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Do cryptocurrency markets react to issuer sentiments? Evidence from Twitter☆

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ABSTRACT

Researchers and practitioners increasingly use posts on Twitter as an additional source of information to analyze cryptocurrency price movements. Previous studies that focus on the stock markets have shown that corporate sentiment disclosure impacts stock returns and trading volume. This study explores the reaction of the cryptocurrency market to the Twitter sentiments of issuers. It is found that cryptocurrency prices react positively to Twitter sentiments, while the trading volume reacts positively to the absolute value of the Twitter sentiments in a timely manner (within a period of 24 h). Further analysis in this study reveals that the market reactions are mainly driven by the incremental change in sentiments found in Twitter posts. This study sheds light on the trading behavior of investors in the cryptocurrency markets.

1. Introduction

Cryptocurrency, with its rise in the past ten years, has increasingly drawn significant attention from both academia and the industry. In cryptocurrency markets, Twitter is a major social media resource that currency issuers use to communicate with their investors. It is also the primary information source of investors, as most of the issuers post announcements and updates on their official Twitter accounts. Literature on cryptocurrency has explored the potential determinants of cryptocurrency prices both in the initial coin offering (ICO) markets (Benedetti and Kostovetsky, 2021) and the secondary markets (Li et al., 2021, 2019; Liu and Tsyvinski, 2021). However, the role of the issuer's sentiments in cryptocurrency secondary markets pricing remains unclear. To address this research gap, this study explores whether the sentiments shown on the official Twitter account of a cryptocurrency play a role in determining its returns and trading volume in the secondary markets.

Previous literature on the relationship between sentiment and asset returns primarily comes from studies on equity markets. It has shown that for equity issuing firms, sentiments exhibited by firms can affect stock prices through two channels. Sentiments disclosed through text in disclosing documents not only matter in how they signal the recent performance of the firm (Loughran and McDonald, 2013), but also disseminate these sentiments to the investors (Risius et al., 2015). Sentiments, when taken by investors as signals for recent firm performance, add to the fundamentals of the stock and affect investor valuation. Meanwhile, how investors perceive the sentiments in the disclosure of the firm affects their own emotions. They then react to this change in emotions accordingly by buying or

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selling the equity (Nofsinger, 2005), so that the prices of the equity may deviate from its fundamental value. Both channels contribute to a price change and a surge in volume after the firm expresses its sentiments to the investors.

This paper investigates whether the sentiments of cryptocurrency issuers have a similar impact as those of equity issuing firms. To cryptocurrency investors, Twitter utterances such as “amazing” and “wonderful” convey more positive sentiments, while “risky” and “adverse” are more pessimistic. If the process in the cryptocurrency markets is similar to that in the equity markets, the relationship between sentiments and returns should be positive, and the relationship between the absolute value of the sentiments and trading volume should be positive. In addition, since cryptocurrency markets are not regulated, investors would need to assess whether the tweets are credible. The trading of the coins in the secondary markets will change with disclosed sentiments on Twitter only if investors believe the tweeted contents.

Currently, whether sentiment information disclosed by issuers on Twitter influences secondary market trading remains mostly unexplored. This paper sets out to address this research gap by investigating the market reaction to the Twitter disclosure of the sentiments of cryptocurrency issuers. This study contributes to the existing literature in two ways. First, the work adds to the growing volume of literature on cryptocurrency pricing determinants (Benedetti and Kostovetsky, 2021; Borri and Shakhnov, 2019), where Borri and Shakhnov (2019) propose a model for the pricing of a cryptocurrency in secondary markets based on risk-related indices specific to Bitcoin and the cryptocurrency of interest. Furthermore, Benedetti and Kostovetsky (2021) find a relationship between initial offering prices and the intensity of Twitter activity. This paper examines the connection between the pricing of cryptocurrency and issuer Twitter sentiments. Secondly, the work extends previous studies on the disclosure of corporate sentiments in the equity markets (Wales and Mousa, 2016; Loughran and McDonald, 2013) by studying the effect of disclosed sentiments of firms in the cryptocurrency markets. By examining the relationship between cryptocurrency returns and issuer sentiments on Twitter, this study helps cryptocurrency investors to understand how the markets react to the tweets of the issuers and whether the markets give creditability to their tweeted posts. Additionally, this study provides issuers with insights into how their phrased tweets affect currency prices. Lastly, the results may help policymakers to understand whether regulations around issuer announcements on social media can stabilize the cryptocurrency markets.

Based on 47 major cryptocurrencies[1] and their trading data, we find that the effect of posting more positive words on Twitter official accounts is significantly positive. Including more positive-feeling words increases the market-adjusted returns in the 24 h after posting the tweets, and the use of more words that are emotionally evoking (either negative or positive emotions) increases the abnormal trading volume of the cryptocurrency.

2. Cryptocurrency markets and regulatory background

Since the creation of Bitcoin in 2008, the cryptocurrency markets have been experiencing exponential growth in the past twelve years and reached a total market capitalization of $272 billion USD in June 2020.[2] Unlike fiat currencies, cryptocurrencies utilize blockchain and distributed ledger technology (DLT) to decentralize transactions by verifying senders and receivers with cryptographic credentials, instead of a central authority. Cryptocurrency also differs from other types of digital currencies (e.g., in-game currencies) due to its convertibility. Fig. 1 shows the taxonomy of the currencies discussed above.

Part of the value of cryptocurrencies comes from human efforts and the work involved to create a new coin, but researchers have not reached a consensus on the other factors that influence the price of cryptocurrencies. One of the common channels for cryptocurrency issuers to raise funds before their cryptocurrency is officially launched is initial coin offerings (ICOs), where issuers publish white papers of their cryptocurrency for the evaluation of investors before they make a purchasing decision. Most of the cryptocurrencies are subsequently listed on exchanges for off-chain trading in the secondary markets. After the ICOs, some of the issuers allow mining, where miners receive newly minted units of a cryptocurrency by meeting the necessary conditions specified by the DLT infrastructure (e.g., finding a valid proof-of-work).

Currently, government regulations for cryptocurrencies primarily focus on their distribution (e.g., ICOs), exchange trading, and taxation. ICOs and exchange trading resemble the activities in traditional equity markets, and thus many of the regulators impose regulations similar to those in the equity markets. For example, cryptocurrency companies in the U.S. are required to register with relevant government institutions (i.e., the Commodity Futures Trading Commission, Financial Crimes Enforcement Network, etc.). The Internal Revenue Service has imposed taxes on cryptocurrency transactions (Hughes, 2017). In countries including Canada and Thailand, the governments have announced that the securities laws apply to ICOs as well, where an exemption requires government consent (Blandin et al., 2019). For exchanges, countries including Germany and Japan have imposed licensing or inspection requirements on cryptocurrency exchanges, while Switzerland, South Korea, the United Kingdom, and many others have adopted Know Your Customer (KYC) guidelines, Combating the Financing of Terrorism (CFT), and anti-money laundering (AML) controls on cryptocurrency exchanges (Blandin et al., 2019).

Although different countries have carried out different measures to eliminate cryptocurrency-related crimes, to date, there is the absence of a regulatory policy that explicitly requires disclosure of the issuer information after an ICO takes place (Cvetkova, 2018; Regulation of Cryptocurrency Around the World, 2020). Issuers themselves decide on the contents of their social media posts, and there are no mandatory requirements for disclosure or remedial sanctions for fictitious disclosing. As a result, the contents of the Twitter accounts of cryptocurrency issuers might be less credible than the corporate disclosures in the stock markets.

[1] See Table 1 for a list of the cryptocurrencies.

[2] according to coinmarketcap.com

Table 1
Cryptocurrencies in the Sample.

	Currency Name	Twitter ID	Ticker
1	Ethereum	ethereum	ETH
2	Xrp	Ripple	XRP
3	Litecoin	litecoin	LTC
4	Binance Coin	binance	BNB
5	Tezos	tezos	XTZ
6	Cardano	Cardano	ADA
7	Ethereum Classic	etcnetherlands	ETC
8	Tron	Tronfoundation	TRX
9	Stellar	StellarOrg	XLM
10	Monero	monero	XMR
11	Dash	Dashpay	DASH
12	Chainlink	chainlink	LINK
13	IOTA	iotatoken	IOTA
14	NEO	NEO_Blockchain	NEO
15	Cosmos	cosmos	ATOM
16	Zcash	ZcashFoundation	ZEC
17	Ontology	OntologyNetwork	ONT
18	Basic Attention Token	AttentionToken	BAT
19	VeChain	vechainofficial	VET
20	Dogecoin	dogecoin_devs	DOGE
21	Qtum	qtum	QTUM
22	FTX Token	FTX_Official	FTT
23	ICON	helloiconworld	ICX
24	Paxos Standard	PaxosStandard	PAX
25	Ravencoin	Ravencoin	RVN
26	Lisk	LiskHQ	LSK
27	0X	0xProject	ZRX
28	Algorand	Algorand	ALGO
29	Omisego	omise_go	OMG
30	Nano	nano	NANO
31	Holo	holochain	HOT
32	Enjin Coin	enjin	ENJ
33	THETA	Theta_Network	THETA
34	Waves	wavesplatform	WAVES
35	Aion	aion_OAN	AION
36	Band Protocol	BandProtocol	BAND
37	Civic	civickey	CVC
38	Dent	dentcoin	DENT
39	EOS	black_one_	EOS
40	FunToken	FunFairTech	FUN
41	HyperCash	HcashOfficial	HC
42	IOST	IOStoken	IOST
43	Mainframe	Mainframe_HQ	MFT
44	NULS	Nuls	NULS
45	Stratis	stratisplatform	STRAT
46	TomoChain	TomoChainANN	TOMO
47	VITE	vitelabs	VITE

This table lists the names, Twitter ID, and the tickers of the cryptocurrencies in the sample.

	Centralized	Decentralized
Convertible	Fiat money, e-Gold	Cryptocurrencies
Non-convertible	In-game currencies, loyalty program rewards	No examples currently exist

Fig. 1. Taxonomy of currencies
Sources: Hughes and Middlebrook (2015) and Lee et al. (2017).

3. Literature review and hypotheses development

3.1. Sentiment analysis in equity markets

One of the crucial assumptions of the research question is that sentiments influence investor decisions. De Long et al. (1990) propose a model that incorporates market sentiments as expectations of asset returns that are not warranted by fundamentals. The model underlines the correlation between the sentiments of individual investors, which can cause stock prices to be higher (lower) than their fundamental value when the sentiments are optimistic (pessimistic). Empirical evidence from the equity markets shows the relevance of sentiments as well. Besides, previous studies on stock markets have confirmed the effects of investor sentiments on stock prices (Tetlock, 2007; Baker and Wurgler, 2006; Lee et al., 2002). Behavioral research, which focuses on the equity markets, has stressed that the emotions of investors and company executives that are distributed through social interactions play an important role in investment decision-making under uncertainty and risk (Nofsinger, 2005). In addition, Cornelli et al. (2006) report evidence of long-run return reversals for IPO stocks when small investors are over-optimistic before their date of issuance.

Additionally, sentiments embedded in many of the company disclosure documents can influence stock returns (Wales and Mousa, 2016; Sprenger et al., 2014; Loughran and McDonald, 2013). As investors recognize the sentiments in firm disclosure documents, investor sentiments change in parallel with the corporate sentiments, and investors react accordingly when making decisions. These works have demonstrated that sentiment in firm disclosures influences equity returns.

Past research has shown that real-time Twitter data can be used to predict the market movement of securities and other financial instruments. Specifically, previous studies have explored how aggregated sentiments towards a firm (sentiments of all the tweets that are related to a firm, but not necessarily tweets posted by the firm itself) on Twitter are associated with equity market returns. Bartov et al. (2018) analyze all tweets on publicly traded firms. They classify each tweet as positive (1), neutral (0), or negative (−1). The aggregate mood for a firm is measured by the average sentiment scores of all related tweets. Their findings show that the aggregate mood towards a firm before the quarterly earnings announcement is useful for predicting the announcement returns of equity.

Gu and Kurov (2020) use a similar approach. They measure the social media sentiment of an investor towards a firm with the Twitter sentiment data provided by Bloomberg. Their work concluded that the Twitter sentiments at the firm-level contain information that is useful for predicting the stock returns next day. Having more positive content on Twitter increases the return of a stock on the next day.

Sul et al. (2017) conduct a similar investigation and concluded that the sentiments in tweets about a specific firm from Twitter users with fewer followers have a significant impact on the stock's returns. However, note that there is no consensus in the stock market literature on the duration of the impact of social media sentiments. While Sul et al. (2017) conclude that the impact is still relevant after ten days, Sprenger et al. (2014) claim that price reaction in the stock markets to the sentiments in the tweets seems to be limited to within one day.

Other studies also examine the causal relationship between social media activities and stock trading volume. Joseph et al. (2011) investigate the relevance of investor sentiments in forecasting trading volume. Their work uses search intensity as a proxy for investor sentiments, as the search intensity would go up whenever the market sentiments become either more positive or more negative. The results in Joseph et al. (2011) imply that there is a positive association between search intensity (more positivity/negativity in the market) and abnormal trading volume.

Oliveira et al. (2017) investigate the impact of microblogging aggregated sentiment on stock trading volume. Using a machine learning approach, they find that adding a microblogging sentiment index as a factor of the machine learning model significantly increases the forecasting power of the model.

Lastly, Sprenger et al. (2014) show that an increased volume of tweets regarding a company is associated with higher stock trading volume. As mentioned in these studies, market sentiments and activities on Twitter can result in the abnormal trading volume of a stock.

3.2. Cryptocurrency return analysis

Similar to the findings in the stock markets, social media sentiments also influence cryptocurrency returns. A number of research papers have focused on the relationship between cryptocurrency returns and activities/sentiments on social media platforms. Benedetti and Kostovetsky (2021) examine how Twitter official account followers and their activities are related to cryptocurrency prices. They use the number of Twitter followers as a proxy of company users and Twitter intensity as a proxy of company announcements, where Twitter activity is defined as the average daily number of tweets. The results show that Twitter intensity is associated with higher cryptocurrency returns, but the previous-day Twitter intensity is negatively associated with the returns. Benedetti and Kostovetsky (2021) explain that the positive relationship between Twitter intensity and market returns is because that firms are more likely to announce good news on Twitter. Moreover, they conclude that the negative coefficient of the Twitter intensity on the previous day is an indication of the reversal of the overreaction to the tweeted information of the previous day.

Georgoula et al. (2015) analyze the Twitter sentiments of Bitcoin and Bitcoin returns. They study all the tweets with the hashtags "Bitcoin", "Bitcoins", and "BTC" and classify the sentiment of all of the tweets as positive, neutral, or negative. Their regression results further show that the ratio of tweeted sentiments with hashtags related to Bitcoin has a positive effect on Bitcoin prices. Georgoula et al. (2015) conclude that measurements of the collective mood on Twitter based on a sentiment analysis contribute to the prediction of short-run movements of the value of Bitcoins. Additionally, Li et al. (2019) focus on an alternative cryptocurrency called ZClassic. They classify tweets related to ZClassic as positive, negative, or neutral and train an Extreme Gradient Boosting Regression Tree Model.

The results indicate that Twitter sentiments can serve as a powerful signal for predicting the price movements of ZClassic. Meanwhile, Aharon et al. (2022) and Wu et al. (2021) find that major cryptocurrency returns are closely connected to uncertainty expressed on social media and economic policy uncertainty, respectively. Lastly, Li et al. (2021) find a preponderance of bi-directional Granger causality of cryptocurrency returns and investor attention, using Twitter as a proxy form of social media and Google as a proxy form of search-engine intensity, with the impact of Twitter being shorter term.

Other empirical works look into the sentiments on platforms other than Twitter. Gurdgiev et al. (2019) find that investor sentiment on 'Bitcointalk.org' successfully predicts the direction of the price of cryptocurrencies. Nasekin and Chen (2020) use recursive neural networks to construct a sentiment index for different cryptocurrencies on a microblogging platform called StockTwits. Their findings show that the sentiment index is informative on cryptocurrency returns.

In summary, studies on the stock markets explain how investor sentiment influences stock prices and emphasize the importance of Twitter sentiments to equity returns. Moreover, some of the works from the crypto field examine the relationship between social media sentiment on platforms other than Twitter and cryptocurrency returns. The work in both Benedetti and Kostovetsky (2021) and Georgoula et al. (2015) is closely related to our research question. Our research question would therefore add to Benedetti and Kostovetsky (2021) after conducting sentiment analysis on the Twitter content and expand on Georgoula et al. (2015) after analyzing non-Bitcoin cryptocurrencies.

3.3. *Equity markets: new information and return predictions*

Each new tweet posted by a cryptocurrency issuer carries new information, with the sentiments embedded in the Twitter announcements. To investors, words such as "amazing" and "wonderful" convey more positive sentiments, while those like "risky" and "adverse" are more pessimistic. Once the tweets are posted, investors may interpret these sentiments as the new signals for the recent performance of a cryptocurrency. The efficient market hypothesis (EMH) claims that stock returns cannot be predicted (Fama, 1970; Fama et al., 1969) because new information can be immediately factored into the stock prices as information becomes available. On a mass media outlet like Twitter, new information can reach a wider audience and aggregate more efficiently (Sprenger et al., 2014). The EMH states that new information travels quickly, and rational investors fully understand the implications of the new information and make investment decisions accordingly. As a result, when investors make mutual trades based on such decisions, stock prices move, and trading volume increases.

Currently, market efficiency in the cryptocurrency markets has been a subject of controversy. For instance, Urquhart (2016), Nadarajah and Chu (2017), and Tiwari et al. (2018) find that the Bitcoin markets are close to efficient. Caporale et al. (2018) point out cryptocurrency markets have a trend to become more efficient. In contrast, Cheah et al. (2018), and Jiang et al. (2018) report results against EMH in Bitcoin Markets. In a recent study, Kang et al. (2022) find that 54 (6.04%) of the total of 893 cryptocurrency units satisfied the weak-form EMH, and 24 (2.695%) met the semi-strong market hypothesis. Among the cryptocurrency exchanges that were established before November 2017, large-size exchanges were more likely to satisfy the weak- and semi-strong-form EMHs.

An alternative process that counters the assumption of the EMH is the gradual information flow (GIF) (Hong and Stein, 2007; Hong et al., 2000). The GIF classifies investors into two groups: ordinary investors and investors who receive value-relevant information before others. In the case of new tweets, some investors may check issuer tweets more often than others, and thus receive information earlier. Those who do so then change their valuation of the stock, while the valuation of the other investors might remain the same. The difference between the valuations of the two groups results in transactions between the two groups, and the prices of the stock subsequently move. In addition, if the GIF applies, whether the new Twitter sentiments are made public to everyone simultaneously or only offered to certain investors does not affect the magnitude of the price movement, but publicly available information spreads more quickly, and price adjustments would take place in a shorter time interval.

While examining the efficiency of the cryptocurrency and stock markets is beyond the scope of this paper, the publication of new information for both markets should affect the stock prices and trading volume as per the EMH and GIF. If the cryptocurrency markets follow a similar stock market process, Twitter sentiments posted on the official account of the issuers should result in price changes and surges in volume.

3.4. *Irrational decisions and sentiment contagion*

Not all investors in the cryptocurrency markets are perfectly rational and view the sentiments in tweets objectively as merely new information. The affective heuristic in the financial markets (Finucane et al., 2000) confirms that the decisions of investors are based not only on rationality but also on their personal feelings during the act of investing.

Sentiments in the tweets made by issuers not only function as a source of new information on the recent performance of the issuing firm, but also transmit the sentiments ingrained in the contents of the tweets to investors who see the tweets. Sentiments are therefore contagious (Schoenewolf, 1990), and there is a tendency to automatically synchronize and imitate emotional expressions, vocalizations, and movements, and converge emotionally (Hatfield et al., 1993). When individuals communicate over written text messages, message senders exchange their emotions with receivers (Risius et al., 2015). If a cryptocurrency issuer shows more positive sentiments like joy, confidence, and pride, the investors reading the tweets will synchronize their feeling positively with the cryptocurrency.

Sentiments affect decision-making (Lucey and Dowling, 2005; Nofsinger, 2005; Loewenstein, 2000; De Long et al., 1990). In the case where an issuer posts more positive words on Twitter, investors synchronize the positivity, and their sentiments toward the cryptocurrency become more positive. The demand for the cryptocurrency intensifies, and the price and returns subsequently change. On the other hand, when an issuer includes negative words in their tweets, investors may internalize the negativity and look for opportunities to unload their cryptocurrency, and then the returns and prices tend to decrease.

Based on the previous discussion on the effects of sentiments, we propose the two following hypotheses.

H1. : Sentiments in the tweets posted by a cryptocurrency issuer are positively associated with the return of the cryptocurrency.

H2. : More positive or more negative tweets posted by a cryptocurrency issuer (larger absolute value of the sentiment scores) increase the trading volume of the cryptocurrency.

4. Data and methodology

The data for this study includes 15,113 tweets posted on the official Twitter accounts of the 47 cryptocurrencies from March 1st, 2019, to February 29th, 2020 (see Tables 1 and 2 for details). These 47 Twitter accounts are the major news announcing platforms of these 47 cryptocurrencies and they come from twelve different countries. The tweets of the cryptocurrency issuers are scraped through the Twitter application programming interface (API). For each tweet, we use R to quantify the sentiments with the AFINN sentiment lexicon.[3] Note that we focus on the tweets posted by the issuers' official accounts only, not all the tweets with the currency name as a hashtag. This is because using all the tweets with a hashtag would be investigating investor sentiments, instead of issuer sentiments.

The data also includes the returns and volume of the coins throughout the year. The returns and volume are obtained from the API of Binance, a leading cryptocurrency exchange.

4.1. Measures of return and volume

This study aims to explore two dependent variables: abnormal cryptocurrency returns and abnormal changes in trading volume. We use the cumulative abnormal returns (*CAR*) of the cryptocurrencies as a measure for abnormal returns. Specifically, we look into the abnormal returns during three different 12-hour time intervals: the abnormal return during a 12-hour interval in which a tweet is created on the account of the issuer (AR_t), cumulative abnormal return within 24 h after posting of the tweet ($CAR2_t$), and cumulative abnormal return over the 36 h after posting of the tweet ($CAR3_t$). By comparing the effect of the Twitter sentiments over these 12-hour time intervals, it may be possible to observe the length of time before investors react to the sentiments on the Twitter account of the coin.

Additionally, in the calculation of the abnormal returns, the raw returns of each cryptocurrency in the sample are adjusted with the market returns in the same time interval. Since Bitcoin is the dominating coin in the cryptocurrency markets, taking over 40% of the total market capitalization,[4] its price trend could represent the price trend in the overall market. Thus, we use its Bitcoin return as a proxy variable for the return of the cryptocurrency market. The market-adjusted return of a cryptocurrency is calculated as the raw returns of the cryptocurrency minus the Bitcoin returns over the same time interval:

$$AR_{i,t} = R_{i,t} - R_{btc,t} \tag{1}$$

$$CAR2_{i,t} = AR_{i,t+1} + AR_{i,t} \tag{2}$$

$$CAR3_{i,t} = AR_{i,t+2} + AR_{i,t+1} + AR_{i,t} \tag{3}$$

where $R_{i,t}$ stands for the raw return of coin i in the 12-hour time interval t in which a new tweet is created on the account of the issuer. $R_{btc,t}$ is the concurrent raw return of Bitcoin in the same time interval as in the calculation of $R_{i,t}$.

For the trading volume, we focus on the raw abnormal volume ($RawABVOL_{i,t}$), and the adjusted abnormal volume ($ABVOL_{i,t}$). Following the methodology of Ahmed and Schneible (2007), we use the cumulative 36-hour trading volume after a Twitter announcement as a percentage of the circulating supply on the day of the announcement, less the median cumulative 36-hour trading volume (as a percentage of the circulating supply) of seven consecutive 36-hour periods prior to the announcement. Using adjusted abnormal volume instead of the raw volume addresses the fact that the predictive power of the Twitter sentiment of a coin could be driven by the size factor:

$$RawABVOL_{i,t} = \frac{CTV_t^{i,t+3}}{SPLY_{i,t}} - median\left(\frac{CTV_t^{i,t'+3}}{SPLY_{i,t'}}, \quad t' \in T'\right) \tag{4}$$

$$ABVOL_{i,t} = RawABVOL_{i,t} - RawABVOL_{btc,t} \tag{5}$$

where $T' = \{-3, -6, -9, -12, -15, -18, -21\}$. $CTV_t^{i,t+3}$ represents the cumulative 36-hour trading volume at time interval t of coin i, and $SPLY_{i,t}$ is the circulating supply of the coin at time t.

[3] We use R packages "rtweet" (Kearney, 2019) and "afinn" (Nielsen, 2011).

[4] According to coinmarketcap.com

Table 2
Number of cryptocurrencies in sample by headquarter countries.

Country	Number of Cryptocurrencies	Percent of Total
Australia	1	2.13
Canada	1	2.13
China	5	10.64
Germany	2	4.26
Hong Kong	1	2.13
Israel	1	2.13
Singapore	8	17.02
Sweden	1	2.13
Switzerland	5	10.64
Thailand	2	4.26
UK	3	6.38
USA	17	36.17
Total	47	100

This table presents the country distribution of the cryptocurrencies in the sample by issuer headquarter. The sample consists of 47 cryptocurrencies from 12 countries. Every cryptocurrency in the sample is issued by an entity that discloses information on Twitter.

4.2. Measure of sentiment

The independent variable of this study is the aggregate sentiment score of the tweets posted by an issuer in 12 h. To measure the sentiments on the issuers' Twitter accounts, we would conduct sentiment analysis on the tweets posted by the issuers. In this paper, we adopt a lexical approach for the sentiment analysis using the AFINN sentiment lexicon. The AFINN lexicon, designed for microblogs analysis, is a list of words that are scored for the sentiments. The AFINN lexicon contains 4095 unique words, and each word has a score between -5 (negative) and $+5$ (positive) (Nielsen, 2011). Words with an AFINN score of 0 are neutral words with no emotional implications. The sentiment analysis algorithm matches the words scraped from Twitter with words in the AFINN lexicon. The algorithm subsequently produces a total score for each tweet that equals to the sum of the scores of all the words being matched in the tweet. The total score (*AFINN*) represents the overall sentiment contained in all tweets that the issuer has posted in a 12-hour interval.

4.3. Research design

The regression specification is:

$$R_{i,t} = \beta_0 + \beta_1 AFINN_{i,t} + \gamma CV_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t} \quad (6)$$

where $R_{i,t}$ represents the three return dependent variables ($AR_{i,t}$, $CAR2_{i,t}$, $CAR3_{i,t}$), α_i represents coin fixed effects, and λ_t represents the date effects. Control variables include the natural logarithm of the market capitalization of each coin in each time interval ($lnMarketCap_{i,t}$), the cumulative 36 h returns in the interval prior to time t ($Car3lag_{i,t}$), the volatility of the dependent variables in the 7 days prior to time t measured by the standard deviation ($CAR3sd_{i,t}$), and a binary variable denoting whether the coin is mineable ($Mineable_i$). See Table 3 for the descriptive statistics and Table 4 for the correlation matrix.

For volume, the independent variable of interest shifts to $absAfinn_{i,t}$, the absolute value of the total AFINN sentiment score in the 12-hour interval. Since H2 states that the effect of being more positive or more negative on trading volume is symmetric, we use the absolute value of the sentiment score in the regressions.

$$V_{i,t} = \beta_0 + \beta_1 absAFINN_{i,t} + \gamma CV_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t} \quad (7)$$

Table 3
Descriptive statistics.

Variable	N	Mean	S.D.	P25	P75
AR	6255	-0.0011	0.0847	-0.0005	0.0005
CAR2	6255	-0.0012	0.1216	-0.0008	0.0007
CAR3	6255	-0.0028	0.1728	-0.0010	0.0011
ABVOL	6255	0.0040	0.0197	-0.0053	0.0090
RawABVOL	6255	0.0045	0.0202	-0.0055	0.0101
AFINN	6255	2.8161	4.0404	0.0000	5.0000
avgAFINN	6255	4.0093	3.5639	1.8000	5.2857
IncAFINN	6255	-1.1932	4.4539	-3.3571	1.1429
lnMarketCap	6255	19.7395	1.7707	18.5743	20.6985
Mineable	6255	0.3464	0.4759	0.0000	1.0000

This table presents the descriptive statistics of the sample. The sample is at the event (tweet) level and contains 6, 255 observations with the full set of necessary data. All of the variable definitions are in Appendix A.

Table 4
Correlation Matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) AR	1.000									
(2) CAR2	0.573	1.000								
(3) CAR3	0.387	0.833	1.000							
(4) ABVOL	0.002	0.013	0.014	1.000						
(5) RawABVOL	0.001	0.012	0.013	1.000	1.000					
(6) AFINN	0.025	0.026	0.011	0.019	0.019	1.000				
(7) avgAFINN	0.024	0.012	-0.009	0.017	0.017	0.319	1.000			
(8) IncAFINN	0.004	0.014	0.017	0.004	0.004	0.652	-0.511	1.000		
(9)lnMarketCap	0.016	0.011	0.008	-0.018	-0.019	0.018	0.014	0.005	1.000	
(10) Mineable	0.014	0.001	-0.006	0.022	0.022	0.009	0.044	-0.027	-0.056	1.000

This table presents the correlation between the variables in the main test. All of the variable definitions are in Appendix A.

where $V_{i,t}$ represents the two dependent variables of volume ($RawABVOL_{i,t}$ or $ABVOL_{i,t}$), and $absAFINN_{i,t}$ is the absolute value of $AFINN_{i,t}$. The regression model for volume also includes both the coin fixed effects and date effects. The control variables include the market capitalization of each coin in each time interval ($lnMarketCap_{i,t}$), the absolute value of cumulative return in the past 36 h ($absCAR3_{i,t}$), volatility of the cumulative 36-hour return of cryptocurrency in the past 7 days, volatility of the dependent variables in the past 7 days measured by using the standard deviation ($RawABVOLsd_{i,t}$ or $ABVOLsd_{i,t}$), and a binary variable that indicates whether the coin is mineable ($Mineable_i$).

5. Empirical results

5.1. Returns

Table 5 shows the regression results for the effects of Twitter sentiments of the coin issuer on cryptocurrency returns. The coefficient on the AFINN sentiment score is significant for both the 12-hour abnormal and 24-hour cumulative returns, but not for the 36-hour abnormal return. Since the first 36-hour abnormal return is insignificant, it is likely that the markets immediately react to the contents of the tweets, and the price adjustments take place within a very short window of fewer than 36 h.

The results are consistent with H1 that, if the official Twitter account of a coin posts more positive words, it will raise the return of

Table 5
Issuer sentiment and return.

	(1) $AR_{i,t}$	(2) $CAR2_{i,t}$	(3) $CAR3_{i,t}$
$AFINN_{i,t}$	0.0005**	0.0008**	0.0005
	(2.11)	(2.23)	(1.19)
$lnMarketCap_{i,t}$	-0.0019	-0.0024	0.0051
	(−0.53)	(−0.41)	(0.52)
$CAR3lag_{i,t}$	0.2100***	0.1840***	0.1780***
	(15.10)	(14.83)	(12.20)
$CAR3sd_{i,t}$	-0.0198	-0.0186	-0.0393**
	(−1.66)	(−1.52)	(−2.14)
$Mineable_i$	0.0127	0.0063	-0.0108
	(1.67)	(0.51)	(−0.53)
$Date_{i,t}$	0.0001	0.0002	-0.0002
	(0.13)	(0.14)	(−0.14)
Constant	0.0313	0.0388	-0.0934
	(0.47)	(0.36)	(−0.51)
Coin FE	Included	Included	Included
Clustered by Coin	Yes	Yes	Yes
N	6255	5941	5806
R-squared(%)	33.47	12.21	6.13

This table presents the influence of issuer sentiment on the return of cryptocurrency. The test model is $R_{i,t} = \beta_0 + \beta_1 AFINN_{i,t} + \gamma CV_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t}$. $R_{i,t}$ represents the three return measure $AR_{i,t}$, $CAR2_{i,t}$, and $CAR3_{i,t}$. $AR_{i,t}$ is the return of currency *i* during the 12-hour interval in which a tweet is created on the official Twitter account of the currency, adjusted with Bitcoin returns during the same interval. $CAR2_{i,t}$ is the cumulative abnormal return of currency *i* within 24 h after posting of the tweet. $CAR3_{i,t}$ is the cumulative abnormal return over the 36 h of currency *i* after posting of the tweet. $AFINN_{i,t}$ is defined as the sentiment score for all tweets that issuer *i* has posted in a 12-hour interval. $CV_{i,t}$ includes a set of control variables whose definitions are in Appendix A. The coefficient of $Date_{i,t}$ is multiplied by 100. The numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

the coin (relative to that of Bitcoin). This further implies that even though the markets are highly unregulated, the investors in general still take sentiments of the issuer as credible information and react accordingly.

Additionally, it is worth noting that the cumulative 36-hour return prior to time interval t has a significantly positive effect on the measures of the returns. If a cryptocurrency experiences a price surge in the past 36 h, it is more likely that its return in the current 12-hour period and cumulative return in the future 24-hour time window will be higher, if all else are kept constant. The R^2 is 33.47% in Column (1) of Table 5, which indicates that the model in this study explains for a large amount of the cryptocurrency returns in the 12-hour window after a Twitter posting.

5.2. Volume

The regression results for volume are listed in Table 6. The absolute value of the AFINN sentiment score is positively associated with both the raw abnormal trading volume, and the abnormal trading volume after adjusting for that of Bitcoin. This implies that when the issuers more openly show their sentiments, whether positive or negative, the trading volume subsequently experiences an increase. For a one-unit increase in the sentiment score, the abnormal volume after adjusting for the volume of Bitcoin is expected to go up by 0.00126 points. The coefficients of the absolute value of the sentiment scores, therefore, show consistency with H2.

Among the control variables, as shown in Table 6, the size of the cryptocurrency, measured by the natural logarithm of the market capitalization, has a positive effect on the two measures of the abnormal trading volume. This means that being a "Big Coin" in the cryptocurrency market is indeed associated with a higher volume of unusual transactions. The absolute value and the volatility of the cumulative return in the past 36 h, and the volatility of the abnormal volume measurements in the past seven days are positively significant, again indicating that the recent performance of the cryptocurrency plays an important role. Besides, mineable cryptocurrencies tend to have a higher abnormal trading volume. Finally, with the positive coefficients for the date effects, the abnormal trading volume of the cryptocurrencies observes an upward time trend throughout the year.

5.3. Supplementary Test 1: incremental sentiment score

It is possible that some of the issuers post more positively on Twitter than their counterparts out of habit. The sentiments of an issuer can be decomposed into two different parts: the average past level of sentiment and the incremental change in sentiment. To increase

Table 6
Issuer sentiment and volume.

	(1) $RawABVOL_{i,t}$	(2) $ABVOL_{i,t}$
$absAFINN_{i,t}$	0.0001*	0.0001*
	(1.77)	(1.84)
$lnMarketCap_{i,t}$	0.0038*	0.0042*
	(1.85)	(2.09)
$absCAR3_{i,t}$	0.0095***	0.0086***
	(6.45)	(6.17)
$CAR3sd_{i,t}$	0.0101***	0.0089***
	(3.57)	(3.33)
$RawABVOLsd_{i,t}$	0.0715***	
	(2.72)	
$ABVOLsd_{i,t}$		0.0727***
		(2.75)
$Mineable_i$	-0.0085*	-0.0096**
	(−1.90)	(−2.16)
$Date_{i,t}$	0.0035***	0.0035***
	(5.71)	(5.82)
Constant	-0.0809**	-0.0895**
	(−2.06)	(−2.29)
Coin FE	Included	Included
Clustered by Coin	Yes	Yes
N	5757	5757
R-squared(%)	10.09	9.96

This table presents the influence of issuer sentiment on the trading volume of cryptocurrency. The test model is $V_{i,t} = \beta_0 + \beta_1 absAFINN_{i,t} + \gamma CV_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t}$. $V_{i,t}$ represents the two volume metrics $RawABVOL_{i,t}$ and $ABVOL_{i,t}$. $RawABVOL_{i,t}$ is the raw abnormal volume of currency *i* after posting of the tweet. $ABVOL_{i,t}$ equals the abnormal volume of currency *i* adjusted with abnormal volume of Bitcoin during the same period of time. $absAFINN_{i,t}$ is defined as the absolute value of the sentiment score for all tweets that issuer *i* has posted in a 12-hour interval. $CV_{i,t}$ includes a set of control variables whose definitions are in Appendix A. The coefficient of $Date_{i,t}$ is multiplied by 100. The numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

the robustness of the regression results and take the past levels of the positivity of the issuer on Twitter into account, we conduct a supplementary test to determine the incremental changes in the AFINN sentiment score of an issuer ($IncAFINN_{i,t}$). The incremental changes in the sentiment score for cryptocurrency i at time t is defined as the difference between the total sentiment score of i at t ($AFINN_{i,t}$) and the average sentiment score of the issuer of cryptocurrency i in the past 7 days ($avgAFINN_{i,t}$). The supplementary test would have the same control variables as those in Eq. (6):

$$IncAFINN_{i,t} = AFINN_{i,t} - avgAFINN_{i,t} \tag{8}$$

As for the regressions for the raw and adjusted abnormal volume, the absolute value of the increments of the AFINN sentiment score of an issuer is calculated as the difference between the absolute value of the current AFINN score ($AFINN_{i,t}$) and the average AFINN score in the past 7 days ($avgAFINN_{i,t}$). The control variables for the regression for the abnormal volume in Eq. (7) are also included.

$$absIncAFINN_{i,t} = |AFINN_{i,t}| - |avgAFINN_{i,t}| \tag{9}$$

Table 7 shows the regression results for the impacts of the incremental change in issuer sentiments on returns. The increments of the AFINN sentiment score of an issuer have a significantly positive relationship with the three abnormal return measures. A positive incremental change in the sentiments shown on Twitter is associated with a higher abnormal return in the current 12-hour window. Investor reaction is less impactful when focusing on the sentiment score level of Twitter sentiments rather than the incremental sentimental change of the tweets, as the former do not show a significant impact on the 24-hour cumulative return, as seen in Table 7. The results for the effects of the incremental change in sentiments towards Twitter postings on the raw and adjusted abnormal volume of a cryptocurrency is shown in Table 8. The incremental change in the absolute value of the AFINN sentiment score of an issuer has a positive impact on both the raw and adjusted abnormal volume. Furthermore, the magnitude of these effects is greater than that of the impacts of the level of the AFINN sentiment score on abnormal volume in Table 6.

In addition, the average past sentiment score ($avgAFINN_{i,t}$), as shown in Tables 7 and 8, does not have a significant impact on the measures of the abnormal returns and the abnormal trading volume. Since the sentiment scores ($AFINN_{i,t}$) can be decomposed into the average past sentiment score ($avgAFINN_{i,t}$) and the incremental change ($IncAFINN_{i,t}$), it is very likely that the effects of the sentiment level of the Twitter postings of the issuer on returns and volume predominantly come from the incremental change in the level of sentiment, and not the average past sentiment score.

Table 7
Effects of incremental sentiment on return.

	(1) $AR_{i,t}$	(2) $CAR2_{i,t}$	(3) $CAR3_{i,t}$
$avgAFINN_{i,t}$	0.0009**	0.0010	0.0009
	(2.51)	(1.29)	(0.76)
$IncAFINN_{i,t}$	0.0005**	0.0010***	0.0009*
	(2.26)	(2.98)	(1.98)
$lnMarketCap_{i,t}$	-0.0024	-0.0016	0.0062
	(−0.70)	(−0.28)	(0.58)
$CAR3lag_{i,t}$	0.2100***	0.1870***	0.1830***
	(14.42)	(14.58)	(12.12)
$CAR3sd_{i,t}$	-0.0194	-0.0142	-0.0354
	(−1.61)	(−1.11)	(−1.80)
$Mineable_i$	0.0193**	0.0145	-0.0133
	(2.60)	(1.17)	(−0.60)
$Date_{i,t}$	-0.0003	0.0002	0.0005
	(−0.33)	(0.13)	(0.27)
Constant	0.0340	0.0148	-0.1190
	(0.53)	(0.14)	(−0.59)
Coin FE	Included	Included	Included
Clustered by Coin	Yes	Yes	Yes
N	6022	5710	5585
R-squared(%)	33.97	12.71	6.48

This table presents the influence of an incremental change of sentiment on the return of cryptocurrency. The test model is $R_{i,t} = \beta_0 + \beta_1 avgAFINN_{i,t} + \beta_2 IncAFINN_{i,t} + \gamma CV_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t}$. $R_{i,t}$ represents the three return measures $AR_{i,t}$, $CAR2_{i,t}$, and $CAR3_{i,t}$. $AR_{i,t}$ is the return of currency i during the 12-hour interval in which a tweet is created on the official Twitter account of the currency, adjusted with Bitcoin returns during the same interval. $CAR2_{i,t}$ is the cumulative abnormal return of currency i within 24 h after posting of the tweet. $CAR3_{i,t}$ is the cumulative abnormal return over the 36 h of currency i after posting of the tweet. $avgAFINN_{i,t}$ is defined as the average sentiment score for all tweets that issuer i has posted in the past 7 days prior to time interval t. $IncAFINN_{i,t}$ is the incremental change in the sentiment score of issuer i in time interval t relative to the average sentiment scores in the past 7 days. $CV_{i,t}$ includes a set of control variables whose definitions are in Appendix A. The coefficient of $Date_{i,t}$ is multiplied by 100. The numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Effects of incremental sentiment on volume.

	(1) $RawABVOL_{i,t}$	(2) $ABVOL_{i,t}$
$absAFINN_{i,t}$	0.0039	0.0049
	(0.21)	(0.26)
$absIncAFINN_{i,t}$	0.0002**	0.0002**
	(2.18)	(2.25)
$lnMarketCap_{i,t}$	0.0039*	0.0044**
	(1.88)	(2.11)
$absCAR3_{i,t}$	0.0095***	0.0086***
	(6.45)	(6.17)
$CAR3sd_{i,t}$	0.0101***	0.0089***
	(3.54)	(3.30)
$RawABVOLsd_{i,t}$	0.0716**	
	(2.69)	
$ABVOLsd_{i,t}$		0.0728***
		(2.72)
$Mineable_i$	-0.0091*	-0.0101**
	(−1.94)	(−2.18)
$Date_{i,t}$	0.0036***	0.0036***
	(5.70)	(5.80)
Constant	-0.0829**	-0.0914**
	(−2.09)	(−2.31)
Coin FE	Included	Included
Clustered by Coin	Yes	Yes
N	5757	5757
R-squared(%)	10.12	9.99

This table presents the influence of an incremental change of sentiment on the trading volume of cryptocurrency. The test model is $V_{i,t} = \beta_0 + \beta_1 absAFINN_{i,t} + \beta_2 absIncAFINN_{i,t} + \gamma CV_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t}$.$V_{i,t}$ represents the two volume metrics $RawABVOL_{i,t}$ and $ABVOL_{i,t}$. $RawABVOL_{i,t}$ is the raw abnormal volume of currency *i* after posting of the tweet. $ABVOL_{i,t}$ equals the abnormal volume of currency *i* adjusted with abnormal volume of Bitcoin during the same period of time. $absAFINN_{i,t}$ is defined as the absolute value of the sentiment score for all tweets that issuer *i* has posted in a 12-hour interval. $absIncAFINN_{i,t}$ is the absolute incremental change in sentiment score of issuer *i* in time interval *t* relative to the average sentiment scores in the past 7 days. $CV_{i,t}$ includes a set of control variables whose definitions are in Appendix A. The coefficients of $absAFINN_{i,t}$ and $Date_{i,t}$ are multiplied by 100. The numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5.4. Supplementary Test 2: volume-price divergence

To further examine whether the impact of the Twitter sentiments of a cryptocurrency issuer differs for coins with small/large market capitalization, we categorize the coins into two groups. One of the groups contains all of the coins with an average market capitalization that is smaller than the median of the sample, while the other group contains all of the coins with an average market capitalization that is larger than the median. By running regressions separately on each group with the models for returns and volume (specified in Eqs. (6) and (7)), the significance of the Twitter sentiments does not converge for small and large coins. When running the regression for returns as shown in Table 9, the effects of the AFINN sentiment score of the issuer is significant for large firms. Meanwhile, the effects of the absolute value of the sentiment score are significant for small coins, as shown in Table 10.

6. Conclusion

The goal of this study is to analyze the explanatory power of sentiments expressed on the official Twitter accounts of cryptocurrency issuers for abnormal returns and abnormal trading volume. Specifically, we use a lexical approach to quantify the Twitter sentiments of the issuer, in which positive words are rated to positive scores and words that imply negative sentiments are assigned negative scores. By analyzing the abnormal cryptocurrency returns and volume in different time intervals, this study provides two key findings: (1) the issuer sentiments on Twitter are positively associated with returns within the following 24 h, and (2) the absolute value of the Twitter sentiments of the issuer is positively associated with the abnormal trading volume of the cryptocurrency. Besides, we decompose the issuer sentiment score into two components: the average sentiment score in the past seven days and the incremental change in the sentiment score. The results show that the impacts of tweets sentiments on the return and trading volume are largely driven by the incremental change in sentiments.

Table 9
Effects of sentiment on return by market capitalization size of coin.

. Dependent variable	(1) $AR_{i,t}$	(2)	(3) $CAR2_{i,t}$	(4)	(5) $CAR3_{i,t}$	(6)
	Coin Market Capitalization					
	small	large	small	large	small	large
$AFINN_{i,t}$	0.0003	0.0007**	0.0005	0.0011**	-0.0001	0.0011
	(0.84)	(2.27)	(0.81)	(2.14)	(−0.16)	(1.40)
$lnMarketCap_{i,t}$	-0.0004	-0.0024	-0.0050	0.0042	-0.0033	0.0130
	(−0.08)	(−0.46)	(−0.55)	(0.48)	(−0.24)	(0.99)
$CAR3lag_{i,t}$	0.1800***	0.2460***	0.1570***	0.2190***	0.153***	0.2110***
	(35.01)	(44.26)	(17.36)	(22.35)	(11.51)	(14.28)
$CAR3sd_{i,t}$	-0.0099	-0.0383***	-0.0008	-0.0491***	-0.0174	-0.0766***
	(−1.39)	(−4.84)	(−0.06)	(−3.33)	(−0.89)	(−3.34)
$Mineable_i$	-0.0012	-0.0059	0.0162	-0.0062	0.0209	0.0027
	(−0.17)	(−0.73)	(1.40)	(−0.45)	(1.20)	(0.13)
$Date_{i,t}$	0.0010	-0.0004	-0.0006	0.0018	0.0006	0.0002
	(0.60)	(−0.28)	(−0.21)	(0.74)	(0.13)	(0.05)
Constant	0.0002	0.0638	0.0866	-0.0870	0.0614	-0.2690
	(0.00)	(0.60)	(0.50)	(−0.48)	(0.24)	(−0.98)
Coin FE	Included	Included	Included	Included	Included	Included
Clustered by Coin	Yes	Yes	Yes	Yes	Yes	Yes
N	3121	3134	2941	3000	2876	2930
R-squared(%)	29	39.2	10	15.2	5.39	7.49

This table presents the subsample results of the influence of issuer sentiment on the return of cryptocurrency. The sample is divided into small and large subsamples by the median market capitalization of coin. $AR_{i,t}$ is the return of currency i during the 12-hour interval in which a tweet is created on the official Twitter account of the currency, adjusted with Bitcoin returns during the same interval. $CAR2_{i,t}$ is the cumulative abnormal return of currency i within 24 h after posting of the tweet. $CAR3_{i,t}$ is the cumulative abnormal return over the 36 h of currency i after posting of the tweet. $AFINN_{i,t}$ is defined as the sentiment score for all tweets that issuer i has posted in a 12-hour interval. All variable definitions are in Appendix A. The coefficient of $Date_{i,t}$ is multiplied by 100. The numbers in parentheses are t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

CRediT authorship contribution statement

Jiahang Zhang: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Chi Zhang**: Formal analysis, Writing – review & editing.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this study and there has been no significant financial support for this work that could have influenced its outcome. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

Appendix A. Definitions of variable

Category	Variable	Definition
Return	*AR*	Return of currency i during the 12-hour interval in which a tweet is created on the official Twitter account of the currency, adjusted with Bitcoin returns during the same interval. $AR_{i,t} = R_{i,t} - R_{btc,t}$.
Return	*CAR2*	Cumulative abnormal return of currency i within 24 h after posting of the tweet. $CAR2_{i,t} = AR_{i,t+1} + AR_{i,t}$.
Return	*CAR3*	Cumulative abnormal return over the 36 h of currency i after posting of the tweet. $CAR3_{i,t} = AR_{i,t+2} + AR_{i,t+1} + AR_{i,t}$.
Volume	*RawABVOL*	Raw abnormal volume of currency i after posting of the tweet. Calculation method originally proposed inAhmed and Schneible (2007). $RawABVOL_{i,t} = \frac{CTV_t^{i,t+3}}{SPLY_{i,t}} - median(\frac{CTV_t^{i,t'+3}}{SPLY_{i,t'}}, t' \in T')$ where $T' = \{-3, -6, -9, -12, -15, -18, -21\}$. $CTV_t^{i,t+3}$ represents the cumulative 36-hour trading volume at time interval t of coin i, and $SPLY_{i,t}$ is the circulating supply of the coin at time t.
Volume	*ABVOL*	Abnormal volume of currency i adjusted with abnormal volume of Bitcoin during the same period of time. $ABVOL_{i,t} = RawABVOL_{i,t} - RawABVOL_{btc,t}$.

(continued on next page)

Table 10
Effects of Sentiment on Volume by Market Capitalization Size of Coin.

. Dependent variable	(1) $RawABVOL_{i,t}$	(2)	(3) $ABVOL_{i,t}$	(4)
	Coin Market Capitalization small	large	small	large
$absAFINN_{i,t}$	0.0003 * *	0.0001	0.0003 * *	0.0001
	(2.34)	(0.59)	(2.34)	(0.72)
$absIncAFINN_{i,t}$	0.0063 * **	0.0019	0.0070 * **	0.0023 *
	(3.73)	(1.35)	(4.24)	(1.66)
$absCAR3_{i,t}$	1.014 * **	0.983 * **	0.907 * **	0.914 * **
	(6.53)	(5.94)	(5.94)	(5.69)
$CAR3sd_{i,t}$	0.0028	0.0182 * **	0.0020	0.0167 * **
	(1.22)	(8.03)	(0.86)	(7.59)
$RawABVOLsd_{i,t}$	0.0706 * **	0.0804 * **		
	(7.81)	(4.59)		
$ABVOLsd_{i,t}$			0.0719 * **	0.0808 * **
			(8.09)	(4.75)
$Mineable_{i}$	0.0027	0.0008	0.0029	0.0003
	(1.28)	(0.40)	(1.40)	(0.14)
$Date_{i,t}$	0.0045 * **	0.0032 * **	0.0044 * **	0.0032 * **
	(7.99)	(7.54)	(8.03)	(7.79)
Constant	-0.1290 * **	-0.0516 *	-0.1430 * **	-0.0591 * *
	(−4.01)	(−1.73)	(−4.51)	(−2.04)
Coin FE	Included	Included	Included	Included
Clustered by Coin	Yes	Yes	Yes	Yes
N	2877	2880	2877	2880
R-squared(%)	11.5	11.5	11.4	11.2

This table presents the subsample results of the influence of issuer sentiment on the trading volume of cryptocurrency. The sample is divided into small and large subsamples by the median market capitalization of coin. $RawABVOL_{i,t}$ and $ABVOL_{i,t}$. $RawABVOL_{i,t}$ is the raw abnormal volume of currency *i* after posting of the tweet. $ABVOL_{i,t}$ equals the abnormal volume of currency *i* adjusted with abnormal volume of Bitcoin during the same period of time. *absAFINN* is defined as the absolute value of the sentiment score for all tweets that issuer *i* has posted in a 12-hour interval. $absIncAFINN_{i,t}$ is the absolute incremental change in sentiment score of issuer *i* in time interval *t* relative to the average sentiment scores in the past 7 days. All variable definitions are in Appendix A. The coefficient of $Date_{i,t}$ is multiplied by 100. The numbers in parentheses are t-statistics. * , * *, and * ** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(*continued*)

Category	Variable	Definition
Sentiment	*AFINN*	Sentiment score for all tweets that issuer *i* has posted in a 12-hour interval.
Sentiment	*absAFINN*	The absolute value of the sentiment score for all tweets that issuer *i* has posted in a 12-hour interval.
Sentiment	*avgAFINN*	Average sentiment score for all tweets that issuer *i* has posted in the past 7 days prior to time interval *t*.
Sentiment	*IncAFINN*	The incremental change in the sentiment score of issuer *i* in time interval *t* relative to the average sentiment scores in the past 7 days. $IncAFINN_{i,t} = AFINN_{i,t} - avgAFINN_{i,t}$.
Sentiment	*absIncAFINN*	The absolute incremental change in sentiment score of issuer *i* in time interval *t* relative to the average sentiment scores in the past 7 days. $absIncAFINN_{i,t} = \|AFINN_{i,t\|} - \|avgAFINN_{i,t}\|$.
Control	*lnMarketCap*	The natural logarithm of the average market capitalization of cryptocurrency *i* in time interval *t*.
Control	*CAR3lag*	The cumulative 36-hour return of cryptocurrency *i* in time interval $t-1$.
Control	*RawABVOLsd*	Volatility of the raw abnormal volume of cryptocurrency *i* in the 7 days prior to time *t*.
Control	*ABVOLsd*	Volatility of the abnormal volume of currency *i* adjusted with abnormal volume of Bitcoin during the same period of time in the 7 days prior to time *t*.
Control	*CAR3sd*	Volatility of the cumulative 36-hour return of cryptocurrency *i* in the 7 days prior to time *t*.
Control	*Mineable*	A binary variable that represents whether cryptocurrency *i*is mineable.
Time FE	*Date*	An integral that represents the date on which a tweet posted by cryptocurrency *i* is created. Since the data covers a year, $Date_{i,t}$ ranges from 1 to 366.

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