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Social media disagreement and financial markets: A comparison of stocks and Bitcoin

Sergen Akarsu[1] **Neslihan Yilmaz**[2]

Abstract

We examine whether disagreement in social media discussions related to financial markets affects subsequent volatility and abnormal trading volume. We also compare how traditional and digital asset markets differ by comparing stocks and Bitcoin. We show that social media disagreement is positively associated with future market volatility and abnormal trading volume in the stock market. The effect of disagreement is more pronounced at the individual stock level than at the index level. A higher level of social media disagreement also increases the probability of extremely negative stock market returns. In contrast, disagreement in Bitcoin-related social media weakly affects subsequent volatility but does not affect trading volume or extremely negative returns. Our findings also reveal that market activity impacts the disagreement in the stock market and Bitcoin communities differently.

Keywords

- disagreement
- trading volume
- volatility
- Bitcoin
- Reddit

JEL codes: G10, G41, D83

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[1] Boğaziçi University, Department of Management, Bebek, Istanbul, 34342, Türkiye, corresponding author: muhammet.akarsu@std.bogazici@edu.tr, https://orcid.org/0000-0002-8746-8575.

[2] Boğaziçi University, Department of Management, Bebek, Istanbul, 34342, Türkiye, neslihan.yilmaz@bogazici.edu.tr, https://orcid.org/0000-0002-5648-7343.

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Introduction

When investors have different beliefs about future market conditions, they can react differently to new information, market events, and changes in economic conditions. Varied expectations, in turn, can result in elevated levels of trading volumes and market volatility. Disagreement on market prospects can also lead to divergent trading strategies and market dynamics. Accordingly, the literature provides evidence of heterogeneous beliefs' volatility and volume-increasing effect in financial markets (Atmaz & Basak, 2018; Banerjee & Kremer, 2010; Carlin et al., 2014). Most studies use analyst forecasts to focus on disagreement among sophisticated investors. Yet analyst forecasts fail to provide information on the beliefs of retail investors, especially those interacting on social media platforms. Building upon the growing body of literature using social media content, we investigate how the disagreement among users of social media related to financial markets affects future market activity.

The rise of social media has provided retail investors with platforms like Twitter, Stocktwits, and Reddit to share their views and discuss their expectations on market movements in real time. The literature increasingly focuses on how social media discussions impact financial markets (Chen et al., 2014; Cookson & Niessner, 2020; Tan & Tas, 2021). However, much of the existing research focuses on the direct impact of social media sentiment and paid less attention to the role of disagreement, which refers to the extent to which investors hold opposing views on market direction. Understanding how heterogeneous beliefs impact market activity is important because they can lead to greater trading volume and volatility as investors act on their differing views. This study explores this possibility by analysing comments on Reddit posted between January 2019 and June 2022. Reddit's community-based structure allows us to link discussions to specific assets and facilitate the examination of disagreement's impact on market activity.

We focus on the opinions shared in two important communities about the stock market and Bitcoin. We hypothesise that increased disagreement in these communities will increase trading volume and volatility, as diverse opinions trigger more buying and selling activity. We also expect that disagreement in the stock market community will have a more substantial effect at the individual stock level compared to the index level, where opinions across various stocks can offset each other and reduce the disagreement's overall impact.

We quantify disagreement using the standard deviation of a binary sentiment index across users within a given day. We first average sentiment scores by means of two popular sentiment tools, VADER and TextBlob, and then convert them into a categorical index to capture positive and negative sentiments. The standard deviation of this index shows the belief dispersion. To measure daily volatility, we use the range between the daily highest and the lowest prices. Range-based volatility measures provide stationary and daily volatility measures and have been frequently used in the finance literature (e.g., Blau & Whitby, 2017).

Our findings reveal key differences between the stock market and Bitcoin communities. Disagreement in the stock market community significantly increases the next day's volatility and abnormal trading volume. On the contrary, disagreement in the Bitcoin community does not statistically significantly affect Bitcoin's volatility or abnormal trading volume. However, the influence of disagreement becomes statistically significant for Bitcoin during periods of market drawdowns. We suggest that the Bitcoin community's focus shifts toward immediate market actions when the market is in unfavourable conditions, which amplifies the effect of social media disagreement in such periods. Furthermore, when only posts from midnight until the markets open are considered, disagreement in both communities significantly increases subsequent trading volume and volatility. Since Bitcoin has no official trading hours, its community receives continuous market feedback, allowing before-the-market disagreement to significantly impact subsequent market activity. Considering that we observe statistically insignificant effects in interday models, the Bitcoin community can have a short-term impact on the markets, with possible intraday prediction ability. We also show that investor attention in both communities can affect future volatility. Our results are consistent with the view that online financial communities facilitate information dissemination, which can induce additional volatility in the near term. We also show that extremely negative returns in the stock market are more likely following increases in social media disagreement. Lastly, focusing on the comments mentioning the tickers of stocks listed in the S&P500 index reveals that the network disagreement effect on volatility and trading volume is more pronounced at the stock level than at the index level.

This study contributes to the literature in several ways. Firstly, we extend previous research on social media and financial markets by shifting the focus from sentiment to disagreement. Secondly, we provide a comparative analysis of the stock market and Bitcoin. By examining two distinct communities on Reddit, we demonstrate the importance of considering asset-specific dynamics in understanding the influence of social media on financial markets. Finally, we examine the discussions on Reddit, which received less attention than Twitter in the literature. Reddit's popularity allows us to reach the beliefs of a wide range of users about the market.

The remainder of the paper is structured as follows. In Section 1, we review related literature. Then, in Section 2, we develop hypotheses and explain our methodology. In Section 3, we report our empirical findings. In the last Section, we give concluding remarks.

1. Literature review

Different opinions, sentiments and strategies across investors concerning asset prices can cause market movements. Hong and Stein (2007) argue that disagreement about the future can emerge from two sources. The first is the different information sets investors might have. Due to gradual information flow or investors' limited attention, some investors can form expectations based on information others do not yet have, resulting in disagreement. The second is the differences in prior beliefs and economic models that allow investors to interpret the same information differently. Different models enable different investors to obtain and pay attention to the same information but reach different conclusions. Both mechanisms can increase disagreement about the future and have significant market implications. Hong and Stein (2007) suggest that for disagreement to create trading volume, investors should agree to disagree, meaning that they should not consider that they may be at an informational disadvantage. Indeed, studies provide evidence of how investors do not constantly update their beliefs based on others' transactions, making disagreement influential in financial markets.

Studies use different measures of disagreement but demonstrate that it significantly affects trading volume and volatility as heterogeneous opinions lead to more active buying and selling behaviours. In early studies, the measure of investor disagreement tends to rely on the dispersion in analyst forecasts and investment newsletter recommendations. These studies frequently explored the relationship between disagreement and trading volume at the stock level. Ajinkya et al. (1991) measure disagreement with dispersion in analyst forecasts and find that it is positively related to trading volume. Similarly, Atiase and Bamber (1994) find that the reaction of trading volume to earnings announcements increases with analyst forecast dispersion. Barron (1995) uses belief revisions and changes in forecast dispersion to measure disagreement. He finds that both disagreement measures are positively related to trading volume. Using analyst forecasts, Bamber et al. (1997) find that disagreement has three aspects that significantly affect trading volume. Their findings show that dispersion in prior beliefs, changes in dispersion, and different belief revisions across investors positively affect trading volume. D. Li and G. Li (2021) examine household belief dispersion in the US and show that disagreement increases trading volume at the market level as well. These findings emphasise the role of disagreement in driving market activity, particularly trading volume.

In addition to trading volume, disagreement is also linked to volatility and volatility-related phenomena. Graham and Harvey (1996) use dispersion in investment newsletters to capture disagreement and find that higher levels of disagreement predict increased future volatility at the market level. Banerjee (2011) shows that disagreement measured by analyst dispersion is positively related to stock volatility. Wang et al. (2023) use the dispersion in analysts' long-term growth forecasts as a measure of disagreement and find that it is significantly related to the idiosyncratic volatility puzzle. These studies demonstrate that market-wide disagreement can have a destabilising effect and increase price fluctuations.

With the advent and widespread use of social media, there has been a noticeable shift in the way studies measure investor disagreement. The practice of people sharing their expectations about financial markets on social media has led to the quantification of investor sentiment in these posts. The extent of dispersion in the opinions of many users has also become observable. The dispersion of sentiment refers to the variability in sentiment scores among different users and serves as a measure of disagreement. A significant part of the literature investigates the market implications of disagreement among online social network interactions. Although the method of measuring disagreement has changed in recent years, its impact on trading volume has consistently been found to be positive. Antweiler and Frank (2004) examine messages posted on Yahoo! Finance and Raging Bull and find that social media disagreement is positively associated with stock-level trading volume. Similarly, Sprenger et al. (2014) use the dispersion in the sentiment of tweets about the stock market and find that disagreement increases trading volume at the stock level. Using tweets from StockTwits, Al-Nasseri and Menla Ali (2018) also show that disagreement increases stock-level trading volume. Although they follow different approaches to measure social media disagreement, both Giannini et al. (2019) and Cookson and Niessner (2020) also find that disagreement leads to higher stock trading volume.

Some studies investigate the impact of social media disagreement on volatility, in addition to the trading volume. Siganos et al. (2017) use the distance between positive and negative sentiment on Facebook's status updates to measure disagreement and find that it is positively associated with both trading volume and volatility at the market level. Similarly, T. Li et al. (2018) also find that higher disagreement leads to higher trading volume and volatility by examining Tweets related to the S&P 100 stocks.

Though disagreement has been widely explored in stock markets, its impact on Bitcoin has seen far less attention. In one of the few studies conducted in this area, Ahn and Kim (2020) find that social media disagreement increases Bitcoin's price volatility. Kantorovitch and Heineken (2021) document that high disagreement in online discussions is positively associated with the volatility of Bitcoin. In a related study, Kim and Ahn (2023) find that heterogeneous emotional feedback increases Bitcoin's intraday volatility.

Previous findings provide significant support for the claim that disagreement inflates trading volume and volatility. It appears that when people's beliefs differ, there are more trades in the market, resulting in increased volatility and trading volume. However, the majority of the findings concern the impact of stock-specific disagreement. The impact of market-wide disagreement or disagreement related to other assets receives little attention in the literature.

2. Hypotheses, data and methodology

In this study, we extend earlier studies by examining two different markets. We examine the effects of social media disagreement on the stock market and Bitcoin. For the stock market, we examine the effects of disagreement both at the index level and the individual stock level. We measure and examine how disagreement in Reddit communities about the stock market and Bitcoin affects abnormal trading volume and volatility.

2.1. Hypotheses

We do not expect differences in how disagreement affects trading volume and volatility; rather, we expect the disagreement to have a stronger effect at the individual stock level than at the index level because, at the index level, some effects can neutralise each other. Thus, our hypotheses are as follows:

H1: Social media disagreement positively affects the next day's trading volume and volatility at both the index level and stock level in the stock market.
H2: Social media disagreement positively affects the next day's trading volume and volatility of Bitcoin.
H3: The positive effect of social media disagreement on the next day's trading volume and volatility is more pronounced at the stock level than at the index level in the stock market.

We investigate the effects of social media disagreement on both trading volume and volatility to provide a more comprehensive analysis. Although some studies have examined these effects separately, the literature shows that disagreement often impacts both trading volume and volatility.

2.2. Social media disagreement

We examine Reddit, a popular discussion platform, to explore the effects of social media disagreement on financial markets. Reddit is a platform allowing people to interact in theme-based online communities called subreddits. We focus on interactions on two subreddits, r/stocks and r/Bitcoin. These subreddits are selected based on their high user activity and relevance to our research topic. We focus exclusively on Bitcoin and do not include other crypto assets due to Bitcoin's dominance in the cryptocurrency market. Bitcoin has significantly higher liquidity, larger trading volumes, and a more active online community than most other cryptocurrencies. In addition, Bitcoin serves as a benchmark for the cryptocurrency market due to its being the first and most widely recognised cryptocurrency, and its dynamics are often representative of the general behaviour of other cryptocurrencies.

We use comments posted in these subreddits using Pushshift Reddit API.[3] Our sample includes approximately 3.5 million comments in the r/stocks and 5 million in the r/Bitcoin posted between January 2019 and June 2022. Both subreddits become more popular in time, with subscribers growing by an average of 0.19% daily for the r/stocks subreddit and 0.11% for the Bitcoin subreddit. The main reason for this difference is the number of subscribers at the starting point. At the start of January 2019, the r/stocks subreddit had approximately 300,000 subscribers, while the r/Bitcoin subreddit had 1,000,000. Online activity for Bitcoin was high from the beginning, while it gained significant importance for stocks during the sampling period.

To calculate social media disagreement, we follow Cookson and Niessner (2020) and use the standard deviation of sentiment scores. Though the literature proposes several proxies to measure the disagreement among investors, such as dispersion in analyst forecasts and forecast revisions, Cookson and Niessner (2020) argue that their measure of disagreement is more practical because it directly captures the distribution of sentiment, does not rely on third-party opinions such as analyst expectations, and is available at a daily frequency. Since our study shares the same features and can benefit from these advantages, we follow this approach. We first determine each post's sentiment in the sample and calculate the standard deviation of sentiment scores across comments within a day.

To calculate the sentiment of comments, we use sentiment analysis tools of VADER and Textblob (Hutto & Gilbert, 2014; Loria, 2020). Both tools are rule-based models and provide a sentiment score ranging from –1 to +1. To reduce the noise that may arise from the differences between the two models and sentiment scores ranging from –1 to +1, we first average the sentiment scores given by both models. Then, we create a sentiment dummy variable that equals 1 if the average is greater than zero and –1 if it is smaller. If both models describe a comment as neutral, we remove that comment from the sample. We remove them because they do not reflect strong opinions that could drive market behaviour. Including them may weaken the impact of dis-

[3] https://github.com/pushshift/api

agreement. Nevertheless, we repeat our analysis with neutral comments as a robustness check.

Finally, we measure the daily disagreement based on the standard deviation of the binary sentiment index across users within a day. We first determine the sentiment of each post as either –1 or 1, then aggregate these to the daily level by calculating $sent_t$, the average sentiment of comments posted on day t. Since the sentiment of each comment is either 1 or –1, our disagreement measure is:

$$disagt_t = \sqrt{1 - sent_t^2} \quad (1)$$

where $disagt_t$ represents the disagreement on day t and $sent_t$ is the average sentiment on day t.

2.3. Data and variables

To investigate how social media disagreement affects the stock market, we first examine the aggregate impact by focusing on the S&P 500 index. Then, we investigate the relationships at the individual stock level. To do this, we filter comments mentioning the tickers of stocks included in the S&P500 at any time during the sample period, excluding those with tickers with generic meanings, such as "T" or "BALL". We only consider comments that mention the ticker of only one stock. If tickers of multiple stocks are mentioned in the same comment, we remove that comment from our sample. To ensure this exclusion does not affect our results, we conduct a robustness check, where we retain comments mentioning multiple stocks and assign the sentiment score to all referenced stocks.

After this elimination, our sample consists of 478 individual stocks that were part of the S&P 500 index during the sample period. After our initial filtering, we begin with 284,575 comments that mention tickers of these stocks. Eliminating comments with neutral sentiment reduces our sample to 233,652 comments. Additionally, we remove 74,368 comments that mention multiple stock tickers to avoid ambiguity in sentiment assignment. These procedures leave us a total of 159,284 comments for our analysis. On average, 127 comments per day mention the ticker of a single stock, with the number of comments ranging from 1 to 513. Per stock, we observe an average of 4 comments per day, ranging from a minimum of 1 to a maximum of 202. The high range between the minimum and maximum number of observations per stock per day reflects the variability in public interest and online discussions for different stocks. To further ensure reliability, we conduct an additional robustness check by removing stocks with only one comment daily. To study how the Bitcoin community affects Bitcoin's trading volume and volatility, we obtain data from CoinMarketCap, a leading data provider on cryptocurrencies.

The calculations of the market variables are as follows:

$$avol_t = \frac{tvol_t}{\sum_{d=t-140}^{t-21} \frac{tvol_d}{120}} - 1 \tag{2}$$

$$prange_t = \ln\left(\frac{high_t}{low_t}\right) \tag{3}$$

where *avol* represents abnormal trading volume and prange represents the range between the intraday highest (*high*) and lowest (*low*) prices within day *t*. Following Cookson and Niessner (2020), we measure abnormal trading volume by comparing the trading volume (*tvol*) on day *t* with the average trading volume of the previous 140 days, leaving out the most recent 20 days.

2.4. Models

To test our hypotheses, we run the Vector Autoregression (VAR) models. In the first set of equations, we examine the impact of social media disagreement on abnormal trading volume:

$$\begin{aligned} avol_t = \alpha + \beta_1 disagt_{t-1} + \beta_2 avol_{t-1} + \beta_3 lnusers_{t-1} + \beta_4 r_{t-1} + \\ + \beta_5 prange_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

$$\begin{aligned} disagt_t = \alpha + \beta_1 disagt_{t-1} + \beta_2 avol_{t-1} + \beta_3 lnusers_{t-1} + \beta_4 r_{t-1} + \\ + \beta_5 prange_{t-1} + \varepsilon_t \end{aligned} \tag{5}$$

In the second set of equations, we shift focus to the relationship between social media disagreement and intraday price range:

$$\begin{aligned} prange_t = \alpha + \beta_1 disagt_{t-1} + \beta_2 prange_{t-1} + \beta_3 lnusers_{t-1} + \\ + \beta_4 r_{t-1} + \beta_5 avol_{t-1} + \varepsilon_t \end{aligned} \tag{6}$$

$$\begin{aligned} disagt_t = \alpha + \beta_1 disagt_{t-1} + \beta_2 prange_{t-1} + \beta_3 lnusers_{t-1} + \\ + \beta_4 r_{t-1} + \beta_5 avol_{t-1} + \varepsilon_t \end{aligned} \tag{7}$$

where $disagt_t$ represents the disagreement in the entire subreddit on day *t*, *avol* represents abnormal trading volume, *prange* represents intraday price range, *lnusers* represents the natural logarithm of the number of users who comment in subreddits, *r* represents market returns in excess of the risk-free rate for the stock market and raw returns for Bitcoin, and *t* represents day. We control for several variables to adjust for the potential effects of investor attention, market activity, and volatility. We include lagged values of abnormal trading volume, price range, user activity, and market returns. We control for the number of users who comment to examine the possible effect of investor attention. Because we use the same controls in both VAR models, equation 5 and equation 7 are identical but belong to different systems of equations. In line with the usual presentation of VAR models, we include $disagt_t$ as the dependent variable in both models, even though the equation structure is the same. We standardise the social media variables so that coefficients show the effect of one standard deviation increase (decrease) in disagreement. The VAR models also provide evidence of how market activity influences future social media disagreement.

To examine the stock-level relationships, we estimate fixed-effects regressions with heteroskedasticity consistent standard errors. We also control for some stock characteristics that can affect trading volume and volatility, such as market value, book-to-market ratio, and relative spread between bid and ask prices. We estimate the following models:

$$avol_{i,t} = \alpha + \beta_1 disagt_{i,t-1} + \beta_2 r_{i,t-1} + \beta_3 prange_{i,t-1} + \beta_4 avol_{i,t-1} + \\ + \beta_5 lnmv_{i,t-1} + \beta_6 lnbm_{i,t-1} + \beta_7 spread_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

$$prange_{i,t} = \alpha + \beta_1 disagt_{i,t-1} + \beta_2 r_{i,t-1} + \beta_3 prange_{i,t-1} + \beta_4 avol_{i,t-1} + \\ + \beta_5 lnmv_{i,t-1} + \beta_6 lnbm_{i,t-1} + \beta_7 spread_{i,t-1} + \varepsilon_{i,t} \tag{9}$$

where *disagt* represents the level of social media disagreement; *avol* and *prange* represent abnormal trading volume and intraday price range; *lnmv*, *lnbm*, *spread*, and *r* represent the natural logarithm of market value, the natural logarithm of book-to-market ratio, relative bid-ask spreads, and stock returns in excess of the risk-free rate; *i* and *t* represent stock and day.

We also investigate whether social media disagreement can predict extreme market movements. To do this, we separately examine extremely negative and extremely positive return days. We define an extremely positive (negative) day as one where the daily return is above (below) the two standard deviations of the prior 120 days. Based on these definitions, we define two categorical variables: *ext_pos* and *ext_neg* that take the value of 1 for days with respectively extremely positive and negative return, and 0 otherwise. We test the impact of social media disagreement with logistic regressions in which the dependent variable is either *ext_pos* or *ext_neg*. The logistic regression model is expressed as follows:

$$logit\left(P(ext\_event_t = 1)\right) = \alpha + \beta_1 disagt_{t-1} + \beta_2 avol_{t-1} + \\ + \beta_3 prange_{t-1} + \beta_4 ext\_event_{t-1} + \varepsilon_t \qquad (10)$$

where *ext_event* represents the extreme event and is either *ext_pos* or *ext_neg*. *disagt* is the social media disagreement, *avol* is abnormal trading volume, *prange* is the range between high and low prices, and t indicates day. We include the one-day lag of the extreme event to capture potential persistence or autocorrelation in extreme market movements.

3. Empirical findings

Before reporting our findings, in Table 1 we first present summary statistics for the key variables used in this study. We see several differences between the r/stocks and r/Bitcoin subreddits. First, the average sentiment in the stock market community is higher compared to the Bitcoin community, but the latter has a smaller range. In addition, disagreement in the Bitcoin community is slightly higher, with less dispersion and a smaller range. Overall, the Bitcoin community seems to be less optimistic but also has a persistently high level of disagreement. The number of comments and commenting users is also higher in the Bitcoin community. The average number of comments per day in the Bitcoin community is 3070, while the stock market community averages 2469 comments. Likewise, the Bitcoin community sees an average of 1869 users commenting per day, compared to 1585 in the stock market community.

Bitcoin exhibits significantly higher volatility and abnormal trading volume than the S&P 500. Bitcoin's average price range is 0.0484, with a standard deviation of 0.0380, whereas the S&P 500's average price range is much lower at 0.0128. Similarly, Bitcoin's abnormal trading volume is also higher than that of the S&P 500. Summary statistics show the significantly higher volatility observed in the cryptocurrency market.

We run VAR models with one lag to examine whether social media disagreement in both communities affects future trading volume and volatility. The results, reported in Table 2 for both subreddits, show strong support for Hypothesis 1, which expects social media disagreement to positively affect the trading volume and volatility of the stock market. In contrast, the evidence for Hypothesis 2, which suggests that social media disagreement positively affects the trading volume and volatility of Bitcoin, is weaker.

The results for the r/stocks subreddit, reported in Panel A, show that social media disagreement significantly increases the subsequent abnormal trading volume and volatility of the stock market. More specifically, one stan-

Table 1. Descriptive statistics

r/stocks and S&P500	Observations	Mean	Standard deviation	Minimum	Maximum
Sentiment	866	0.3586	0.0752	0.1324	0.6279
Disagreement	866	0.9300	0.0288	0.7783	0.9912
Number of Comments	866	2469	1855	43	19285
Number of Commenting Users	866	1585	1083	71	8741
Return	866	0.0005	0.0144	–0.1198	0.0938
Abnormal Trading Volume	866	0.0233	0.3339	–0.6820	1.8289
Price Range	866	0.0128	0.0102	0.0017	0.0842
r/Bitcoin and Bitcoin	**Observations**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
Sentiment	1255	0.3121	0.0441	0.1269	0.4410
Disagreement	1255	0.9489	0.0142	0.8975	0.9919
Number of Comments	1255	3070	1906	16	18745
Number of Commenting Users	1255	1869	1075	20	8220
Return	1255	0.0019	0.0384	–0.3717	0.1875
Abnormal Trading Volume	1255	0.1774	0.5743	–0.6861	6.6917
Price Range	1255	0.0484	0.0380	0.0046	0.4894

Source: own elaboration.

dard deviation increase in disagreement increases the next day's abnormal trading volume by 1.68% and volatility by five basis points. The volatility response roughly equals 4% of the sample mean volatility of 1.3%. In Panel B of Table 2, we see that, unlike our expectations, disagreement in the Bitcoin community is not significantly associated with the next day's trading volume. Nonetheless, it positively affects the next day's volatility, which is weakly significant at the 10% significance level. The disagreement's effect on volatility is slightly more pronounced for Bitcoin. One standard deviation increase in disagreement increases volatility by 16 basis points.

Differences in the asset-specific characteristics and dynamics of online communities can help explain the differences in the impact of social media disagreement on the stock market and Bitcoin. Bitcoin exhibits higher volatility and greater return dispersion compared to the stock market. External factors such as regulatory changes can cause significant price movements in cryptocurrency markets and may weaken the effect of social media disagreement. While interactions within the Bitcoin community can be related

Table 2. Disagreement, abnormal trading volume and volatility

	Dependent variable							
	Panel A: r/stocks				Panel B: r/Bitcoin			
	Model 1: *avol*		Model 2: *prange*		Model 1: *avol*		Model 2: *prange*	
	$avol_t$	$disagt_t$	$prange_t$	$disagt_t$	$avol_t$	$disagt_t$	$prange_t$	$disagt_t$
$disagt_{t-1}$	0.0168**	0.3758***	0.0005**	0.3758***	–0.0038	0.4396***	0.0016*	0.4396***
	(0.0082)	(0.0321)	(0.0002)	(0.0321)	(0.0107)	(0.0260)	(0.0010)	(0.0260)
$lnnodes_{t-1}$	–0.0036	0.0950***	0.0004*	0.0950***	–0.0130	–0.0587*	0.0086***	–0.0587*
	(0.0074)	(0.0288)	(0.0002)	(0.0288)	(0.0126)	(0.0304)	(0.0011)	(0.0304)
$avol_{t-1}$	0.6665***	0.2898**	0.0057***	0.2898**	0.7800***	–0.1288***	0.0024	–0.1288***
	(0.0305)	(0.1196)	(0.0009)	(0.1196)	(0.0200)	(0.0484)	(0.0018)	(0.0484)
r_{t-1}	0.1740	–2.1262	–0.0268*	–2.1262	0.1528	–0.2036	–0.0573**	–0.2036
	(0.4796)	(1.8807)	(0.0144)	(1.8807)	(0.2749)	(0.6663)	(0.0246)	(0.6663)
$prange_{t-1}$	4.7474***	16.1685***	0.6132***	16.1685***	–0.6350*	1.7411**	0.3350***	1.7411**
	(1.0691)	(4.1920)	(0.0321)	(4.1920)	(0.3488)	(0.8454)	(0.0312)	(0.8454)
Constant	0.2806***	–0.4944***	–0.0008	–0.4944***	0.0692***	–0.0611	0.0318***	–0.0611
	(0.0253)	(0.0992)	(0.0008)	(0.0992)	(0.0188)	(0.0456)	(0.0017)	(0.0456)
Observations	858	858	858	858	1247	1247	1247	1247
Granger	4.20**	5.87**	4.62**	14.88***	0.13	7.10***	2.84*	4.24**

Notes: The Granger row reports the χ^2 values from the Granger causality tests. Asterisks represent statistical significance: *** < 0.01, ** < 0.05, and * < 0.1.

Source: own elaboration.

to immediate price movements, they often involve long-term ideological debates, which may not necessarily correlate with immediate market activity. As a result, opinions in the Bitcoin community may become more static and entrenched. The Bitcoin community has many participants who follow an ideological perspective that values long-term trust in Bitcoin's technology over short-term market conditions (Knittel et al., 2019). Therefore, participants in the Bitcoin community may be less likely to adjust their trading behaviour based on social media discussions. Indeed, our data shows that sentiment levels are more stable in the Bitcoin community than in the stock market community, with significantly lower average daily sentiment change. Shifts in sentiment are more closely associated with market activity and volatility of the stock market, while sentiment in the Bitcoin community is less likely to drive immediate trading behaviour. Vlahavas and Vakali (2024) suggest that discussions in online cryptocurrency communities concentrate more on immediate market actions and focus less on regulatory issues during market downturns. Considering this finding, we further test whether the disagreement in the Bitcoin community is related to future market activity during unfavourable market conditions. To do this, we first calculate drawdowns in Bitcoin prices. Then, we run a regression model with an interaction term between social media disagreement and drawdowns. The estimation results that we do not report for brevity purposes are available upon request. Briefly, we see that disagreement decreases the next day's abnormal trading volume and volatility on days Bitcoin has no drawdowns. However, as we expected, the interaction term is significant and positive. Our results show that social media disagreement increases future abnormal trading volume and volatility as drawdowns increase. The possible shift of focus in discussions within the Bitcoin community toward immediate market actions during market downturns allows social media disagreement to play a more pronounced role in driving market activity in such periods.

In Table 2, we see that investor attention also affects market activity. Increases in the number of users in the stock market community, which serve as a proxy for investor attention, can only predict the increases in volatility, but the statistical significance is weak, with a p-value of 0.07. The effect size is similar to that of disagreement, with volatility increasing by approximately four basis points following one standard deviation increase in the number of users. In Panel B, we see that investor attention is more important for Bitcoin. One standard deviation increase in the number of users increases subsequent volatility by 86 basis points. This increase in volatility is consistent with the investor attention literature, which attributes this effect to the increase in information being processed into the prices because of increased information acquisition (Andrei & Hasler, 2015; Aouadi et al., 2013). Andrei and Hasler (2015) argue that information is gradually incorporated into prices when learning is slow, and investors pay little attention to the news, making greater investor attention lead to higher volatility. Social media participation and interactions can represent more attention to the market, which allows people to obtain and process more information and increases short-term volatility. Thus, our results imply that information transfer exists between participants in social media, and that information dissemination becomes easier as participation increases. Nevertheless, the results and our interpretation should be approached with caution because the statistical significance is weak for the stock market community.

We also detect that market dynamics affect the subsequent disagreement in social media. We see that prior volatility is particularly essential for both subreddits. Increases in market volatility lead to greater future disagreement, which, in turn, amplifies the subsequent volatility. Furthermore, prior trading volume and investor attention play significant roles for both communities, although with distinct implications for each. Following an abnormally high volume of transactions, disagreement significantly increases in the stock market community but decreases in the Bitcoin community. We also observe the same pattern for the number of users who comment, which has a positive effect on the disagreement of the stock market community and a negative impact on the disagreement of the Bitcoin community. However, the latter is statistically significant only at the 0.1 level. These differences may arise from the distinct factors that contribute to the trading volume of each asset. Abnormally high trading volume in the stock market can signal that market participants interpret information differently or have diverse expectations about the future. On the other hand, an abnormally high Bitcoin volume may reflect periods of market stability, since there is significant controversy about its existence and future use. That is why higher volume can indicate widespread adoption, increased confidence in the asset, and reduced uncertainty about its future. Consistent with these differences, Table 2 shows that volatility has a positive effect on the future trading volume of the stock market but a negative impact on Bitcoin's volume. Furthermore, the r/stocks subreddit can have participants interested in different individual stocks or industries, whereas the r/Bitcoin subreddit can be relatively more homogenous. Participants of the Bitcoin community may share a common interest in adopting Bitcoin, which can enable them to converge with similar opinions following high trading volume. The impact of the number of users on disagreement is consistent with this argument. The results show that as more people comment about the stock market community and interact with one another, overall disagreement tends to increase, implying that giving a dissenting opinion and debating may be more common in the stock market community than in the Bitcoin community. On the contrary, disagreement tends to decrease in the Bitcoin community. It appears that participants in the Bitcoin community have a greater tendency to be in an echo chamber because Bitcoin is more controversial as an asset class than stocks.

Our findings show that social media dynamics affect financial markets to some degree of confidence. The positive effect of disagreement on abnormal trading volume and volatility implies that divergence in people's sentiments in online communities can serve as a proxy for the overall disagreement in the markets. Additionally, the effect of social media participation on volatility suggests that people disseminate information among social media users. More involvement in online financial communities induces additional volatility in the near term, suggesting that people can get more information due to online social interactions. We see that the social media activity of the previous day can influence the markets, but evaluating the timing of interactions can lead to a better understanding of the implications of social media on financial markets. Social media disagreement before trading activity begins may provide additional insights if pre-market discussions have more future-oriented content. To test this possibility, we conduct a separate examination of the period from midnight until the markets open. Although Bitcoin exchanges do not have official trading hours, we apply the same methodology to see whether we still observe differences between the two asset classes. Table 3 reports the results of Hypothesis 1 for the r/stocks subreddit, and Table 4 reports the results of Hypothesis 2 for the r/Bitcoin subreddit.

In Table 3, we see that the effect of before-the-market disagreement on abnormal trading volume and market volatility is similar to that of one-day lagged disagreement. One standard deviation increase in disagreement before the market opens increases the abnormal trading volume by 1.26% and volatility by six basis points. The results of the Bitcoin community reported in Table 4 further demonstrate the importance of the timing of interactions. Although one-day-lagged social media dynamics do not have significant predictive power for Bitcoin, comments made from midnight until the market opening reveal pronounced and considerable effects. One standard deviation increase in the before-the-market disagreement in the Bitcoin community creates a 2.23% increase in abnormal trading volume and a 33-basis-points increase in volatility. These results show that even though there are no official trading hours for Bitcoin, the timing of interactions also matters for it, and pre-market interactions have more substantial effects. The results support our initial premise that the interactions before market opening are more future-oriented. Additionally, the fact that Bitcoin does not have official trading hours and its community receives price feedback even during pre-market hours suggests that the Bitcoin community has predictive power over the short term, with intraday implications.

In addition to investigating the effects of social media disagreement on abnormal trading volume and volatility, we also examine how it affects extreme market movements by isolating negative and positive return days. Further examining extreme movements may be helpful for predictive insights and anomaly detection. Considering this reason, we investigate the

Table 3. The effects of before-market disagreement in the r/stocks

	$avol_t$	$prange_t$
$disagt\_before_t$	0.0126**	0.0006***
	(0.0064)	(0.0002)
$lnnodes_{t-1}$	–0.0024	0.0004**
	(0.0063)	(0.0002)
r_{t-1}	0.1340	–0.0271
	(0.6137)	(0.0271)
$prange_{t-1}$	5.1443***	0.6204***
	(1.3929)	(0.0417)
$avol_{t-1}$	0.6654***	0.0056***
	(0.0506)	(0.0013)
Constant	0.2771***	–0.0008
	(0.0376)	(0.0011)
Observations	857	857
R^2	0.6414	0.6542

Notes: Asterisks represent statistical significance: *** < 0.01, ** < 0.05, and * < 0.1.

Source: own elaboration.

Table 4. The effects of before-market disagreement in the r/Bitcoin

	$avol_t$	$prange_t$
$disagt\_before_t$	0.0232***	0.0033***
	(0.0082)	(0.0012)
$lnnodes_{t-1}$	–0.0103	0.0088***
	(0.0249)	(0.0013)
r_{t-1}	0.1849	–0.0590*
	(0.4280)	(0.0352)
$prange_{t-1}$	–0.7645	0.3280***
	(0.8636)	(0.0517)
$avol_{t-1}$	0.7827***	0.0024
	(0.1010)	(0.0018)
Constant	0.0743**	0.0320***
	(0.0309)	(0.0024)
Observations	1244	1244
R^2	0.5943	0.2638

Notes: Asterisks represent statistical significance: *** < 0.01, ** < 0.05, and * < 0.1.

Source: own elaboration.

predictive power of social media disagreement over extremely negative or positive returns.

We conduct logistic regressions to test whether social media disagreement can successfully categorise extremely positive and negative days. Table 5 reports estimation results. In Panel A, we observe that social media disagreement is positively associated with the probability of an extremely negative return event in the stock market. More specifically, the likelihood of an extremely negative return event doubles following one standard deviation increase in disagreement. Higher levels of disagreement can be a sign of varying quality of information within the community. Increased disagreement among social media users can reflect uncertainty or conflicting interpretations of market conditions, increasing the likelihood of extreme negative events. This finding shows that social media dynamics can be a risk management tool. Disagreement is important when assessing the probability of extreme negative return events, which can prevent investors from suffering high drawdowns. Nevertheless, in Panel B, we see that social media disagreement does not have a statistically significant coefficient, demonstrating that social media dynamics cannot predict extreme return movements of Bitcoin.

We further investigate the relationship between social media disagreement and the stock market at the individual stock level. While investigating the effect of disagreement at the index level provides a broad overview of how social

Table 5. Disagreement and extreme returns

	Panel A: r/stocks		Panel B: r/Bitcoin	
	ext_neg_t	ext_pos_t	ext_neg_t	ext_pos_t
$disagt_{t-1}$	0.719***	0.460	0.015	–0.030
	(0.267)	(0.363)	(0.157)	(0.184)
$avol_{t-1}$	0.559	1.744***	0.316	0.252
	(0.678)	(0.485)	(0.220)	(0.187)
$prange_{t-1}$	0.221	0.194	0.434***	0.461***
	(0.235)	(0.198)	(0.150)	(0.122)
ext_neg_{t-1}	–1.479*		0.000	
	(0.894)		(0.000)	
ext_pos_{t-1}		–1.802		–0.063
		(1.553)		(0.685)
Constant	–3.443***	–4.311***	–3.778***	–3.435***
	(0.216)	(0.311)	(0.202)	(0.168)
Observations	865	865	1224	1254

Notes: Asterisks represent statistical significance: *** < 0.01, ** < 0.05, and * < 0.1.

Source: own elaboration.

media dynamics impact overall market activity, examining the relationship at the individual stock level provides a detailed perspective and allows us to observe stock-specific effects that are not evident at the index level. Separately examining how individual stocks are affected by social media discussions also enhances the validity of our study and acts as a robustness check. Stocks with an active social media presence may experience more significant effects, as information can disseminate rapidly within their community, influencing market dynamics. Therefore, the impact of social media disagreement may be more substantial at the individual stock level than at the index level. We closely follow our methodology but adjust for additional variables such as market value, book-to-market ratio, and bid-ask spreads to account for stock-specific factors that can confound our results. We include these variables to control for stock-specific factors that may affect trading volume and volatility independently of social media disagreement, as they have been linked to trading volume and volatility due to factors such as visibility, liquidity, and information asymmetry (Aouadi et al., 2013; Ding & Hou, 2015). We are still testing hypothesis 1, investigating the effect of social media disagreement on abnormal trading volume and volatility. The results are reported in Table 6.

Table 6. Lagged effects of disagreement at the individual stock level

	$avol_t$	$prange_t$
$disagt_{t-1}$	0.0592***	0.0008***
	(0.0107)	(0.0001)
r_{t-1}	2.4455***	–0.0277***
	(0.8900)	(0.0076)
$prange_{t-1}$	9.0845***	0.5475***
	(1.0071)	(0.0210)
$avol_{t-1}$	0.2152***	0.0000
	(0.0011)	(0.0000)
$lnmv_{t-1}$	–0.1241	–0.0023
	(0.1602)	(0.0020)
$lnbm_{t-1}$	–0.0788	0.0038***
	(0.1243)	(0.0013)
$spread_{t-1}$	0.4572	0.0363**
	(0.3198)	(0.0142)
Constant	1.1214	0.0451**
	(1.6157)	(0.0217)
Observations	30416	30416
R^2	0.8363	0.3927

Notes: Asterisks represent statistical significance: *** < 0.01, ** < 0.05, and * < 0.1.

Source: own elaboration.

We see that stock-specific disagreement can significantly predict the next day's abnormal trading volume and volatility. One standard deviation increase in disagreement leads to a subsequent rise in abnormal trading volume of approximately 6%. This effect is much more significant compared to the abnormal trading volume response of 1.68% observed at the index level. As expected, we see more pronounced effects of disagreement on the stock market when we precisely match disagreement with individual stocks. At the index level, some community effects are attenuated, resulting in smaller increases in trading volume. We demonstrate similar findings for the impact of disagreement on stock volatility. One standard deviation increase in stock-specific disagreement induces an additional eight-basis-points increase in the next day's volatility. This impact on stock volatility is 60% higher than the disagreement's effect on index volatility.

We also investigate whether disagreement's predictive power over extreme return movements exists at the individual stock level. Table 7 reports our results. We see that disagreement is still significantly associated with future extreme movements but provides less precision. Increases in disagreement are positively related to extreme negative returns at the 0.1 level of significance, but they are also positively associated with extreme positive returns at the 0.01 level. In other words, while an increase in disagreement is associated with a higher probability of subsequent extreme movement at the individual stock level, it cannot provide reliable information about its direction as it does at the index level. More specifically, one standard deviation increase in disagreement increases the probability of subsequent extremely negative returns by 7% and extremely positive returns by 12%. Social media disagreement is still a volatility-increasing factor, but its ability to act as a warning signal diminishes at the individual stock level.

To test the robustness of our results, we conduct additional analyses by including neutral comments in the disagreement calculation. For the sake of brevity, we summarise these results without reporting complete estimations. We obtain results similar to those of our main models in most cases. At the stock market level, the effects of social media disagreement on the next day's volatility and the likelihood of extreme negative returns remain. We also still observe the significant effects of disagreement on both abnormal trading volume and volatility at the individual stock level. However, we observe some slight changes. Specifically, the effect of disagreement on the next day's abnormal trading volume in the stock market becomes statistically insignificant when neutral comments are included. Similarly, for Bitcoin, including neutral comments reveals before-the-market results to become insignificant. Although the results are similar in most cases, they suggest that opinions without strong sentiment may weaken the measurement of disagreement.

In addition, we run a robustness check to test the impact of excluding comments that mention multiple stock tickers. Instead of removing these com-

Table 7. Disagreement and extreme returns at the individual stock level

	ext_neg_t	ext_pos_t
$disagt_{t-1}$	0.0635*	0.1098***
	(0.0338)	(0.0312)
$lnmv_{t-1}$	0.5153***	–0.0411
	(0.0876)	(0.0743)
$lnbm_{t-1}$	0.0931	0.2206**
	(0.0927)	(0.0865)
$avol_{t-1}$	0.0707***	–0.0005
	(0.0185)	(0.0021)
$prange_{t-1}$	0.2192***	0.2186***
	(0.0180)	(0.0158)
ext_neg_{t-1}	0.4034***	
	(0.0956)	
ext_pos_{t-1}		0.0387
		(0.0956)
Observations	27091	27755

Notes: Asterisks represent statistical significance: *** < 0.01, ** < 0.05, and * < 0.1.

Source: own elaboration.

ments, we assign their sentiment scores to all referenced stocks. The results remain consistent with our primary findings and show that excluding comments with multiple stock tickers does not affect our overall results. We observe no significant changes in the effects of social media disagreement on abnormal trading volume or volatility.

Moreover, we perform a robustness check for our stock-level results by excluding stocks with only one comment per day to ensure that these minimal observations do not skew the results. The results remain consistent with our primary findings. The positive impact of social media disagreement on abnormal trading volume and volatility is robust to eliminating stocks with only one daily comment.

Finally, to see the impact of social media disagreement over a longer period, we rerun our VAR models using lags of up to five days. The results indicate that only the one-day lag model produces statistically significant effects on abnormal trading volume and volatility. The effects of social media disagreement on markets appear to be short-lived, with no significant results observed for longer lags. These findings demonstrate the short-term nature of the relationship between social media disagreement and market dynamics.

Conclusions

In this study, we examine how social media disagreement affects future trading volume and volatility in financial markets. We investigate this relationship in two popular Reddit communities related to the stock market and Bitcoin to compare and examine whether different asset classes exhibit different community effects. Our findings show that social media disagreement is more influential in the stock market than Bitcoin. Specifically, disagreement is positively associated with increased trading volume and volatility in the stock market, whereas for Bitcoin, disagreement only weakly predicts future volatility. We also show that higher levels of social media disagreement increase the likelihood of extreme negative returns in the stock market. Disagreement at the individual stock level also creates more substantial increases in both trading volume and volatility compared to disagreement at the index level. We also demonstrate high autocorrelation in abnormal trading volume and price range, which emphasises the persistence of these market measures.

Our study highlights the role of disagreement on social media platforms, which has received less attention than sentiment in prior research. We use established methodologies in the literature to explore discussions about different asset classes on social media platforms. Our results suggest that the dispersion of beliefs in online financial communities plays a significant role in market dynamics, particularly in the stock market, where disagreement drives short-term market behaviour. We also demonstrate the differences between the stock market and Bitcoin communities. Unlike the stock market community, the Bitcoin community frequently discusses Bitcoin's underlying technology and usefulness and tends to be more ideologically driven. As a result, participants in the Bitcoin community are less likely to react to daily market fluctuations based on social media disagreements. However, our findings suggest that during significant market drawdowns, the impact of disagreement becomes more pronounced. A shift of focus in discussions in the Bitcoin community from ideological discussions to market activity may explain the stronger influence of disagreement during downturns.

Our study has some limitations that should be acknowledged. First, we only focus on two communities on Reddit. Future studies can expand the scope to include other social media platforms or less popular subreddits and investigate other crypto assets, such as Ethereum or other less liquid altcoins. Moreover, exploring additional characteristics that drive differences between asset classes and communities could further refine our understanding of social media's influence on investor behaviour. Lastly, understanding the behavioural or cultural factors that drive disagreement might contribute to a better understanding of the relationship between social media and financial markets.

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