next 7 days and find a similar pattern. Overall, results in columns (3) and (4) are consistent with our conjecture: as social interactions trigger more sentiment changes, there is an increase in noise trading by users, which subsequently raises the volatility of returns in the market.

5.4 Social Learning and Bubbles

Bubbles have long been recognized as episodes featuring elevated investor sentiment and irrational exuberance, along with a rapid rise in both asset prices and trading volume. Researchers are fascinated by these features and the underlying mechanisms behind them. The Bitcoin market provides a valuable opportunity to investigate bubbles: in the past decades, Bitcoin prices have experienced several drastic changes not easily explainable by fundamentals. Therefore, our data allows us to shed light on some important features of bubbles from a social learning perspective. We present an explanation from a social perspective regarding the high trading volume during bubbles.

5.4.1 Bitcoin Bubbles

To identify bubble episodes, we first label each trading day in our sample as one if the cumulative Bitcoin return over the past 90 days exceeds 200%, and zero otherwise. Next, we focus exclusively on sequences of consecutive days with a label of one that last for more than 2 quarters.[10] For each such a sequence of days, we identify the peak day as the day when the cumulative returns achieved the maximum. Finally, we designate the period between the start day and peak day as a bubble episode.

Our choice of 200% return conforms to the notion (e.g., Fama) that a bubble is associated with a substantial price run-up. A return threshold of 200% effectively captures the majority of episodes that anecdotal evidence suggests were Bitcoin bubbles, including the episode towards the end of 2017. It is worth

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[10] We also conducted robustness checks with alternative windows, and our results remained qualitatively the same.

noting that we define bubbles ex-post by relying on future information. This approach does not undermine our analysis since we do not aim to predict bubbles.

We identify four bubble episodes within our sample horizon. The first one starts on June 4, 2013, and extends to December 4, 2013. The second one begins on June 16, 2017, and ends on December 16, 2017. The third one spans from December 26, 2018, to June 26, 2019. The fourth one starts on September 13, 2020, and continues until March 13, 2021.

In Table 13, we present some key features of the identified Bitcoin bubble episodes and compare them to the non-bubble episodes. The differences in features between the bubble and non-bubble episodes are statistically significant, as supported by the joint F-statistic of 15.49 obtained from seemingly unrelated regression analysis.[11] Panel A shows that, in the identified bubble episodes, the daily average Bitcoin return is more than 8 times higher (calculated as 4.050/0.491) compared to the non-bubble episodes, and the daily return volatility is larger by 8.108% (calculated as 0.040/0.037 - 1). The total dollar volume nearly doubles during the bubble episodes. When considering news reports, the RavenPack news sentiment rises from 0.040 to 0.168, which is more than four times higher than the sentiment level in the non-bubble episodes. Moreover, Google search volume surges from 0.017 to 0.085. To summarize, the identified episodes exhibit rapid increases in returns, volume, and market fluctuations. Furthermore, there is a noticeable prevalence of optimism in media coverage, along with a surge in investor attention. All these characteristics align well with the commonly described attributes of a bubble (Shiller (2001)).

5.4.2 Social Learning and High Trading Volume in Bubbles

Why do investors trade so frequently during bubbles? Explaining the heightened trading volume presents an intriguing challenge for researchers.[12] In this section, we offer a novel perspective based on social learning, specifically the intensified contagion of optimism during bubbles. The intuition builds upon our previous findings that sentiment contagion in social interactions prompts investors to trade, subsequently predicting the trading volume at the aggregate market level. Since the contagion of optimism intensifies during bubble episodes, we expect a surge in trading volume during these periods.

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[11] See, e.g., Greenwood et al. (2019) who apply seemingly unrelated regression to test the joint significance of bubble features.

[12] See Barberis et al. (2018), DeFusco et al. (2017), Liao et al. (2021).

Social Interactions during Bubbles Sharp changes in market conditions would plausibly impact conversation patterns in various ways, including shifts in content and attitudes. In Panel B of Table 13, we summarize the crucial aspects of investor sentiment and social interactive activities during bubble episodes.

When it comes to investor sentiment, it is unsurprising to observe that users tend to be more optimistic during bubble episodes. The user sentiment increases by 12.132% (calculated as 0.305/0.272 - 1), indicating a pervasive sense of optimism in social sentiment. At the same time, user sentiment becomes less dispersed in bubbles—the standard deviation of sentiment drops by 2.232%. Such a drop in disagreement is remarkable, especially given the 14.831% (calculated as 133.504/116.261 - 1) increase in the total number of users participating in the conversations during bubbles.

In terms of social interactions, there is a significant increase in the total number of posts per day by 7.428% (calculated as 188.764/175.713 - 1). This indicates a heightened intensity in social interactions during bubbles. It is worth noting that the number of posts with positive sentiment increases disproportionately: the fraction of posts with positive sentiment increases by 5.233%. This asymmetric pattern is potentially connected to the self-enhancing transmission bias (Han et al. (2022)).[13] We provide supportive evidence in Table A7 and A8. Moreover, we observe a significant decline of 16.156% in the fraction of sophisticated users during bubbles (calculated as 1 - 0.301/0.359). This suggests that a disproportionately large number of novice investors participate in conversations during bubble episodes. These identified features of social interactions in Panel B generally align with the descriptions of bubble episodes in Shiller (2001).

Elevated Contagion of Optimism The salient features of social interactions may further reshape social learning in bubbles. As evidenced in Panel B of Table 13, the change in the fraction of positive and negative sentiment is asymmetric. To emphasize the difference in sentiment contagion between optimism and pessimism during bubbles, we present two distinct measures in Panel C of Table 13. Specifically, we identify users who become more optimistic after encountering positive social sentiment as *positively infected users*. Similarly, we define *negatively infected users*. We use the number of positively and negatively infected users each day to investigate social learning in two directions during bubbles.

Our findings reveal a robust propagation of optimism and a diminished propagation of pessimism

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[13] Days in bubbles tend to exhibit high past returns, which in turn increases the likelihood of investors publishing posts with positive sentiment.

during bubbles. Compared to a day in non-bubble episodes, the number of positively infected users significantly increases by 8.927% (calculated as 16.704/15.335 - 1) in bubbles. In contrast, the number of negatively infected users on average experiences a significant decrease of 15.998% (calculated as 0.61/3.813). Collectively, the overall propagation of optimism shows a notable increase of 24.925% within one day during bubble episodes.

The notable features of social interactions in bubbles (Panel B of Table 13) provide valuable insights into the pattern. Firstly, users would frequently run into conversations with an overall positive sentiment in bubbles, as social sentiment in these periods exhibits pervasive optimism. Secondly, during bubbles, there is an increasing participation of naive investors in discussions. As we have discussed in section 4.1, these investors are more susceptible to social sentiment. Additionally, sentiment contagion becomes stronger during periods of high uncertainty. The heightened volatility in bubble episodes further amplifies the spread of optimism.

Propagation of Optimism and Trading Volume in Bubbles To effectively demonstrate the strong correlation between the propagation of optimism and trading volume in Bitcoin bubbles, a plot serves as the most suitable method. In Figure 5, we observe the temporal trend for both the number of positively infected investors (indicated by the red dashed line) on day t, and the trading volume on day $t+1$ (depicted by the blue bars). The trading volume is measured in millions of U.S. dollars. Furthermore, we provide an illustration of the Bitcoin price dynamics (represented by the green solid line) in the identified bubble episode.

We identify four Bitcoin bubble episodes spanning from 2013 to 2021, but for brevity, we will focus on the earliest episode (episode 1) and the most recent episode (episode 4).[14] In both episodes, we observe a synchronous pattern between the number of positively infected users and the trading volume on the following day. In the upper panel, we plot the bubble formation episode from January 2013 to July 2013. When the number of positively infected investors increases, the trading volume on the next day tends to increase sharply. The correlation coefficient between the number of positively infected users and trading volume is statistically significant at 0.669 (p-value = 0.00). The remarkably high correlation in episode 1 becomes reasonable once we consider the dominant representativeness of the Bitcointalk forum in the early 2010s. During that time,

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[14] The patterns in other identified episodes are similar. See Figure **??**.

Bitcointalk was one of the few platforms where Bitcoin investors could communicate with each other. In the lower panel, we focus on the most recent bubble-formation episode from September 2020 to May 2021. The correlation coefficient is still statistically positive, but the magnitude drops to 0.335 (p-value =0.00). This may reflect the fact that while Bitcointalk still holds significant influence, it has faced competition from other emerging social network platforms. As Bitcoin investors continue to participate in a more diverse range of social network platforms, the representativeness of Bitcointalk is inevitably decreasing.

In summary, Figure 5 presents compelling evidence illustrating the significant influence of social interactions on high trading volumes during Bitcoin bubbles, particularly through the propagation of optimism. Our results not only offer empirical validation for well-established hypotheses regarding bubbles (Shiller (2001)), but also correspond with contemporary efforts to link social dynamics with bubble phenomena (Hirshleifer (2020); Burnside et al. (2016)).

5.5 Social Learning and Market Crashes

Social learning inherently connects to price dynamics: the percolation of sentiment through social learning could influence investor demand and impose significant price pressure on the market. Moreover, with its salient nature, such as selectiveness (discussed in section 4.4), social learning can lead to the systematic proliferation of extreme sentiment. The propagation of optimism during the bubble episode is one example. This accumulated optimism may destabilize the market by initially driving asset prices too high, eventually causing a drastic correction as sentiment reverts back to normal. Consequently, we anticipate that social learning can offer a social explanation for price dynamics such as price decline and market crashes.[15]

Investors can become either more optimistic or pessimistic after social learning, leading to different directions of pressure on the price of Bitcoin. Therefore, to measure the overall price pressure associated with social learning, we define the Net SCI indicator as follows:

$$NetSCI_t = PosSCI_t - NegSCI_t. \tag{6}$$

The $NetSCI_t$ indicator quantifies the difference within day t in the numbers of users who are positively

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[15] In the presidential address, Hirshleifer (2020) also highlights the error-prone feature corresponding to the impact of social activities on the market and attributes a large part of it to the selective dissemination of sentiment, namely the social transmission bias.

infected (denoted as $PosSCI_t$) and negatively infected (denoted as $NegSCI_t$). The definitions of positively infected and negatively infected users follow section 5.4.2. To capture the cumulative impact of social learning, we further calculate the sum of the Net SCI over the past 14 days. Finally, we normalize the cumulative Net SCI indicator to have a mean of zero and a standard deviation of one. We examine our hypothesis by running a Probit regression, using the cumulative net SCI as the key explanatory variable:

$$Pr[\text{Price Dynamics}_{t+N} = 1] = \Phi[\beta_0 + \beta_1 \text{Cumulative Net SCI}_t + \gamma_m \text{Controls}_{t,m} + u_{t+N}]. \tag{7}$$

We use two distinct variables to measure price dynamics. The first indicator is a return dummy, taking a value of one if the cumulative return falls below zero within a specific future horizon, and zero otherwise. This return dummy captures the price declines in the Bitcoin market. Columns (1) to (3) of Table 14 present our findings, and we report the marginal effects. An increase in the cumulative Net SCI indicator significantly elevates the probability of subsequent price declines in the Bitcoin market. Specifically, taking column (1) as an example, the interpretation of the reported marginal effects is as follows: a one standard deviation increase in cumulative Net SCI leads to a 1.813% increase in the probability of the price falling the next day in the Bitcoin market. Furthermore, as time horizons expand, the probability of further price declines also increases. For instance, in column (3), a one standard deviation increase in cumulative Net SCI raises the probability of the price falling within a 14-day window by approximately 6.228%, which is about three times higher than the probability within the next day. Overall, our findings confirm that cumulative net SCI significantly predicts future price declines.

We then zoom into the tails and link social learning to market crashes. For the dependent variable in the Probit regression (equation 7), we construct a future crash indicator that takes a value of 1 if at least one daily return falls below the 5th percentile in the future N days ($N = 1, 7, 14$). The key explanatory variable and control variables remain the same as above. Columns (4) to (6) of Table 14 demonstrate a significant relationship between increases in the SCI indicator and the probability of crashes in the Bitcoin market, as indicated by the reported marginal effects. A one standard deviation increase in the cumulative Net SCI today is associated with a statistically significant 1.038% rise in the crash probability for the following day in the Bitcoin market. This one standard deviation increase corresponds to an approximate 20.76% increase in the probability of a crash event (calculated as 1.038%/5%). As the predictive window expands from 1 day to 7 days and 14 days (columns (2) and (3)), the elevation in crash probability further amplifies to 5.696%

and 9.157%, respectively. Overall, social learning strongly predicts future crashes in the Bitcoin market.

6 Conclusion

Drawing on the calls for "transition from behavioral finance to social finance" (Hirshleifer (2020)) and to gain a better understanding of "the epidemiology of narratives" (Shiller (2017)), this paper presents direct evidence for social learning. Utilizing textual analysis to extract investor sentiment from posts on Bitcointalk, a prominent online investment platform, we establish a robust channel for investors' sentiment on Bitcoin to spread through conversations.

We demonstrate that social learning is non fully rational in our context: sentiment expressed in conversations does not predict Bitcoin returns, yet investors respond to them and become more optimistic (pessimistic) about Bitcoin following social interactions on Bitcointalk that are on average positive (negative). We find evidence of both selective participation of social interactions consistent with the echo chamber effect and selective interpretation of social signals in investors' belief updating consistent with confirmation bias. Naive, less central and less informed investors are more susceptible to the influence of peers' sentiment in social interactions.

Moreover, we find that social interactions exert a substantial impact on individual investors' trading decisions as well as market outcomes. Consistent with Giglio et al. (2021), we provide supportive evidence for the connection between investor beliefs and trading decisions. Using individual trading records for a subsample of Bitcointalk users, we document that the direction of investors' trading in Bitcoin is significantly and positively related to the peer sentiment in social interactions. At the market level, the intensity of daily sentiment contagion significantly predicts Bitcoin volume and return volatility. Additionally, we develop measures of optimism derived from social interactions to assess the error-prone nature of social activities. Our results indicate that socially constructed optimism measures are significantly and positively related to the probability of future crashes of Bitcoin and its volatility.

We also contribute novel insights on bubbles from the perspective of sentiment contagion. During the bubble formation episodes, we observe a contagion of optimism and a wave of new investors engaging in social interactions. The contagion of optimism accounts for a significant portion of the variations in trading volume during bubbles. Therefore, social learning provides a fresh perspective for understanding the elevated trading volume during bubbles.

This paper strongly advocates for the significance of social finance in comprehending investors' decision-making processes and market dynamics. The documented phenomenon of sentiment contagion through conversations not only provides fresh perspectives on investors belief dynamics but also underscores the potential of social interactions in elucidating various financial phenomena. The online investment community serves as an ideal platform for investigating other pertinent questions in the realm of social finance, and we leave these inquiries to future research endeavors.

Bitcoin Forum > Economy > Economics > Speculation > **What does the future of bitcoin look like??**

The board title and topic title

Pages: « 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 [**23**] 24 25 26 27 28 29 30 31 32 »

DavidLuziz
Newbie
Activity: 26
Merit: 0

Re: What does the future of bitcoin look like??
May 31, 2018, 05:37:35 AM #448

I think that We can only guess or guess the price of bitcoin and other crypto currency, but no one knows for sure.
Kiss Kiss

User DavidLuziz' prior. We call it prior sentiment.

chipchip331
Newbie
Activity: 8
Merit: 0

Re: What does the future of bitcoin look like??
May 31, 2018, 05:45:50 AM #449

Other users' post #1

This is a look back at my bitcoin future: Bitcoin will be the past
1. Bitcoin does not have an application, it was created only to let the world know that blockchain can solve the problem.
2. Currently bitcoin transaction fees are high but the rate is slow.
3. The government does not admit and will never admit it affects its own currency.
4. No currency fluctuates as large as bitcoin. One can dare to keep the currency that day fluctuates by 10%.
Bitcoin will disappear, keeping it as a memorial, a marker marking the presence of blockchain, after all, Blockchain is left behind with its decentralized application in archiving and decryption.

DarrinEspacio
Newbie
Activity: 90
Merit: 0

Re: What does the future of bitcoin look like??
May 31, 2018, 06:02:06 AM #450

The future of bit coin and also the users of bitcoin both has a bright future.

Other users' post # 2

rowan.thomas
Newbie
Activity: 81
Merit: 0

Re: What does the future of bitcoin look like??
May 31, 2018, 06:51:31 AM #451

i think will gonna increase the number of users and the value of it, if people have more knowledge on how to use bitcoin i'm sure bitcoin will gonna soar high. bitcoin will become brighter and wealth someday when many people use bitcoin for their life and also for their future.

Other users' post #3

DiegoPatterson.9909
Newbie
Activity: 8
Merit: 0

Re: What does the future of bitcoin look like??
May 31, 2018, 07:03:16 AM #452

In the near future technology will bring great impact in our lives, so as this bitcoin will gonna fly together with the demand of technology.

Other users' post #4

hrz
Full Member
Activity: 476
Merit: 100
ELISIA

Re: What does the future of bitcoin look like??
May 31, 2018, 07:33:58 AM #454

bitcoin in the future will be more advanced and more bitcoin digging bitcoin and more and more are looking for bitcoin because future bitcoin estimates will be expensive.

Other users' post #5

social sentiment = average sentiment of post #1 to post #5

DavidLuziz
Newbie
Activity: 26
Merit: 0

Re: What does the future of bitcoin look like??
May 31, 2018, 07:50:10 AM #455

Although, Sometimes bitcoin price gone down but it's not for permanent. I think in recent future, Bitcoin will me more popular then present. So, it's sure that future of Bitcoin is very Bright and I am hopeful about it's success.

User DavidLuziz's post: we focus on how sentiment in this post is formed. We call it ex-post sentiment.

Figure 1: Example of Conversation and Illustration of Empirical Strategy

This figure presents an example for a conversation in our sample and our empirical strategy. We measure sentiment changes by calculating the difference between sentiment in post[0] and post[1]. We measure social sentiment by calculating the average sentiment of others' post in conversations.

Figure 2: Most Common Words in Posts

This word cloud shows the most frequent words present in posts. The size of the words depends on their relative frequency, hence more common words are larger.

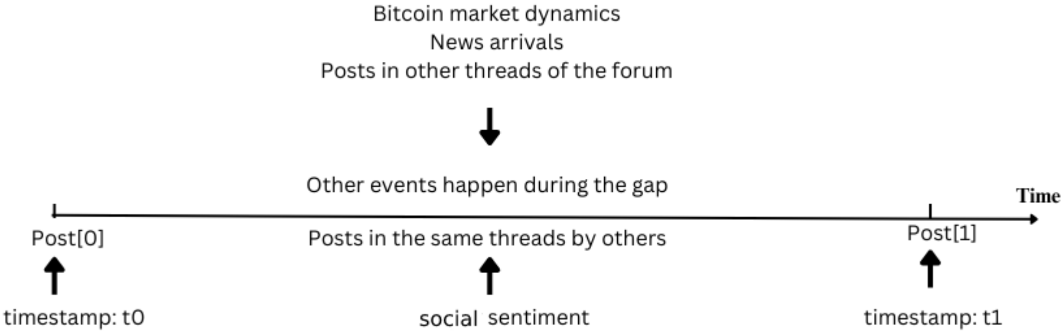

Figure 3: Timeline and Illustration of Empirical Strategy

This figure presents the timeline of post[0], post[1] and social sentiment. It also provides a formal demonstration of our empirical strategy.

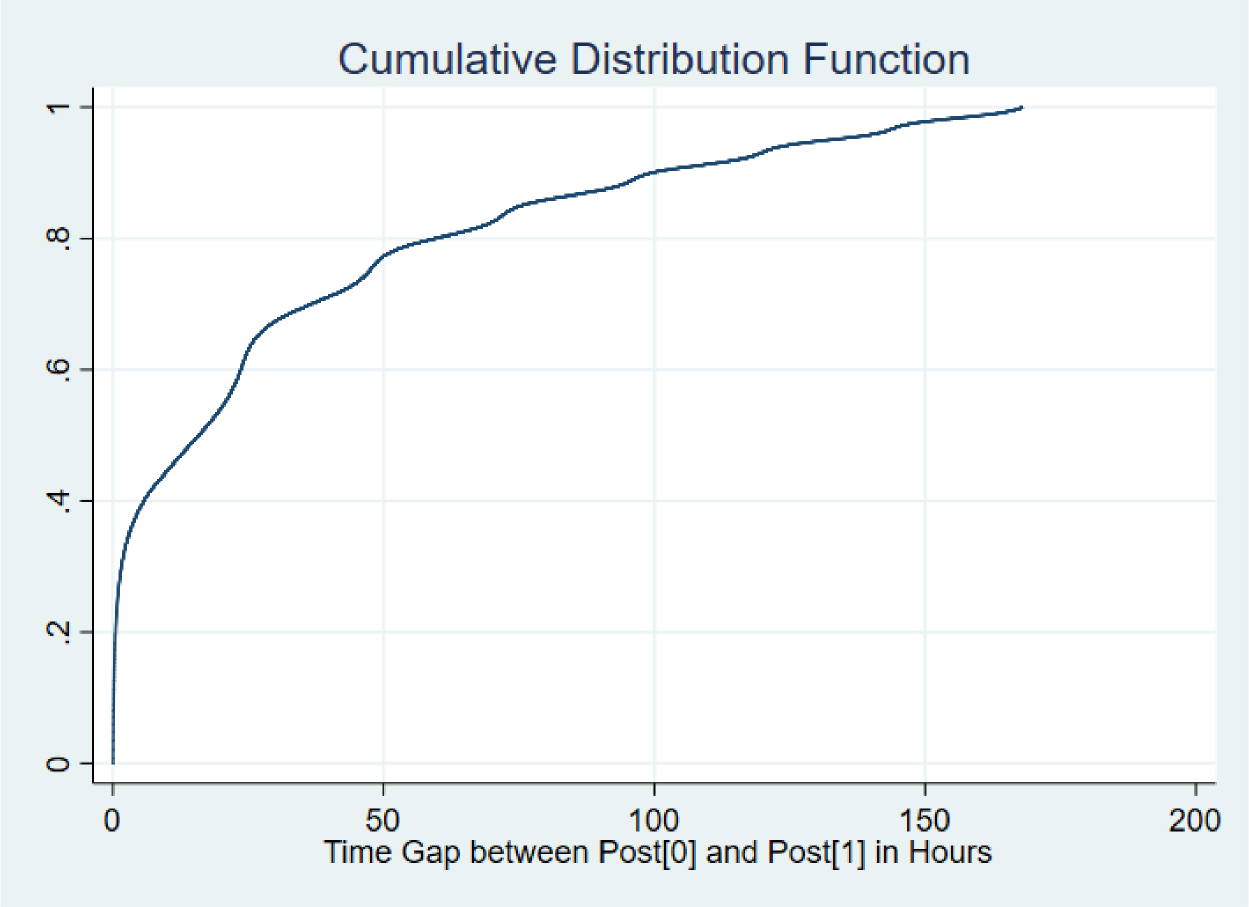

Figure 4: Cumulative Distribution Function of Time Gap

This figure presents the cumulative distribution function of the time gap between two consecutive posts by the same user.

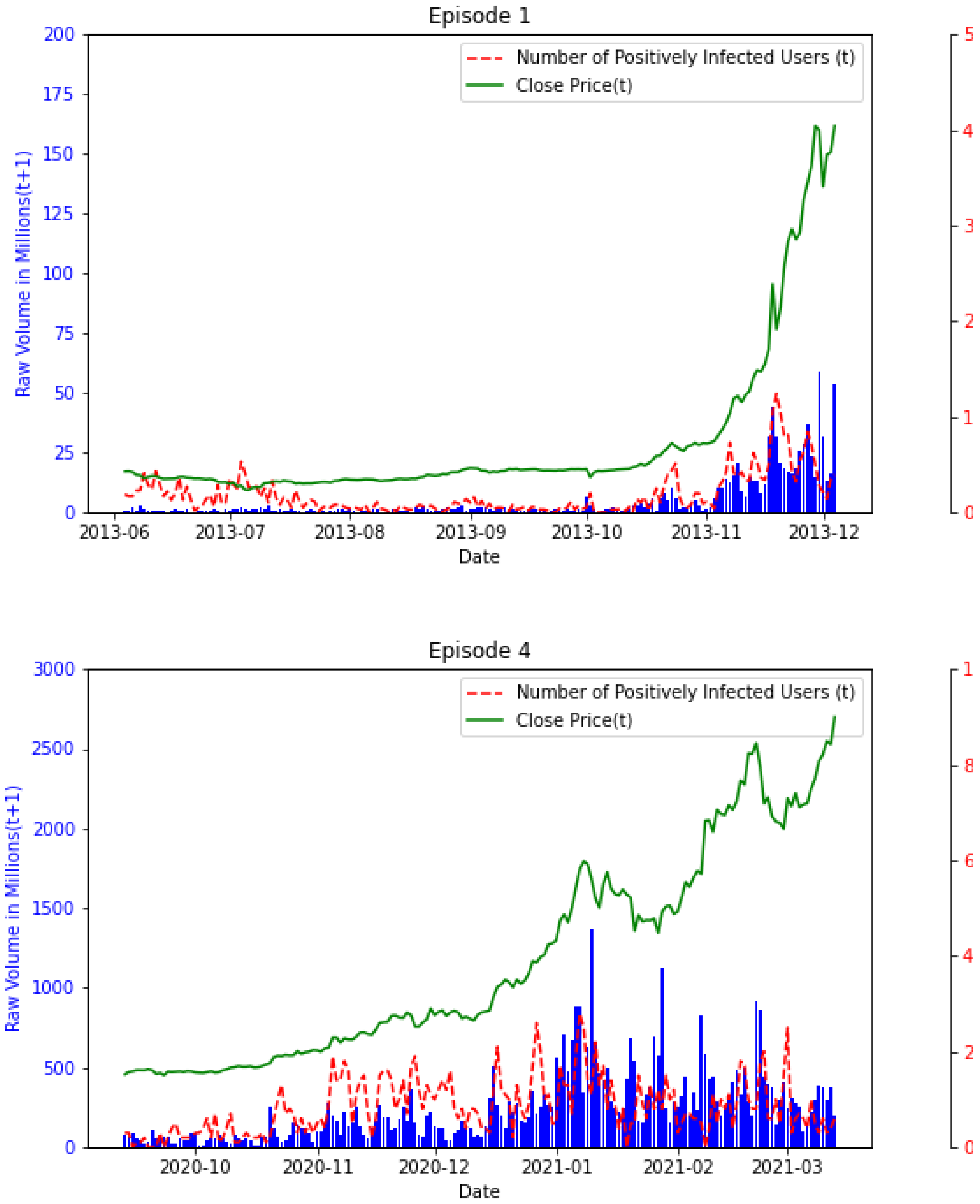

Figure 5: Sentiment Contagion and Trading Volume in Bubble Episodes

This figure plots the number of positively infected users on day t (the red dash line) and trading volume (the blue bars; in millions) on day $t+1$, along with the Bitcoin price index on day t (the green solid line). We illustrate the first (upper panel) and last (lower panel) identified bubble episodes in our sample.

Table 1: Summary Statistics

This table tabulates the summary statistics of the key variables. In Panel A, we present statistics of user sentiment in posts aggregated at the user level. To obtain the summary statistics for the average sentiment, we first calculate the mean sentiment of posts published by each user, then report the corresponding statistics based on the whole user population. In Panel B, we present statistics of user sentiment aggregated at the daily level. In Panel C, we present statistics of user sentiment aggregated at the thread level. In Panel D, we present summary statistics of market variables, RavenPack news sentiment and google search volume. Mean Return is the annualized average daily return of Bitcoin. Return Volatility (within Day) is the within-day volatility of Bitcoin based on the hourly Bitcoin return. Number of Transactions is the total number of Bitcoin transactions within one day. Number of Bitcoins Traded is the total number of Bitcoins being traded within one day. Total Dollar Volume (in millions) is the total dollar trading volume of Bitcoin measured in millions of dollars within one day. RavenPack News Sentiment is the sentiment score for the news on Bitcoin in the RavenPack database. We normalize the sentiment score to be between $[-1, 1]$. Google Search (Bitcoin) records the detrended Google Search Index for Bitcoin on a daily basis. Our sample spans from May 1, 2012 to July 30, 2022.

	count	mean	p50	sd	min	max
Panel A: Post Activities at User level						
Average Sentiment	44,356	0.324	0.333	0.512	-1.000	1.000
Standard Deviation of Sentiment	28,077	0.608	0.640	0.297	0.000	1.414
Number of Posts	44,356	15.015	2.000	72.469	1	3851
Panel B: Post Activities at Daily level						
Average Sentiment	3,737	0.279	0.282	0.118	-0.250	0.833
Standard Deviation of Sentiment	3,736	0.669	0.672	0.054	0.392	0.917
Number of Users	3,737	119.601	85.000	113.390	1	980
Number of Posts	3,737	178.219	128.000	160.778	1	1400
Panel C: Post Activities at Thread level						
Average Sentiment	18,799	0.237	0.250	0.324	-1.000	1.000
Standard Deviation of Sentiment	17,191	0.646	0.659	0.189	0.000	1.414
Number of Users	18,799	24.838	11.000	55.594	1	2589
Number of Posts	18,799	35.428	13.000	551.522	1	73859
Median Gap in Days between Consecutive Posts	17,214	0.573	0.033	16.568	0.000	1129.115
Panel D: Other Data Sources						
Daily Return(Annualized)	3,743	1.190	0.714	16.166	-177.093	146.518
Return Volatility(Within Day)	3,743	0.037	0.029	0.035	0.000	0.599
Number of Transactions	3,743	16471.536	11376.000	17268.770	0	181616
Number of Bitcoins Traded	3,743	9358.724	6660.652	9697.557	0	137070.178
Total Dollar Volume (in millions)	3,743	56.499	18.834	97.465	0.000	1372.717
RavenPack News Sentiment	3,743	0.041	0.000	0.330	-0.660	0.660
Google Search (Bitcoin)	3,743	0.031	-0.046	0.417	-0.905	6.595

Table 2: Contagion Effect

This table presents the panel regression analysis of sentiment change on social sentiment. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. The main explanatory variable is the social sentiment defined as the average sentiment of others' posts within the conversation, published between the timestamps of post[0] and post[1]. We control for simultaneous events between post[0] and post[1], such as Bitcoin return and volatility, activities in other conversations within the forum, and news arrivals documented in the RavenPack database. We also include lagged news arrivals to capture a delay in response. In all columns, we include a prior fixed effect. The t-statistics (in parentheses) are based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Sentiment Change				
	(1)	(2)	(3)	(4)	(5)
Social Sentiment	8.888***	5.328***	2.838***	3.088***	4.216***
	(21.56)	(13.51)	(6.81)	(6.01)	(6.89)
RavenPack News Sentiment				-0.032	1.574*
between Post[0] and Post[1]				(-0.04)	(1.70)
RavenPack News Sentiment				1.385	1.682*
24 hours before Post[0]				(1.45)	(1.86)
RavenPack News Sentiment				-1.030	-0.012
48 hours before Post[0]				(-1.03)	(-0.01)
Bitcoin Return				30.723***	32.434***
				(5.90)	(5.61)
Bitcoin Volatility				12.925	5.416
				(0.81)	(0.30)
Forum Sentiment				-4.679***	1.639
				(-4.42)	(1.36)
Prior FE	YES	YES	YES	YES	YES
User FE	NO	YES	YES	YES	NO
Day FE	NO	NO	YES	YES	NO
User X Week FE	NO	NO	NO	NO	YES
Controls	NO	NO	NO	YES	YES
Adjusted R-Squared	0.338	0.345	0.344	0.345	0.322
N	218,268	212,647	212,623	175,750	143,092

Table 3: Contagion Effect: Propagation on the Network

This table presents the propagation of the contagion effect through the network. Specifically, we track the participation of other users in each conversation (referred to as “neighbors”) and examine the sentiment expressed by their neighbors (referred to as “neighbors’ neighbors”) in previous conversations within the 24-hour window prior to joining the current conversation. Since neighbors’ neighbors are indirectly connected to the user through their neighbors, we refer to the average of their sentiment as the “indirect social sentiment.”. We are interested in how the indirect social sentiment affects the user’s sentiment updating. Therefore, the main explanatory variable is the average sentiment of the neighbors’ neighbors, while the control variables remain identical to those in Table 2. In all columns, we include a prior fixed effect. The t-statistics (in parentheses) are based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Sentiment Change				
	(1)	(2)	(3)	(4)	(5)
Indirect Social Sentiment	18.783***	7.375***	3.078*	3.458*	6.740***
	(13.67)	(5.18)	(1.87)	(1.84)	(2.86)
RavenPack News Sentiment between Post[0] and Post[1]				-0.489	0.731
				(-0.34)	(0.41)
RavenPack News Sentiment 24 hours before Post[0]				1.533	1.498
				(0.89)	(1.03)
RavenPack News Sentiment 48 hours before Post[0]				-0.326	0.097
				(-0.17)	(0.07)
Bitcoin Return				25.853***	30.882***
				(3.87)	(3.82)
Bitcoin Volatility				-1.577	5.655
				(-0.08)	(0.26)
Forum Sentiment				-2.686*	1.264
				(-1.77)	(0.68)
Prior FE	YES	YES	YES	YES	YES
User FE	NO	YES	YES	YES	NO
Day FE	NO	NO	YES	YES	NO
User X Week FE	NO	NO	NO	NO	YES
Controls	YES	YES	YES	YES	YES
Adjusted R-Squared	0.342	0.348	0.347	0.346	0.327
N	97,724	93,419	93,164	75,548	55,715

Table 4: Placebo Test

The table displays the results of a placebo test examining the contagion effect. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. The independent variable is the average sentiment level in N random conversations ($N = 1, 3, 10$) that the user did not participate in, which occurred between the timestamps of post[0] and post[1]. The control variables remain identical to those in Table 2. In all columns, we include a prior fixed effect. The t-statistics (in parentheses) are based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Sentiment Change					
	One Conversation		Three Conversations		Ten Conversations	
	(1)	(2)	(3)	(4)	(5)	(6)
Random Conversation	0.158	0.264	-0.061	0.493	-0.079	0.191
	(0.36)	(0.52)	(-0.14)	(0.92)	(-0.15)	(0.27)
RavenPack News Sentiment	0.216	1.718**	0.356	1.736*	0.903	1.576
between Post[0] and Post[1]	(0.27)	(1.98)	(0.42)	(1.95)	(0.96)	(1.61)
RavenPack News Sentiment	1.232	1.869**	1.678*	2.116**	1.520	1.692*
24 hours before Post[0]	(1.39)	(2.26)	(1.80)	(2.42)	(1.49)	(1.82)
RavenPack News Sentiment	-1.361	-0.096	-1.006	0.071	-0.238	0.289
48 hours before Post[0]	(-1.42)	(-0.12)	(-1.03)	(0.09)	(-0.22)	(0.30)
Bitcoin Return	30.583***	35.076***	30.916***	34.957***	30.741***	32.253***
	(6.36)	(6.39)	(6.13)	(6.16)	(6.17)	(5.69)
Bitcoin Volatility	9.781	0.757	8.801	5.574	11.997	12.126
	(0.71)	(0.05)	(0.67)	(0.37)	(0.77)	(0.75)
Forum Sentiment	-5.292***	0.272	-7.831***	1.112	-15.231***	1.347
	(-5.45)	(0.24)	(-6.24)	(0.76)	(-7.19)	(0.56)
Prior FE	YES	YES	YES	YES	YES	YES
User FE	YES	NO	YES	NO	YES	NO
Day FE	YES	NO	YES	NO	YES	NO
User X Week FE	NO	YES	NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.345	0.321	0.346	0.321	0.346	0.321
N	195,635	161,629	180,813	147,339	148,284	116,113

Table 5: Effect of Social Sentiment: Heterogeneity across Users

In this table, we explore different users' responses to social sentiment. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. In columns (1) and (2), we examine whether naive users, indicated by a dummy variable that equals one for users with non-lengendary status on Bitcointalk forum, are more susceptible to social sentiment. In columns (3) and (4), we investigate whether users who have participated in more conversations are less influenced by social sentiment. This user feature measures a user's centrality based on past posts on the social network, where two users are considered connected if they have participated in the same thread. In columns (5) and (6), we study whether less informed users, defined as those whose post sentiment has a low correlation with future Bitcoin returns in 7 days (correlation < 25th percentile), are more subject to social sentiment. In columns (1), (3), and (5), we include user and day fixed effects. In columns (2), (4), and (6), we include user-week interactive fixed effects. In all columns, we include a prior fixed effect. The coefficients are multiplied by 100, and the t-statistics (in parentheses) are based on standard errors clustered by user and day.

	Naive Users		Central Users		Less Informed Users	
	(1)	(2)	(3)	(4)	(5)	(6)
User Feature * Social Sentiment	3.585***	3.321***	-0.047***	-0.047***	2.664**	3.293**
	(3.46)	(2.64)	(-3.82)	(-3.41)	(1.98)	(1.99)
Social Sentiment	1.125	2.477***	4.086***	5.466***	2.105***	3.821***
	(1.52)	(2.89)	(7.28)	(7.94)	(3.49)	(5.44)
User Feature	0.000	0.000	-0.006	0.128	-0.268	-1.116
	(0.00)	(0.00)	(-0.66)	(0.91)	(-0.36)	(-0.90)
Prior FE	YES	YES	YES	YES	YES	YES
User FE	YES	NO	YES	NO	YES	NO
Day FE	YES	NO	YES	NO	YES	NO
User X Week FE	NO	YES	NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.345	0.322	0.345	0.322	0.343	0.322
N	175,750	143,092	175,750	143,092	139,873	118,433

Table 6: Time-varying Sentiment Contagion

In this table, we examine sentiment contagion intensity variations across episodes. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. In columns (1) and (2), we investigate the impact of informative days on sentiment contagion by defining informative days based on the number of news arrivals documented in the RavenPack database. If there are no news arrivals on a specific day, we assign a value of 0. We construct a dummy variable called *informative days* that takes the value of 1 on a given day if the total number of news arrivals is higher than the sample median. In columns (3) and (4), we investigate how information uncertainty affects sentiment contagion. To identify days of high information uncertainty, we use the standard deviation of news sentiment within the day documented in the RavenPack database. We construct a dummy variable called *high information uncertainty*, which takes the value of 1 if this standard deviation is higher than the sample median and 0 otherwise. If there are no news arrivals on a specific day, we assign a value of 0 to the dummy. In columns (5) and (6), we examine whether Bitcoin return volatility affects sentiment contagion. To do so, we calculate the standard deviation of hourly Bitcoin return within the past 24-hour window before the first post is published. We construct a dummy variable called *high Bitcoin volatility*, which equals 1 if the standard deviation is higher than the sample mean and 0 otherwise. In columns (1), (3), and (5), we include user and day fixed effects. In columns (2), (4), and (6), we include user-week interactive fixed effects. In all columns, we include a prior fixed effect. The coefficients are multiplied by 100, and the t-statistics (in parentheses) are based on standard errors clustered by user and day.

	Informative Days		High Uncertainty		High Bitcoin Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Episode Feature * Social Sentiment	0.959	0.858	3.714***	3.851**	2.515***	2.919**
	(0.92)	(0.69)	(3.01)	(2.36)	(2.62)	(2.50)
Episode Feature		0.448		-1.059	-0.667	-1.501*
		(0.50)		(-1.10)	(-0.66)	(-1.96)
Social Sentiment	2.664***	3.874***	2.415***	3.613***	1.957***	2.856***
	(3.76)	(4.74)	(4.23)	(5.42)	(2.93)	(3.59)
Prior FE	YES	YES	YES	YES	YES	YES
User FE	YES	NO	YES	NO	YES	NO
Day FE	YES	NO	YES	NO	YES	NO
User X Week FE	NO	YES	NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.345	0.322	0.345	0.322	0.345	0.322
N	175,750	143,092	175,750	143,092	175,750	143,092

Table 7: Social Sentiment and Future Returns

This table presents the panel regression analysis of future Bitcoin returns on social sentiment constructed from Bitcointalk posts. The dependent variable is the Bitcoin returns in future K hours (K = 6, 24, 48, 72, and 168), starting from the ending hour of post[1]. The key predictor is the conversation-level social sentiment. Control variables are identical to those in Table 2. In all columns, we add user and day fixed effect. In all columns, we include a prior fixed effect. The t-statistics (in parentheses) are based on standard errors clustered by user and day. We multiply each coefficient by 100.

	(1) 6 Hours	(2) 24 Hours	(3) 48 Hours	(4) 72 Hours	(5) 168 Hours
Social Sentiment	-0.012	-0.094**	-0.119***	-0.111**	-0.114**
	(-0.38)	(-2.17)	(-2.69)	(-2.31)	(-2.57)
RavenPack News Sentiment	-0.733***	-1.859***	-1.831***	-1.369***	-1.786***
between Post[0] and Post[1]	(-3.43)	(-5.61)	(-6.76)	(-5.42)	(-5.09)
RavenPack News Sentiment	-1.566***	-2.586***	-2.778***	-2.223***	-2.624***
24 hours before Post[0]	(-4.28)	(-5.93)	(-7.26)	(-7.66)	(-6.79)
RavenPack News Sentiment	-0.735***	-1.570***	-1.030***	-0.862***	-1.524***
48 hours before Post[0]	(-2.93)	(-4.10)	(-2.77)	(-2.71)	(-4.67)
Bitcoin Return	-21.330***	-35.052***	-39.628***	-41.422***	-41.485***
	(-13.37)	(-8.78)	(-7.81)	(-9.48)	(-10.99)
Bitcoin Volatility	17.717	15.433	45.070***	41.646***	37.695***
	(1.44)	(0.75)	(5.30)	(5.36)	(3.04)
Forum Sentiment	-0.245***	-0.537***	-0.499***	-0.420***	-0.418***
	(-3.82)	(-4.68)	(-4.51)	(-3.68)	(-3.39)
Prior FE	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Adjusted R-Squared	0.268	0.675	0.824	0.878	0.939
N	175,750	175,750	175,750	175,750	175748

Table 8: Sentiment Contagion of Posts by Different Types of Users

This table presents how users respond to social sentiment published by different types of users with different level of informedness. We examine three user features: (i) legendary users whose ranking on Bitcointalk is labeled as "Legendary"; (ii) central users who have participated in more conversations; (iii) informed users whose post sentiment has a high correlation with future Bitcoin returns in 7 days (the correlation exceeds the 25th percentile of the population). In Panel A, we analyze how social sentiment by different types of users predict future 24-hour returns, with a similar setting in Table 7. In Panel B, we investigate how users revise their beliefs after reading social sentiment by users of different types. To account for variations, we include user and day fixed effects as well as a prior fixed effect in all columns of Panel B. Control variables are identical to those in Table 2. The t-statistics (shown in parentheses) are based on standard errors that are clustered by user and day. Additionally, we multiply each coefficient by 100 in all panels.

Panel A: Informativeness (future 24-hour returns)

	Legendary		Central		Informed	
	(1)	(2)	(3)	(4)	(5)	(6)
Social Sentiment	-0.054		-0.085**		-0.079*	
by Featured Users	(-1.12)		(-2.23)		(-1.78)	
Social Sentiment		-0.061*		-0.036		-0.179***
by NonFeatured Users		(-1.71)		(-0.99)		(-2.58)
Prior FE	YES	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.674	0.676	0.673	0.695	0.674	0.676
N	138938	161144	159205	119231	136962	36580

Panel B: Response

	Legendary		Central		Informed	
	(1)	(2)	(3)	(4)	(5)	(6)
Social Sentiment	0.804*		2.897***		2.712***	
by Featured Users	(1.66)		(5.55)		(4.80)	
Social Sentiment		2.399***		1.925***		4.897***
by NonFeatured Users		(4.94)		(2.84)		(3.90)
Prior FE	YES	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.347	0.345	0.345	0.346	0.344	0.338
N	138,938	161,144	173,477	43,701	136,962	36,580

Table 9: Confirmation Bias: Echo Chambers

In this table, we use the Probit model to examine how users with different priors selectively participate in conversations. We focus on consecutive pairs of posts (post[0] and then post[1]) published within a 24-hour period by the same user. Our primary explanatory variable is "positive prior", which takes a value of 1 if the user's prior sentiment (i.e., sentiment in post[0]) is positive and 0 otherwise. The dependent variable reflects the attitude of the subsequent conversation in which the user takes part (i.e., the conversation to which post[1] belongs) and is represented by a dummy variable that equals 1 if it signals positive sentiment and 0 otherwise. To determine whether the subsequent conversation signals positive sentiment, we employ two methods. In columns (1) and (2), we set the dependent variable to 1 if the thread to which post[1] belongs has a starting post with positive sentiment. In columns (3) and (4), we set the dependent variable to 1 if the social sentiment (i.e., the average sentiment of the posts between post[0] and then post[1]) is positive. The control variables are identical to those in Table 2. We report the average marginal effects. The t-statistics (in parentheses) are computed using standard errors clustered by user and day. Additionally, we multiply each coefficient by 100.

	Positive Sentiment of First Post		Positive Social Sentiment	
	(1)	(2)	(3)	(4)
Positive Prior	6.738***	5.726***	4.252***	3.534***
	(19.65)	(15.97)	(17.84)	(14.39)
Controls	No	Yes	No	Yes
Adjusted R-Squared	0.004	0.019	0.002	0.013
N	190,085	131,407	142,871	123,084

Table 10: Confirmation Bias: Selective Interpretation

This table investigates whether users' response to social sentiment varies depending on whether the sentiment aligns with their priors. To do so, we decompose social sentiment into two parts. Social sentiment (+) is the positive part of social sentiment, and Social sentiment (-) is the negative part. In the first two columns, we analyze the subset of users with positive priors and observe how they respond to positive and negative social sentiment. In column (1), the explanatory variable is the average sentiment in conversations. In column (2), the explanatory variables are two separate sentiment variables. In the last two columns, we investigate the response of users with negative priors to positive and negative social sentiment. In column (3), the explanatory variable is the average sentiment in conversations. In column (4), the explanatory variables are two separate sentiment variables. We include user and day fixed effects in all columns. We report t-statistics in parentheses based on standard errors clustered by user and day. Finally, we multiply each coefficient by 100.

	Positive Priors		NonPositive Priors	
	(1)	(2)	(3)	(4)
Social Sentiment	4.279***		3.294***	
	(6.06)		(4.68)	
Social Sentiment(+)		5.012***		2.764***
		(4.96)		(2.74)
Social Sentiment(-)		2.687		4.283***
		(1.61)		(2.78)
User FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Adjusted R-Squared	0.044	0.044	0.249	0.249
N	85,949	85,949	86,237	86,237

Table 11: Social Learning and Individual Trading

This table presents the regression analysis of one individual's trading decisions on the social sentiment that an investor encounters. The dependent variable is an indicator of whether the individual net buys on day $t + 1$. The main explanatory variable is the social sentiment, and the definition follows section **??**. Control variables are identical to those in Table 2. In all columns, we include user fixed effect and a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Probability of net buying in the next day		
	(1)	(2)	(3)
I(Social Sentiment>0)	0.409***	0.387***	0.350***
	(3.71)	(3.36)	(3.15)
Prior FE	YES	YES	YES
User FE	YES	YES	YES
Date FE	NO	NO	YES
Controls	NO	YES	NO
Adjusted R-Squared	0.081	0.081	0.096
N	249,449	249,180	249,449

Table 12: Social Learning, Market Volume and Market Volatility

This table presents the predictive power of social learning on the future volume and volatility in the Bitcoin market. The main explanatory variable is the SCI indicator, which measures the daily number of users who adjust their sentiment to align with the social sentiment in conversations. We eliminate the time trend by regressing the raw number series (in logarithm) on year-month indicators and weekday dummies. We obtain our SCI indicator by further normalizing the residual series to have a mean of zero and a standard deviation of one. In columns (1) and (2), the primary dependent variable is the future dollar trading volume of Bitcoin (in billions) for the upcoming 1 day and 7 days. We normalize the trading volume by subtracting its average in the past two weeks. For columns (3) and (4), the main dependent variable is the future volatility of Bitcoin returns over the next 1 day and 7 days. To account for news arrivals, we include the average levels of sentiment in RavenPack news over the past 14 days as control variables. Additionally, we incorporate two Bitcoin market variables: Bitcoin Volatility and the Number of Transactions. Each variable represents the cumulative sum over the past 14 days. To gauge sentiment in online forums, we calculate the average sentiment of posts on the Bitcointalk forum published in the previous 14 days. We report t-statistics in parentheses based on Newey-West corrected standard errors using a lag of 14 days. We multiply each coefficient by 100.

	Abnormal Trading Volume		Return Volatility	
	(1) 1 Day	(2) 7 Days	(3) 1 Day	(4) 7 Days
SCI	0.447***	0.333***	0.530***	0.370***
	(3.85)	(3.04)	(5.45)	(4.33)
Bitcoin Volatility	-4.678***	-5.702***	11.237***	8.597***
in Past 14 Days	(-2.92)	(-3.04)	(7.60)	(8.81)
RavenPack News Sentiment	-0.291	0.273	-0.512***	-0.425***
in Past 14 Days	(-1.01)	(1.16)	(-4.41)	(-4.45)
Forum Average Sentiment	0.447	0.819	-1.555***	-1.600***
in Past 14 Days	(0.95)	(1.38)	(-3.92)	(-3.43)
Bitcoin Return	3.509***	4.059***	2.539***	3.913***
in Past 14 Days	(3.26)	(3.55)	(2.75)	(3.17)
Adjusted R-Squared	0.038	0.101	0.263	0.374
N	3,734	3,734	3,734	3,734

Table 13: Social Learning in Bubbles

This table highlights the features of social learning in bubble. We identify bubble episodes following the procedure described in section 5.4.1. In Panel A, we describe the market conditions in bubbles. In Panel B, we highlight the features of social activities in bubbles. In Panel C, we describe sentiment contagions in bubbles. In all panels, we compare features between bubble and non-bubble episodes. We rely on seemingly unrelated regression (SUR) to test the joint significance of differences in all features. We report the joint F-statistic and its corresponding p-value. Our sample spans from May 1, 2012 to July 30, 2022.

	Bubble Episode		Non-Bubble Episode		Bubble Episode minus Non-Bubble Episode	
Features	Mean	Std	Mean	Std	Difference	t-statistic
Panel A: Market Variables						
Daily Return(Annualized)	4.050	17.66	0.491	15.72	3.56	5.352
Return Volatility(Within Day)	0.040	0.03	0.037	0.04	0.003	2.413
Total Dollar Volume (in millions)	94.071	148.80	47.503	77.63	46.568	11.784
RavenPack News Sentiment	0.168	0.42	0.040	0.43	0.127	5.894
Google Search (Bitcoin)	0.085	0.48	0.017	0.40	0.068	3.961
Panel B: Social Interactions						
Average Sentiment	0.305	0.11	0.272	0.12	0.033	6.761
Standard Deviation of Sentiment	0.657	0.05	0.672	0.05	-0.015	-6.635
Number of Posts	188.764	147.95	175.713	163.66	13.052	1.968
Number of Users	133.504	105.61	116.261	114.97	17.243	3.692
Total Number of Positive Posts	104.671	87.03	90.834	87.47	13.837	3.837
Fraction of Posts with Positive Sentiment	0.543	0.09	0.516	0.09	0.028	7.563
Fraction of Sophisticated Users	0.301	0.10	0.359	0.14	-0.058	-10.523
Panel C: Sentiment Contagion						
Number of Positively Infected Users	16.704	16.24	15.335	17.33	1.369	1.938
Number of Negatively Infected Users	3.203	4.63	3.813	5.84	-0.61	-2.629
Joint F-statistic						15.49
p-value (Probability>F)						0.00

Table 14: Social Learning and Market Crashes

This table presents the predictive power of social learning on future market declines and crashes in the Bitcoin market. The main explanatory variable is the cumulative Net SCI indicator, which measures the difference in the numbers of positively affected users and negatively affected users within the past 14 days. The positively (negatively) affected users are those who adjust their sentiment upward (downward) to align with the social sentiment in conversations. We normalize it to have a zero mean and unit standard deviation. In columns (1) to (3), the dependent variables are dummy variables for returns that equal one if the cumulative return within a given horizon falls below zero. In columns (4) to (6), the dependent variable is a crash indicator, taking a value of 1 if, within a given horizon, at least one daily return falls below the 5th percentile of daily returns. Control variables are identical to those in Table 12. We report the average marginal effects. We report t-statistics in parentheses based on standard errors clustered by day. The coefficients are multiplied by 100.

	Dummy (Return < 0)			Crash (below 5% perc.)		
	(1)	(2)	(3)	(4)	(5)	(6)
	1 day	7 days	14 days	1 day	7 days	14 days
Cumulative Net SCI	1.813*	4.539***	6.228***	1.038***	5.696***	9.157***
in Past 14 Days	(1.88)	(4.74)	(6.52)	(2.87)	(7.43)	(10.05)
Bitcoin Volatility	-3.349	-23.316***	-14.375*	12.148***	45.829***	78.608***
in Past 14 Days	(-0.41)	(-2.91)	(-1.82)	(4.40)	(6.02)	(8.65)
RavenPack News Sentiment	-0.663	2.167	-5.177***	0.016	-2.286	1.848
in Past 14 Days	(-0.35)	(1.13)	(-2.73)	(0.02)	(-1.41)	(1.02)
Forum Average Sentiment	-5.163	-3.890	2.261	-0.098	5.083*	8.525**
in Past 14 Days	(-1.41)	(-1.07)	(0.63)	(-0.06)	(1.68)	(2.56)
Bitcoin Return	-9.877**	-21.082***	-9.197**	-0.522	4.478	14.380***
in Past 14 Days	(-2.34)	(-4.77)	(-2.17)	(-0.32)	(1.26)	(3.56)
Adjusted R-Squared	0.002	0.009	0.012	0.040	0.055	0.083
N	3,734	3,734	3,734	3,734	3,734	3,734

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Table A1: Contagion Effect: Ex-Post Sentiment as Dependent Variable

This table presents the panel regression analysis of ex-post sentiment on social sentiment. The dependent variable, ex-post sentiment, refers to the sentiment in the second post of two consecutive posts (post[0] and post[1]). The main explanatory variable is social sentiment, which is the average sentiment of others' posts within the conversation published between the timestamps of post[0] and post[1]. Control variables are identical to those in Table 2. We also control for the prior sentiment. In all columns, we include a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by investor and day. We multiply each coefficient by 100.

	Ex-Post Sentiment				
	(1)	(2)	(3)	(4)	(5)
Social Sentiment	11.029***	6.663***	3.478***	3.940***	5.237***
	(26.17)	(17.72)	(9.03)	(8.18)	(9.42)
Prior Sentiment		0.609***	-0.498**	-0.544**	-11.370***
		(2.65)	(-2.20)	(-2.16)	(-25.68)
RavenPack News Sentiment				0.511	2.242***
between Post[0] and Post[1]				(0.66)	(2.72)
RavenPack News Sentiment				1.554*	2.295***
24 hours before Post[0]				(1.71)	(2.85)
RavenPack News Sentiment				-0.954	0.177
48 hours before Post[0]				(-1.05)	(0.23)
Bitcoin Return				31.329***	36.187***
				(6.66)	(7.01)
Bitcoin Volatility				-4.900	-8.263
				(-0.30)	(-0.49)
Forum Sentiment				-5.883***	1.778*
				(-6.61)	(1.93)
User FE	NO	YES	YES	YES	NO
Day FE	NO	NO	YES	YES	NO
User X Week FE	NO	NO	NO	NO	YES
Controls	NO	NO	NO	YES	YES
Adjusted R-Squared	0.005	0.033	0.038	0.039	0.050
N	218,270	212,647	212,623	175,750	143,092

Table A2: Contagion Effect: Max of Sentiment

In this table, we use the max of sentence sentiment to measure sentiment at the post level. We present the panel regression analysis of sentiment change on social sentiment. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. The main explanatory variable is the social sentiment defined as the average sentiment of others' posts within the conversation, published between the timestamps of post[0] and post[1]. Control variables are identical to those in Table 2. In all columns, we include a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Sentiment Change				
	(1)	(2)	(3)	(4)	(5)
Social Sentiment	9.164***	5.265***	2.562***	2.726***	4.050***
	(22.65)	(13.63)	(6.34)	(5.50)	(6.85)
RavenPack News Sentiment				0.463	2.338**
between Post[0] and Post[1]				(0.49)	(2.27)
RavenPack News Sentiment				1.179	1.660
24 hours before Post[0]				(1.08)	(1.62)
RavenPack News Sentiment				-1.758	0.290
48 hours before Post[0]				(-1.61)	(0.32)
Bitcoin Return				37.514***	41.362***
				(6.93)	(6.68)
Bitcoin Volatility				9.714	6.044
				(0.57)	(0.30)
Forum Sentiment				-5.321***	1.330
				(-5.37)	(1.15)
Prior FE	YES	YES	YES	YES	YES
User FE	NO	YES	YES	YES	NO
Day FE	NO	NO	YES	YES	NO
User X Week FE	NO	NO	NO	NO	YES
Controls	NO	NO	NO	YES	YES
Adjusted R-Squared	0.376	0.385	0.385	0.386	0.372
N	218,268	212,647	212,623	175,750	143,092

Table A3: Contagion Effect: Sum of Sentiment

In this table, we use the summation of sentence sentiment to measure sentiment at the post level. We present the panel regression analysis of sentiment change on social sentiment. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. The main explanatory variable is the social sentiment defined as the average sentiment of others' posts within the conversation, published between the timestamps of post[0] and post[1]. Control variables are identical to those in Table 2. In all columns, we include a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Sentiment Change				
	(1)	(2)	(3)	(4)	(5)
Social Sentiment	8.978***	5.091***	2.550***	2.788***	3.811***
	(20.08)	(11.19)	(5.42)	(4.93)	(5.49)
RavenPack News Sentiment				0.927	3.516**
between Post[0] and Post[1]				(0.62)	(2.26)
RavenPack News Sentiment				0.379	1.953
24 hours before Post[0]				(0.23)	(1.28)
RavenPack News Sentiment				-3.092**	-0.551
48 hours before Post[0]				(-2.03)	(-0.43)
Bitcoin Return				47.551***	52.880***
				(4.35)	(5.22)
Bitcoin Volatility				17.104	10.720
				(0.80)	(0.36)
Forum Sentiment				-5.194***	1.171
				(-4.75)	(0.97)
Prior FE	YES	YES	YES	YES	YES
User FE	NO	YES	YES	YES	NO
Day FE	NO	NO	YES	YES	NO
User X Week FE	NO	NO	NO	NO	YES
Controls	NO	NO	NO	YES	YES
Adjusted R-Squared	0.306	0.310	0.310	0.311	0.281
N	218,268	212,647	212,623	175,750	143,092

Table A4: Contagion Effect: Same Conversation

This table presents the panel regression analysis of sentiment change on social sentiment when post[0] and post[1] are published in the same thread within a 24-hours window. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. The main explanatory variable is the social sentiment defined as the average sentiment of others' posts within the conversation, published between the timestamps of post[0] and post[1]. Control variables are identical to those in Table 2. In all columns, we include a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Sentiment Change				
	(1)	(2)	(3)	(4)	(5)
Social Sentiment	5.461***	4.225***	2.165***	1.821*	3.652***
	(8.91)	(6.49)	(3.14)	(1.91)	(3.03)
RavenPack News Sentiment				-1.657	0.115
between Post[0] and Post[1]				(-0.81)	(0.05)
RavenPack News Sentiment				0.662	-1.265
24 hours before Post[0]				(0.33)	(-0.63)
RavenPack News Sentiment				0.184	-0.037
48 hours before Post[0]				(0.09)	(-0.02)
Bitcoin Return				33.676***	35.570***
				(3.81)	(3.54)
Bitcoin Volatility				20.998	-17.294
				(0.74)	(-0.51)
Forum Sentiment				-2.373	2.054
				(-1.52)	(1.20)
Prior FE	YES	YES	YES	YES	YES
User FE	NO	YES	YES	YES	NO
Day FE	NO	NO	YES	YES	NO
User X Week FE	NO	NO	NO	NO	YES
Controls	NO	NO	NO	YES	YES
Adjusted R-Squared	0.341	0.340	0.335	0.335	0.323
N	73,466	70,814	70,388	53,283	42,902

Table A5: Contagion Effect: Sentiment Change over the Next 12, 48, and 72 Hours

This table presents panel regression analysis of sentiment change on social sentiment when post[0] and post[1] are published within a 12-, 48- and 72-hours window. The dependent variable is the sentiment change defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. The main explanatory variable is the social sentiment defined as the average sentiment of others' posts within the conversation, published between the timestamps of post[0] and post[1]. Control variables are identical to those in Table 2. In all columns, we include a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by user and day. We multiply each coefficient by 100.

	12 Hours		48 Hours		72 Hours	
	(1)	(2)	(3)	(4)	(5)	(6)
Social Sentiment	2.575***	3.936***	3.975***	5.024***	4.235***	5.158***
	(4.31)	(5.19)	(8.45)	(9.00)	(9.17)	(9.70)
RavenPack News Sentiment	0.627	2.678*	0.220	2.470***	0.192	2.440***
between Post[0] and Post[1]	(0.56)	(1.88)	(0.29)	(3.32)	(0.28)	(3.57)
RavenPack News Sentiment	1.211	1.316	0.183	1.433**	0.475	1.168*
24 hours before Post[0]	(0.90)	(1.10)	(0.26)	(2.15)	(0.80)	(1.94)
RavenPack News Sentiment	-1.692	-0.107	-0.806	-0.110	-0.200	-0.162
48 hours before Post[0]	(-1.11)	(-0.09)	(-1.13)	(-0.17)	(-0.33)	(-0.28)
Bitcoin Return	28.611***	27.871***	24.719***	31.343***	21.591***	28.988***
	(4.56)	(3.67)	(5.32)	(5.94)	(5.37)	(6.29)
Bitcoin Volatility	5.691	9.019	14.377	-2.341	15.457	-1.280
	(0.31)	(0.49)	(0.97)	(-0.13)	(1.06)	(-0.07)
Forum Sentiment	-3.348***	0.895	-5.744***	1.636	-6.421***	1.413
	(-2.99)	(0.67)	(-5.52)	(1.43)	(-6.17)	(1.25)
Prior FE	YES	YES	YES	YES	YES	YES
User FE	YES	NO	YES	NO	YES	NO
Day FE	YES	NO	YES	NO	YES	NO
User X Week FE	NO	YES	NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.345	0.326	0.348	0.321	0.350	0.319
N	108,372	84,010	245,944	206,206	283,588	239,714

Table A6: Social Learning and Individual Trading: Between Consecutive Pairs

This table presents the regression analysis of individuals' trading decisions on the sentiment change between post[0] and post[1]. The dependent variable is an indicator of whether the individual actively increased her portfolio by at least 0.1 Bitcoins. The main explanatory variable is the sentiment change, defined as the revision in sentiment between a user's two consecutive posts post[0] and post[1]. Control variables are identical to that in Table 2. Additionally, we include the time gap between t_0 and t_1 as an additional control, as trading is more likely to occur over longer time windows. In all columns, we include user and date fixed effects, as well as a prior fixed effect. We report t-statistics in parentheses based on standard errors clustered by user and day. We multiply each coefficient by 100.

	Probability buy in [t0, t1]	Probability buy in [t0, t1],t1-t0>2 hours	Probability buy in in [t1, t1+7days]
Sentiment Change	8.035***	10.229***	0.436*
	(2.71)	(3.35)	(1.96)
Prior FE	YES	YES	YES
User FE	YES	YES	YES
Date FE	YES	YES	YES
Controls	YES	YES	YES
Adjusted R-Squared	0.238	0.250	0.632
N	203	189	9,284

Table A7: Post Decisions and Recent Bitcoin Returns

This table presents the association between users' post decisions and Bitcoin returns in the past 14 days. In columns (1) and (2), the dependent variable $PostDecisions_{i,t}$ is a dummy variable that equals one if user i makes at least one post on day t and zero otherwise. We focus on users' active days after their registration. In columns (3) to (6), we investigate how, conditional on users posting, recent Bitcoin returns affect the post sentiment. In columns (3) and (4), the dependent variable $PositivePosts_{i,t}$ equals to one if user i publishes a positive posts on day t and zero otherwise. In columns (5) and (6), the dependent variable $PessimisticPosts_{i,t}$ equals to one if user i publishes a negative posts on day t and zero otherwise. We calculate the average levels of sentiment in RavenPack news in the past 14 days as controls for news arrivals. We control for market information by controlling for two Bitcoin market variables: Bitcoin Volatility and Number of Transactions. Each of two variable is the cumulative sum in the past 14 days. We calculate forum average sentiment as the average sentiment of posts on the Bitcointalk forum published in the past 14 days. In all columns, we add user fixed effect. We multiply each coefficient by 100. We report t-statistics in parentheses based on standard errors clustered by user and date.

	(1) Post Decisions	(2) Post Decisions	(3) Positive Posts	(4) Positive Posts	(5) Pessimistic Posts	(6) Pessimistic Posts
Bitcoin Return	0.210***	0.299***	6.676***	2.549***	-4.920***	-2.373***
in Past 14 Days	(3.96)	(4.92)	(10.00)	(3.81)	(-9.54)	(-4.59)
Bitcoin Volatility		1.016***		2.728**		0.047
in Past 14 Days		(11.12)		(2.28)		(0.05)
RavenPack News Sentiment		-0.042***		2.446***		-1.986***
in Past 14 Days		(-3.15)		(10.33)		(-11.86)
Forum Sentiment		-0.231**		43.072***		-26.911***
in Past 14 Days		(-2.08)		(19.20)		(-15.59)
User FE	YES	YES	YES	YES	YES	YES
Date FE	NO	NO	NO	NO	NO	NO
Controls	NO	YES	NO	YES	NO	YES
Adjusted R-Squared	0.055	0.055	0.039	0.039	0.020	0.023
N	122,046,111	121,971,272	649,710	403,816	649,710	403,816

Table A8: Fraction of Positive and Negative Posts and Recent Bitcoin Returns

This table presents the association between the fraction of positive and negative posts in the forum within a day and Bitcoin returns in the past 14 days. In columns (1) and (2), the dependent variable is the fraction of positive posts on the forum within a given day. In columns (3) and (4), the dependent variable is the fraction of negative posts in the forum within one day. We calculate the average levels of sentiment in RavenPack news in the past 14 days as controls for news arrivals. We control for Bitcoin Volatility which is based on the returns in the past 14 days. We multiply each coefficient by 100. We report t-statistics in parentheses based on standard errors clustered by date.

	(1)	(2)	(3)	(4)
Bitcoin Return in Past 14 Days	5.434***	4.382***	-4.545***	-3.803***
	(6.03)	(5.41)	(-7.73)	(-7.28)
Bitcoin Volatility in Past 14 Days		-9.334***		6.638***
		(-8.17)		(9.03)
RavenPack News Sentiment in Past 14 Days		2.448***		-1.731***
		(7.56)		(-8.12)
Adjusted R-Squared	0.014	0.042	0.025	0.060
N	3,743	3,743	3,743	3,743

Table A9: Optimism in Conversations and Future Market Crashes

In this table, we study how optimism in conversations predicts the occurrence of crashes using the probit model. The dependent variable is a future crash indicator, which takes on a value of 1 if there is any return crash in the next K hours (K =6, 24, 48, and 72) and 0 otherwise. We classify the event of return crash in a given hour if the future Bitcoin return within the subsequent 24 hours is less than -15%. Our key predictor for the future crash is the Optimism variable, and we define it in two distinct ways. In columns (1), (3) and (5), Optimism in summation is the aggregated sentiment in the current hour, where the aggregated sentiment is simply the summation of sentiment across posts published within an hour. In columns (2), (4) and (6), Optimism in fraction is the fraction of hours with positive aggregated sentiment in the past 7*24 hours, where the aggregated sentiment is simply the summation of sentiment across posts published within an hour. We report the average marginal effects. We report t-statistics in parentheses based on standard errors clustered by day. Finally, we multiply each coefficient by 100.

	(1) 6 Hours	(2) 6 Hours	(3) 24 Hours	(4) 24 Hours	(5) 72 Hours	(6) 72 Hours
Optimism in Summation	0.179*		0.419**		1.312***	
	(1.95)		(2.16)		(3.58)	
Optimism in Fraction		0.414**		1.182***		2.782***
		(2.24)		(3.24)		(4.38)
RavenPack News Sentiment	0.039	-0.184	0.519	-0.215	1.002	-0.751
in Past 7*24 Hours	(0.06)	(-0.29)	(0.44)	(-0.19)	(0.50)	(-0.39)
Bitcoin Return Volatility	170.494***	167.886***	441.053***	422.925***	1021.164***	981.951***
in Past 7*24 Hours	(4.78)	(4.76)	(6.16)	(6.27)	(8.16)	(8.18)
Cumulative Bitcoin Return	-4.347	-3.308	-12.444*	-9.780	-18.378	-10.586
in Past 7*24 Hours	(-1.02)	(-0.78)	(-1.65)	(-1.27)	(-1.44)	(-0.82)
Adjusted R-Squared	0.109	0.116	0.127	0.141	0.140	0.153
N	17,953	17,953	17,953	17,953	17,953	17,953

Table A10: Optimism in Conversations and Future Volatility

In this table, we study how optimism in conversations predicts future number of transactions volume. The dependent variable volatility is the standard deviation of hourly returns in the next K hours (K = 6, 24, 72). We adjust the standard deviation to the daily level. Our key predictor for the future volatility is the Optimism variable, and we define it in two distinct ways. In columns (1), (3) and (5), Optimism in summation is the aggregated sentiment in the current hour, where the aggregated sentiment is simply the summation of sentiment across posts published within an hour. In columns (2), (4) and (6), Optimism in fraction is the fraction of hours with positive aggregated sentiment in the past 7*24 hours, where the aggregated sentiment is simply the summation of sentiment across posts published within an hour. We multiply each coefficient by 100. In this Table, we use Bootstrap standard errors from a simulation of 1000 times.

	(1) 6 Hours	(2) 6 Hours	(3) 24 Hours	(4) 24 Hours	(5) 72 Hours	(6) 72 Hours
Optimism in Summation	0.288***		0.260***		0.221***	
	(9.29)		(10.37)		(10.83)	
Optimism in Fraction		0.207***		0.215***		0.203***
		(6.75)		(9.01)		(10.44)
RavenPack News Sentiment	-0.351***	-0.442***	-0.121	-0.232**	0.137	0.023
in Past 7*24 Hours	(-2.96)	(-3.52)	(-1.12)	(-2.02)	(1.55)	(0.25)
Bitcoin Return Volatility	426.657***	433.016***	405.186***	409.712***	363.787***	366.767***
in Past 7*24 Hours	(28.08)	(28.43)	(29.94)	(30.06)	(32.86)	(32.71)
Cumulative Bitcoin Return	-17.934**	-16.988**	-15.784***	-14.915***	-8.160**	-7.411**
in Past 7*24 Hours	(-2.57)	(-2.43)	(-3.26)	(-3.07)	(-2.39)	(-2.17)
Adjusted R-Squared	0.286	0.282	0.328	0.324	0.331	0.328
N	17,953	17,953	17,953	17,953	17,953	17,953

Table A11: Correlations between SCI and Other Indicators

This table shows the correlations between SCI indicator and other variables of interest measured at daily frequency. SCI indicator measures the daily number of users who adjust their sentiment to align with the social sentiment in conversations. We use its logarithmic form and eliminate time-fixed effects by regressing on year-month indicators and weekday dummies. Forum Average Sentiment reflects the average level of sentiment in posts published on the forum. RavenPack News Sentiment represents the daily mean sentiment level in news documented in the RavenPack news database. RavenPack News Coverage denotes the number of news articles regarding Bitcoin within a single day. Google Search Bitcoin records the detrended Google Search Index for Bitcoin on a daily basis. Our sample spans from May 1, 2012 to July 30, 2022.

Variables	SCI	Forum Average Sentiment	RavenPack News Sentiment	RavenPack News Coverage	Google Search Bitcoin
SCI	1.000				
Forum Average Sentiment	0.006	1.000			
	(0.696)				
RavenPack News Sentiment	-0.003	0.347	1.000		
	(0.876)	(0.000)			
RavenPack News Coverage	0.004	-0.085	-0.082	1.000	
	(0.842)	(0.000)	(0.000)		
Google Search (Bitcoin)	0.238	-0.032	0.024	0.296	1.000
	(0.000)	(0.050)	(0.265)	(0.000)	