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On the predictive power of tweet sentiments and attention on bitcoin

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ABSTRACT

This paper investigates the predictive power of information contained in social media tweets on bitcoin market dynamics. Using Valence Aware Dictionary for Sentiment Reasoning (VADER), we extract useful information from tweets and construct two factors – *sentiment dispersion* (SD) and *investor attention* (IA) – to test their predictive power. We show that investors face greater return volatility for rising sentiment dispersion associated with more significant market uncertainty. Further, IA is found to predict bitcoin trading volume but not returns and volatility. Finally, we design an IA-induced trading strategy that yields superior performance to the passive buy-and-hold strategy in 2018. However, it does not deliver superior performance in other years during the sample period suggesting that investor attention alone as a trading parameter does not produce superior performance over the long term.

1. Introduction

Cryptocurrencies have drawn significant interest from investors, companies and governments. Of the many cryptocurrencies in the market, bitcoin has emerged as a new asset class, which is evident given its acceptance as a form of payment by more than 19,000 physical retailers worldwide[1] as well as its future contracts are traded on the Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE). Given bitcoin's recognition as a new asset class, the pricing of bitcoin has become a paramount research issue among academic researchers and industry practitioners, notably since it lacks intrinsic value (Baur et al., 2018). Traditional finance theories on rational pricing models, such as discounted cash flow model, purchasing power parity and covered interest rate parity, do not provide any predictions and valuable insights into the pricing of bitcoin (Kristoufek, 2013). Kristoufek (2013) argues that there are no fundamentals that govern bitcoin to the extent that it is difficult to yield its "fair" pricing. Instead, its price is driven by investors' belief in its growth potential. Accordingly, investor sentiment plays a crucial role and is expected to drive bitcoin prices.

Baker and Wurgler (2006) argue that investor sentiment, a behavioural factor that the rational pricing models ignore, can significantly impact securities whose valuation is highly subjective. They find that varying sentiment can drive security price away from its equilibrium value, causing mispricing. The findings of Baker and Wurgler (2006) carry significant implications for bitcoin, as existing rational finance theories fail to estimate its fair value, and its valuation is highly subjective. Scant evidence has been reported in the cryptocurrency literature regarding the pricing issues of bitcoin associated with investor sentiment and attention. For example,

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[1] Source: Coinmap.org.

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Kraaijeveld and De Smedt (2020) argue that investor sentiment in the cryptocurrency market is driven by social media news since traditional media lacks coverage on this new market. Utilising the tweet-based investor sentiment variable, they find that tweet sentiment predicts bitcoin return. However, their tweet-based investor sentiment variable aggregated sentiment of both optimistic and pessimistic investors and neglected to consider sentiment dispersion within the investor group. In traditional financial markets, it is well established that sentiment dispersion which proxies for uncertainty in the market is positively correlated with risk premium (Anderson et al., 2009; Liu et al., 2005; Maenhout, 2004; Xiong et al., 2020). The rationale is that investors demand a higher risk premium for an asset if there are higher uncertainties about the possible returns of the asset (Anderson et al., 2009). Yet little is known about the importance of uncertainty, proxied by investor sentiment dispersion, in predicting bitcoin returns volatility.

This study pursues this line of inquiry to examine the predictive power of investors' sentiment dispersion on bitcoin returns volatility. Utilising a lexicon-based sentiment analysis method known as the Valence Aware Dictionary and Sentiment Reasoner (VADER), we propose and construct a novel investor sentiment dispersion measure for bitcoin using relevant information extracted from a comprehensive Twitter data set. In contrast to Kraaijeveld and De Smedt (2020), our measure focuses on sentiment dispersion, a proxy for bitcoin market uncertainty, rather than aggregate sentiment. This study contributes to the literature by exploring the relationship between investor sentiment dispersion and bitcoin returns volatility. As greater uncertainty is reflected in the wider dispersion of sentiments, our Hypothesis predicts a positive relationship between investor sentiment dispersion and the riskiness of bitcoin returns.

This study further contributes to the literature by proposing a refined measure of investor attention for bitcoin. Shen et al. (2019) measure investor attention in the bitcoin market using the number of tweets. They find that investor attention predicts bitcoin trading volume and volatility, but it lacks predictive power over bitcoin return. It is well known that raw Twitter data contain a lot of noise, so we argue that the number of tweets calculated using tweets downloaded directly from Twitter (described as raw Twitter data) does not accurately reflect investor attention. Hence, the noisy signals in tweets must be removed from the tweet sample to eliminate any potential bias in the investor attention measure. To improve the quality of the existing bitcoin investor attention factor proposed by Shen et al. (2019), we identify and remove the noisy signals, such as URLs, emojis and hashtags, and the tweets containing nil information about bitcoin from the raw Twitter data. Following Shen et al. (2019), we then estimate a refined investor attention index and revisit the predictive power of investor attention on bitcoin return, volatility and trading volume.

Our first set of empirical results on the sentiment dispersion shows a significant positive relationship between the conditional volatility of bitcoin returns and sentiment dispersion. This finding indicates that bitcoin investors face greater risk when exposed to higher uncertainty levels. The second set of empirical results based on the refined investor attention measure shows some interesting findings. In contrast to Shen et al. (2019) findings that investor attention predicts realised volatility and trading volume, our results indicate that the refined investor attention measure has only significant predictive power on bitcoin trading volume. This finding suggests that the predictive power of investor attention on bitcoin volatility could be driven by the noisy signals in the tweets as the predictive power vanishes once the noisy signals are removed. Furthermore, we exploit the information content of the investor attention measure by examining an investor attention-induced trading strategy. The trading strategy results show that the investor attention-based trading strategies outperform the passive strategy in 2018. Still, the investor attention-induced trading strategy underperforms the passive strategy over the whole sample period. The practical implication is that using investor attention alone as a trading parameter does not produce superior performance over the long term.

The remainder of this paper is organised as follows. Section 2 reviews the relevant studies; Section 3 describes the data and research method; Section 4 discusses the empirical results; Section 5 concludes this study.

2. Literature review

2.1. Research on cryptocurrencies

The literature concerning cryptocurrencies is considerably diverse, focusing on various aspects of the cryptocurrency markets. Starting from the definition of cryptocurrencies, Yermack (2015) determines whether bitcoin is a medium of exchange or speculative investment. He argues that bitcoin resembles a speculative investment rather than a currency as it fails to satisfy three criteria of a currency: a medium of exchange, a unit of account and a store of value. Many other studies have consistent views that cryptocurrencies are speculative investments rather than a medium of exchange (Baek & Elbeck, 2015; Baur et al., 2018). However, Dyhrberg (2016) and Blau (2017) argue to the contrary, suggesting that bitcoin can be used as a medium of exchange.

There is a growing body of studies that focus on the characteristics of cryptocurrency markets. Several studies show that the bitcoin market resembles a price bubble (Cheah & Fry, 2015; Corbet et al., 2018; Fry & Cheah, 2016; Garcia et al., 2014). Jakub (2015) finds that bitcoin price behaviour supports the Efficient Market Hypothesis because its price reacts to publicly announced information. For example, the bitcoin price was higher during days of positive events and lower otherwise. On the other hand, Urquhart (2016) finds that bitcoin returns show signs of inefficiency in the early sample period but not in the later sample period and suggests that the bitcoin market is becoming more and more efficient. Recent studies report significant momentum returns in cryptocurrency, suggesting that the market is inefficient. Caporale et al. (2018) find that cryptocurrency markets exhibit positive persistence, while Cheah et al. (2018) find that bitcoin markets show heterogenous inefficiency, allowing speculators to make profits. Nguyen et al. (2020) find that the cryptocurrency market's short-term momentum effect explains cryptocurrency portfolios' returns. This significant momentum anomaly drives the inefficiency in the cryptocurrency market.

The market microstructure study of Scaillet et al. (2020) uses the database leak of Mt. Gox exchange to analyse the price dynamics of bitcoin from June 2011 to November 2013. The tick transaction-level data reveal jumps in bitcoin returns which occur frequently and tend to cluster in time. The occurrence of these jumps increases with more significant order flow imbalance, the presence of aggressive traders like large investors, and a widening of the bid-ask spread – a proxy of illiquidity. The post-jump analysis of the market conditions shows that most indicators are exacerbated. This includes the trading volume, the number of traders, the order flow imbalance, the bid-ask spread, the realised variance, the microstructure noise variance, and the proportion of aggressive traders. However, these indicators revert quickly to their anterior level in less than half an hour. Finally, jumps have a persistent impact on bitcoin prices, with positive (negative) jumps occurring in locally bearish (bullish) trends.

Finally, there is a stream of research into designing market neutral trading strategy involving a basket of cryptocurrencies by exploiting the relative behaviour of these assets. These trading strategies are based on the idea that while each asset may not be forecastable, the relative behaviour of assets can be forecasted. Leung and Nguyen (2019) construct a cointegrated portfolio of cryptocurrencies comprising Bitcoin, Ethereum, Bitcoin Cash, and Litecoin. They identify a mean-reverting and tradable portfolio that frequently crosses the entry and exit levels. They show that setting greater entry and exit levels can lead to more significant profits than a stop-loss exit or trailing stop trading strategies. Lintilhac and Tourin (2017) develop a dynamic pairs trading model for a portfolio of cointegrated cryptocurrencies. They use classical stochastic control techniques to compute the optimal portfolio weights. Their trading model is related to the classical double-threshold strategy, which they implement with live trading examples. Figà-Talamanca et al. (2021a) employ the dynamic factor model to capture the behaviour of a basket of cryptocurrencies comprising Bitcoin, Ethereum, Litecoin and Monero. They identify two dynamic factors, one of which is nonstationary and the other is stationary. In the presence of these factors, they show a multiple long-short trading strategy can generate profit. Using the same basket of cryptocurrencies, Figà-Talamanca et al. (2021b) analyse the presence of common regimes among these cryptocurrencies, which they exploit to build profitable long–short trading strategies.

2.2. Investor sentiment in traditional financial markets

The role of investor sentiment is not well-supported by the rational finance theories since the impact of irrational investors on financial markets is offset by arbitrageurs with no substantial net effect on prices. However, empirical findings on the role of investor sentiment tend to reject the prediction of rational finance theories. For example, Baker and Wurgler (2006) find that speculative stocks earn subsequent low returns with high investor sentiment. In addition, Baker and Wurgler (2007) find stocks that are difficult to arbitrage are affected mainly by investor sentiment.

In traditional financial markets, investor sentiment is commonly measured using financial media news. Tetlock (2007) shows that when media pessimism is high, there is downward pressure on market prices followed by a reversal. When media pessimism is low or unusually high, high market trading volume ensues. Bollen et al. (2011) examine whether Twitter posts can predict Dow Jones Industrial Average (DJIA). By employing OpinionFinder that measures positive and negative moods and the Google-Profile of Mood States (GPOMS) that quantify moods in six categories (Calm, Alert, Sure, Vital, Kind and Happy), they find that variation of public moods predicts changes of DJIA. Stambaugh et al. (2012) explore the role of investor sentiment in 11 anomalies[2] in cross-sectional stock returns and find that investor sentiment influences the anomalies, with each anomaly showing a more substantial effect following a high level of sentiment. Baker et al. (2012) construct sentiment indices on major stock markets and find that stocks that are difficult to arbitrage are affected mainly by sentiment. Huang et al. (2015) investigate whether investor sentiment predicts the aggregate stock market and find significant results for their sentiment index, which stems from investor's biased beliefs about the future cash flows. Gao and Süss (2015) examine the exposure of sentiment in the commodity futures market. Their findings indicate that investor sentiment explains co-movement among various commodity futures, with the sentiment index retaining its explanatory power after controlling for macroeconomic and equity-related variables.

2.3. Uncertainty studies in traditional financial markets

There is extensive literature concerning uncertainty in traditional financial markets. Anderson et al. (2009) define an event as uncertain if the outcome and the distribution of the outcomes are unknown. They argue that uncertainty should be priced in asset returns. Using disagreement of professional forecasters as a proxy for uncertainty, they observe a strong relationship between uncertainty and market excess return. By assuming that investors are uncertainty averse, Liu et al. (2005) find that uncertainty, measured using rare events, is priced in the risk premium of options. Dzielinski (2012) models economic uncertainty using internet searches and finds a significant relationship between economic uncertainty and aggregate stock returns and volatility. Overall, there is a consensus in the literature that uncertainty impacts the returns and volatilities of the traditional assets and investors should be compensated when uncertainty increases.

2.4. Investor sentiment and attention on bitcoin

Recent studies have explored how investor sentiment and attention affect bitcoin returns using different approaches. Kristoufek (2013) argues that the fundamentalist segment of the bitcoin market does not exist, so it is impossible to set a "fair" price for bitcoin. Thus, the market sentiment becomes a crucial determinant for bitcoin. The author finds that sentiment, measured by the frequency of

[2] The anomalies examined by Stambaugh et al. (2012) are financial distress, net stock issues and composite stock issues, total accruals, net operating assets, momentum, gross profitability premium, asset growth, return on assets and investments-to-assets.

search terms related to bitcoin on Google Trends and Wikipedia, positively correlates with bitcoin price. Polasik et al. (2015) find that the investor sentiment expressed in newspapers determines bitcoin return. Ciaian et al. (2016) find that investors' attraction to bitcoin rather than macroeconomic factors drives bitcoin price. Kraaijeveld and De Smedt (2020) argue that the cryptocurrency market is driven by news disseminated via social media, such as Twitter, as traditional media lacks coverage of this newly emerged asset class. Utilising a lexicon sentiment analysis approach to measure investor sentiment, they find that investor sentiment measured using tweets has predictive power on bitcoin returns.

Liu and Tsyvinski (2018) investigate whether classical asset pricing models, including Capital Asset Pricing Model and Fama and French five-factor model, major macroeconomic and cryptocurrency-specific factors explain bitcoin returns. They find that the rational asset pricing factors and the macroeconomic factors do not explain bitcoin returns. Still, investor attention measured using Twitter post count and the number of Google searches shows significant predictive power over bitcoin returns. Shen et al. (2019) examine the relationship between investor attention, proxied by tweet volume, bitcoin returns, trading volume and realised volatility. They find that investor attention drives realised volatility and volume but not bitcoin returns.

By relying on advanced sentiment analysis methods, several studies examine the relationship between sentiment and bitcoin. Georgoula et al. (2015) utilise a machine learning approach to perform sentiment analysis on Twitter data from October 2014 to January 2015. They find that the Twitter sentiment ratio for bitcoin has a positive short-run impact on bitcoin prices. Matta et al. (2015) use 'SentiStrength', a lexical-based sentiment analysis approach, to measure sentiment using tweets. They find that positive tweets predict bitcoin price movements over the sample period of January 2015 to March 2015. Abraham et al. (2018) find that tweet volume and Google Trends from March 2018 to June 2018 predict price changes of bitcoin and ethereum. Nonetheless, they find that tweets sentiment obtained from the *VADER* sentiment analysis method fails to predict price changes of bitcoin and ethereum.

2.5. Hypotheses development

Based on the discussions above, the current literature on bitcoin sentiment and attention is far from abundant. Some pertinent issues, such as investor sentiment dispersion and noise-eliminated attention, have not been investigated due to this asset class' complexity and newly emerged understanding. Moreover, most relevant studies are limited by their sample size or period since data collection for cryptocurrency studies can be overwhelming. This study contributes to the literature by (1) exploring the effect of investor sentiment dispersion on bitcoin returns volatility and (2) measuring investor sentiment dispersion and attention using innovative computational approaches.

As investor sentiment dispersion is a proxy for uncertainty, we hypothesise that market participants are exposed to greater bitcoin returns volatility when faced with more significant uncertainty. Accordingly, Hypothesis 1 predicts a positive relationship between bitcoin returns volatility and investor sentiment dispersion.

Hypothesis 1. Sentiment dispersion is positively related to bitcoin returns volatility.

Shen et al. (2019) argue that informed bitcoin investors disseminate bitcoin news via Twitter. Thus, bitcoin-related tweets may contain valuable information about bitcoin, which attracts attention. They also argue that volume count on raw tweets can serve as a proxy for investor attention (IA) and find that investor attention predicts realised volatility and trading volume of bitcoin but not bitcoin returns. We argue that since raw tweets contain many noisy signals (Abraham et al., 2018), we propose a refined bitcoin investor attention measure by eliminating the noisy signals from the raw Twitter data set. We then revisit the relationships between investor attention and bitcoin returns, volatility and trading volume. Hypothesis 2 sums up this prediction. The hypothesis is as follows:

Hypothesis 2a. Investor attention (IA) predicts bitcoin returns.

Hypothesis 2b. Investor attention (IA) predicts bitcoin volatility.

Hypothesis 2c. Investor attention (IA) predicts bitcoin trading volume.

Karalevicius et al. (2018) employ a lexicon-based sentiment analysis method to quantify bitcoin-related news portals and construct media sentiment. By examining how investors react to the news portals, they construct a trading strategy. The study finds that news from specific sources (e.g., CoinDesk, CoinTelegraph and NewsBTC) can predict semi-short-term bitcoin price movements. However, a trader who exploits these price movement patterns cannot earn abnormal returns. On the other hand, Garcia and Schweitzer (2015) find that algorithmic trading strategies constructed from a mix of economic signals (e.g., trading volume and adoption of bitcoin technology) and social signals (e.g., search volumes, word-of-mouth, emotional valence and opinion polarisation) could generate high returns for bitcoin. Motivated by these studies, we hypothesise that an attention-induced trading strategy can produce superior performance than a passive buy-and-hold strategy, as investor attention has significant predictive power on bitcoin market dynamics.

Hypothesis 3. Attention-induced trading strategy produces superior performance compared to a passive buy-and-hold trading strategy.

3. Data and research design

3.1. Data

We collect bitcoin price data from Coinmarketcap.com, which provides cryptocurrency data for research. Bitcoin price data consist of opening, closing, low, high prices and daily trading volume. In addition, we use the 3-month US Treasury-bill (T-bill) rate as the proxy for the risk-free rate obtained from the Federal Reserve Board of St. Louis database. The sample period covers January 1, 2016 to December 31, 2020.

Tweets are obtained from Twitter, which permits the use of tweets for non-commercial academic research purposes.[3] Following Tavazoee et al. (2017) and Lan et al. (2019), we use an optimised version[4] of an algorithm[5] to obtain tweets. In addition, we use the keyword "#Bitcoin"[6] to collect specific tweets related to bitcoin, which is in line with Matta et al. (2015), Abraham et al. (2018) and Shen et al. (2019), as well as the bitcoin tweet collection procedure detailed on Bitinfocharts.com.[7] Further, we use Twitter's official Application Programming Interface (API) to extract tweets related to "#Bitcoin". Our tweets dataset on bitcoin comprises approximately 22.51 million bitcoin-related tweets. While the tweets are collected with the following information: date, username, to, replies, retweets, favourites, text, geo, mentions, hashtags, id and permalink, we are primarily interested in the date the tweet is created and its content.

3.2. Research design

3.2.1. Extracting information from twitters

The raw tweets are processed before extracting and analysing information from them. First, we remove the following from the initial sample: username, to, replies, retweets, favourites, geo, mentions, hashtags, id and permalink. We then clean the raw tweets by removing noisy signals such as URLs, twitter handles (@), special characters, numbers, punctuations, emojis, unwanted space, any words that are less than or equal to 2 alphabets (e.g., of, to) and duplicate tweets as they are not relevant for sentiment analysis. Finally, we retain tweets written in English. As a result, the sample reduces from 22.51 million tweets to 19.53 million tweets after removing the irrelevant information.

Measuring sentiment is not a straightforward task. However, it is common to rely on computational sentiment analysis methods to facilitate this process. Two known methodologies to quantify text sentiment are machine learning (ML) techniques and lexical or dictionary-based methodology (Shapiro, Sudhof, & Wilson). They are part of Natural Language Processing text sentiment analysis techniques. Machine learning techniques rely on developing complex models and training the models with a large quantity of data to sufficiently quantify sentiments. On the other hand, Lexical-based methodology relies on a pre-defined list of words or phrases with which each word is assigned a score following the emotion attached to the words. Given the nature of our data and the efficiency of existing techniques, we use a lexical-based method known as *VADER*.

The *Valence Aware Dictionary and Sentiment Reasoner (VADER),* developed by Gilbert and Hutto (2014), is an advanced lexicon-based sentiment analysis method. *VADER* uses a lexicon[8] that is specifically adapted to microblog-like contexts to measure sentiments. It accounts for the contextualised meaning of sentences through the application of heuristics or rules. The heuristics are punctuation, capitalisation, degree modifiers, negation and contrastive conjunction "but". These heuristics consider the context of a sentence to increase the accuracy of quantification of sentiments.[9] In the comparison tests conducted by Gilbert and Hutto (2014) on the effectiveness of *VADER* against several benchmarks sentiment analysis methods[10], *VADER* dominates all of these sentiment measures. These benchmark sentiment analysis methods include namely Linguistic Inquiry and Word Count (LIWC), Affective Norms for English Words (ANEW), the General Inquirer, SentiWordNet, Machine-learning oriented techniques relying on Naïve Bayes, Maximum Entropy and Support Vector Machine (SVM) algorithms. In addition, *VADER* performs exceptionally well in quantifying sentiments in social media platforms making it a suitable choice for our study to quantify sentiments based on Twitter data.

VADER works as follows: *VADER* uses a lexicon containing over 7500 lexical features with a validated valence score that provides sentiment polarity (positive/negative) scores and sentiment intensity scores ranging from -4 to $+4$; the most negative is -4, and the most positive is $+4$. Essentially, each word is given a score incorporating the intensity and polarity (positive or negative). *VADER* then employs the set of five generalisable heuristics (see footnote 9) to account for the context of a word in a sentence and multiplies the net

[3] Source: https://developer.twitter.com/en/developer-terms/agreement-and-policy.

[4] Source: https://github.com/marquisvictor/Optimized-Modified-GetOldTweets3-OMGOT.

[5] Source: https://github.com/Jefferson-Henrique/GetOldTweets-python.

[6] Hashtags are primarily used to categorize keywords or topics so that the keywords or topics are easily found.

[7] Bitinfocharts.com is a credible website that provides data on various matrices related to cryptocurrencies. It also provides bitcoin-related tweet volume data where the keyword "#Bitcoin" is used so that only tweets containing the word "Bitcoin" are counted to calculate bitcoin tweet volume.

[8] The lexicon is available on the GitHub page - https://github.com/cjhutto/vaderSentiment.

[9] Gilbert and Hutto (2014) provides several examples of each of these heuristics. *Punctuation* – "The food here is good!!!" has more intensity than "The food here is good."; *Capitalisation* – "The food here is GREAT!" has more strength than "The food here is great!"; *Degree modifiers* – "The service here is extremely good" has more intensity than "The service here is good."; *Negation* – "The food here isn't really all that great." Here the meaning of the sentence changes completely; *Contrastive conjunction* – "The food here is great but the service is horrible." Here the secondary clause dictates the meaning.

[10] A brief discussion of these sentiment analysis methods is provided in Gilbert and Hutto (2014).

aggregate score of a sentence accordingly to its context to give the polarity score. Lastly, a compound score is computed by normalising between −1 (most extreme negative) and +1 (most extreme positive). The formula to calculate the compound score is as follows:

$$compound\ score = \frac{x}{\sqrt{x^2 + \alpha}} \tag{1}$$

where x is the sum of polarity scores for all words and α is a constant.

Using the compound score, *VADER* provides standardised thresholds to classify sentences as positive, negative and neutral. The thresholds are compound score ≥ 0.05 for positive, compound score ≤ -0.05 for negative and $-0.05 <$ compound score < 0.05 for neutral. Table 1 documents a few examples of tweets with their compound sentiment scores computed via *VADER* sentiment analysis. Appendix A provides further examples of bitcoin-related tweets, compound VADER sentiment scores, and the associated polarity.

We run the *VADER* sentiment algorithm on our dataset of 19.53 million tweets. Out of the 19.53 million tweets, approximately 9.03 million tweets (i.e., about 46% of the tweets) are given compound scores of 0, indicating those tweets contain nil sentiment information about bitcoin. In line with Sohangir et al. (2018), we remove all tweets with a compound score of 0. Thus, our final tweet sample comprises 10.50 million tweets, and each tweet contains useful sentiment information.

3.2.2. *Measuring sentiment dispersion*

In the literature, uncertainty can be measured as the dispersion of opinions, forecasts and sentiments across individuals. For example, Bomberger and Frazer (1981) argue that forecast error standard deviation measures the dispersion of opinions among individual forecasts of inflation. Thus, it is a proxy of inflation uncertainty. Ackert and Athanassakos (1997) define the standard deviation of earnings forecast as a proxy for uncertainty where they study the relation between analysts' over-optimism and uncertainty. Poncela and Senra (2017) define uncertainty in the premise of survey forecasts as "the variance of the future outcome of the target indicator conditional to the available information".

We define *sentiment dispersion* as the standard deviation of *VADER* sentiment scores of individual tweets, and we calculate it as follows:

$$sentiment\ dispersion\ (SD) = \sqrt{\sum_{i=1}^{N} \frac{(x_i - \mu)^2}{N-1}} \tag{2}$$

where x is the sentiment score, μ is the average sentiment scores per day, and N is the number of observations.

3.2.3. *Measuring investor attention*

We use the *VADER* processed Twitter data set to measure investor attention (IA). Our final Twitter data set comprises 10.50 million tweets with useful sentiment information as noisy signals, and nil sentiment information tweets are eliminated to avoid capturing any bias in the investor attention estimation. As a result, our refined investor attention variable is computed as:

$$investor\ attention\ (IA)_t = \ln(30 day\ moving\ average\ of\ tweet\ volume_t) \tag{3}$$

3.2.4. *Empirical method for Hypothesis 1*

Engle et al. (1987) argue that the degree of uncertainty in asset returns varies over time to the extent that the reward received by risk-averse investors holding these assets should be time-varying. We estimate a time-varying bitcoin returns volatility using the Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model, which captures the smooth changes in returns volatility. In addition to smooth persistent changes in volatility, bitcoin returns exhibit large discrete jumps (Chaim & Laurini, 2018). Because of the vast literature showing GARCH models is a good first approximation to the conditional variance, we estimate a GARCH-jump mixture model. The discrete-time jump intensity and jump size distribution are both time-invariant. While there are models that permit a time-varying conditional jump intensity and jump size distribution (for example, Chan and Maheu, 2002), our data, which spans only five years, does not deem the time-varying specification jump intensity as necessary. Therefore, a constant jump intensity-GARCH model akin to the models estimated by Vlaar and Palm (1993) and Nieuwland et al. (1994) is adequate in characterising bitcoin returns data. Furthermore, modelling the jump property of bitcoin returns is consistent with Scaillet et al. (2020), who show that jumps are frequent events in bitcoin returns and have a short-term positive impact on market activity and illiquidity besides inducing a persistent change in the price.

Define the information set at time t to be the history of returns $\Phi_t = \{R_t, \ldots, R_1\}$ where returns are defined as $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100$ such that P is the closing price of bitcoin. The jump model for bitcoin returns is:

Table 1
Sample tweets sentiment score.

Tweets	VADER Score	Polarity
International bitcoin survey launches promising big rewards bitcoin fintech btc cryptopic	0.700	Positive
South Korea plans ban cryptocurrency trading rattles market bitcoin	−0.557	Negative
What are your views Bitcoin	0.000	Neutral

$$R_t = \mu + \sum_{i=1}^{l} \varphi_i R_{t-i} + \sqrt{h_t} z_t + \sum_{k-1}^{u_t} Y_{t,k} \tag{4}$$

where $z_t \sim NID(0,1)$ and $Y_{t,k} \sim N(\theta, \delta^2)$. Both z_t and the jump size $Y_{t,k}$ are assumed to be independent normal random variables for ease of constructing the likelihood. In addition, let n_t denote the discrete counting process governing the number of jumps that arrive between t-1 and t such that it is distributed as a Poisson random variable with the parameter $\lambda > 0$ and density:

$$P(n_t = j|\Phi_{t-1}) = \frac{\exp(-\lambda)\lambda^j}{j!} \tag{5}$$

for $j = 0, 1, 2, \ldots$The mean and variance of the Poisson random variable are both λ, which is also the jump intensity. The conditional volatility dynamics of returns follow a GARCH(1,1) process (Bollerslev, 1986), that is:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \varphi x_t \tag{6}$$

where x_t is the sentiment dispersion given in equation (2), and $\varepsilon_t = R_t - \mu - \sum_{i=1}^{l} \varphi_i R_{t-i} - \theta\lambda$. The specification of ε_t contains the expected jump component and permits it to propagate and affects future volatility through the GARCH process. It can be shown that the conditional mean and variance of returns are, respectively:

$$E(R_t|\Phi_{t-1}) = \mu + \sum_{i=1}^{l} \varphi_i R_{t-i} + \theta\lambda \tag{7}$$

and

$$var(R_t|\Phi_{t-1}) = h_t + (\delta^2 + \theta^2)\lambda. \tag{8}$$

The model is estimated using the maximum likelihood method. Our measure of risk is obtained from $\sqrt{var(R_t|\Phi_{t-1})}$ which is the conditional standard deviation of bitcoin returns in equation (8). In this way, we can determine whether the sentiment dispersion is related to the volatility of bitcoin returns in line with the previous literature. If sentiment dispersion is positively related to bitcoin returns volatility, then the φ estimate will be positively signed and statistically significant.

3.2.5. Empirical method for Hypothesis 2

Shen et al. (2019) estimate three bivariate vector autoregressive models (VAR) to examine the predictive power of investor attention on bitcoin trading volume, returns and volatility. Given that there are possible lead-lag relationships between bitcoin returns, trading volume and volatility as shown in our empirical results, we estimate the VAR model involving the improved measure of investor attention, returns, trading volume and volatility instead of estimating a bivariate model involving only investor attention and the variable of interest. The four variables VAR(p) model is as follow:

$$Y_t = c + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \ldots + \pi_p Y_{t-p} + \varepsilon_t \tag{9}$$

where $Y_t = (vol, \Delta tvol, returns, \Delta IA)'$, π_i are 4×4 coefficient matrices and ε_t is an unobservable zero-mean white noise vector process. Here, $returns = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$ where P_t is the closing price of bitcoin on day t, the volatility of bitcoin returns is computed using the Parkinson (1980) extreme value estimator, $\sigma_p^2 = (.361) \cdot \left[\ln\left(\frac{H_t}{L_t}\right)\right]^2$ where H and L denote the high and low price on day t. Standard unit root test reveals that both the logarithm of trading volume (*tvol*) and investor attention are nonstationary. The first difference of these variables will ensure that these series are stationary. We estimate a VAR(7) model based on the Akaike information criterion. Granger causality tests are performed to determine the predictive power of ΔIA on volatility, trading volume and returns of bitcoin. Further, given the bitcoin price hike in late 2017 and 2020, we employ the sequential structural break test to determine the break date in the mean return of bitcoin. However, the test result does not indicate any structural break in the mean returns for the sample period.

Table 2 reports the summary statistics for the variables examined in the VAR models. It is observed that the logarithm of the moving average of cleaned tweets volume, which is the investor attention (IA) factor, has a maximum value of 10.1447 and a minimum value

Table 2
Data summary statistics.

	Mean	Std dev	Max	Min	Kurtosis	Skewness
Log of Tweet Volume	8.4769	0.7428	10.1447	0.6931	27.2568	−3.3861
Volatility	0.0013	0.0034	0.0865	0.0000	234.8951	11.8121
Log of Trade Volume	21.7792	2.2657	25.0295	17.1659	1.9705	−0.6232
Returns	0.0023	0.0395	0.2251	−0.4647	17.1288	−0.9223

of 0.6931. Its distribution is negatively skewed and is leptokurtic. The mean of the log-tweet volume is 8.4769, implying that there are sufficient cleaned tweets each day. The mean of volatility is 0.0013 with a standard deviation of 0.0034 and positive skewness. The mean logarithm of trading volume is very high, indicating the highly liquid bitcoin market over the sample period with a maximum value of 25.0295 and a minimum value of 17.1659. The mean of bitcoin returns is 0.23%. The returns distribution is negatively skewed and is leptokurtic. The maximum (minimum) return is 22.51% (−46.47%).

3.2.6. *Empirical method for Hypothesis 3*

To test Hypothesis 3, we construct an active attention-induced trading strategy to examine whether the information in the investor attention factor can produce superior performance compared to a passive buy-and-hold trading strategy. Since the investor attention factor is constructed from tweets volume, a higher (lower) value would indicate increased (decreased) attention towards bitcoin. Thus, we design the attention-induced trading strategy according to the growth rate of the IA factor given by $\frac{IA_t - IA_{t-1}}{IA_{t-1}}$. The trading strategy involves taking a long (short) position on bitcoin when the IA growth rate is larger (smaller) than zero. This trading strategy is executed over daily, weekly and monthly intervals.

4. Empirical results

4.1. *Sentiment dispersion and bitcoin returns volatility (Hypothesis 1)*

Fig. 1 shows bitcoin prices and returns over the sample period, and Fig. 2 illustrates the time-varying volatility of bitcoin returns estimated using the GARCH (1,1)-jump mixture model. We observe a price hike in late 2017 and toward the end of the sample period in Fig. 1. The volatility of bitcoin returns reaches its peak in late 2017 and decreases in 2018 in Fig. 2. Finally, the volatility of bitcoin returns exhibits a sharp spike in early 2020, coinciding with the dramatic fall in returns.

Fig. 3 shows the sentiment dispersion proxied by the standard deviation of the sentiment scores computed via *VADER* sentiment analysis. We apply the Hodrick-Prescott filter to the standard deviation of the sentiment scores to obtain a smoothed series represented by the smoothed line that tracks the original noisy series. There is an upward trend towards the end of 2017, which implies a broader *sentiment dispersion*. During this period bitcoin price fluctuated significantly and reached its peak in a short period. The upward trend in late 2017 is associated with more significant uncertainty. The second half of 2018 observes a declining sentiment dispersion movement, and the sentiment dispersion level reaches a new low in 2019. The trend adjusts upward in the first half of 2020 and declines again in the second half of 2020. The positive relationship between bitcoin returns volatility and the sentiment dispersion is depicted in the conditional variance regression results reported in Table 3.

Table 3 reports the estimation results of the GARCH (1,1)-constant intensity jump model from which the risk is estimated. Initial attempts to fit a higher-order autoregressive model to capture autocorrelation in the conditional mean of bitcoin returns fail to deliver statistically significant estimates. As such, we estimated bitcoin returns on an intercept in the mean specification. A GARCH(1,1) model

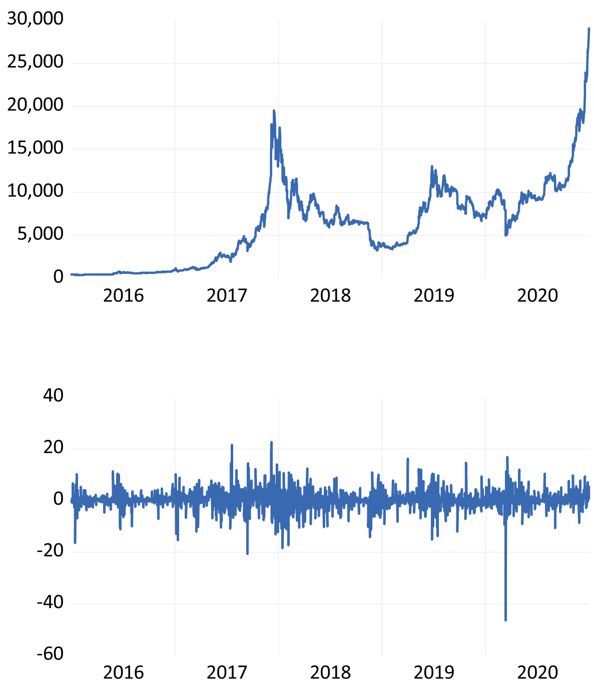

Fig. 1. Bitcoin Price and Returns. *Note*: The y-axis indicates the price in US dollars (% returns) in the upper (lower) panel.

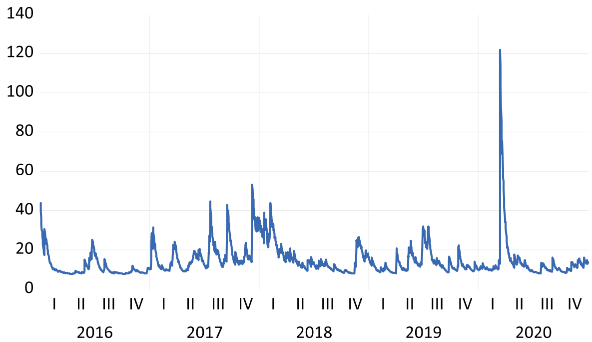

Fig. 2. Conditional Variance of Bitcoin Returns. *Note*: The conditional variance of bitcoin returns is computed based on $var(R_t|\Phi_{t-1})$ in equation (8).

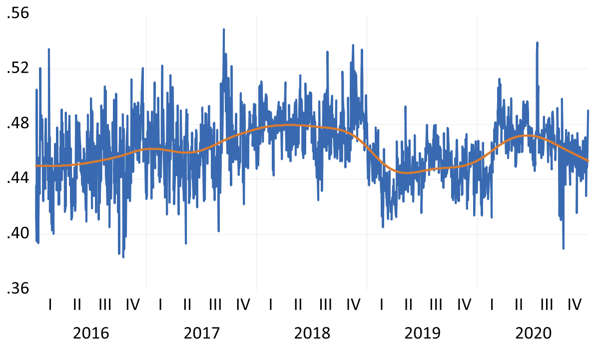

Fig. 3. Sentiment Dispersion. *Note*: Sentiment dispersion is computed following equation (2). The smoothed line is obtained by applying the Hodrick-Prescott filter to the sentiment dispersion series.

Table 3
GARCH-JUMP model estimates.

Variable	Coef	Std Error	Z-stat	P-Value
μ	0.2543	0.1022	2.4890	0.0128
ω	0.0151	0.0009	15.5288	0.0000
α	0.0980	0.0121	8.1203	0.0000
β	0.8708	0.1152	7.5590	0.0000
φ	0.0205	0.0021	9.7619	0.0000
δ	1.3461	0.4951	2.7188	0.0065
θ	−0.6453	0.1553	−4.1536	0.0000
λ	0.4196	0.1831	2.2913	0.0219
Q^2	17.08 [0.3141]	Log-likelihood	−3772.4297	
Q_{ε_t}	18.60 [0.2323]			

Note: Q^2 is the modified Ljung-Box portmanteau test robust to heteroscedasticity and serial correlation in the squared standardised residuals with 15 lags. Q_{ε_t} is the modified Ljung-Box portmanteau test for serial correlation in the jump intensity residuals. Figure in [ ] denotes the p-value of the test statistic.

Table 4
Granger Causality Results for the VAR models. Full Sample (January 01, 2016–December 31, 2020).

Ho: IA does not Granger Cause Return	5.6265	Ho: Return does not Granger Cause IA	8.7717
Ho: IA does not Granger Cause Volatility	6.5837	Ho: Volatility does not Granger Cause IA	2.9099
Ho: IA does not Granger Cause Volume	23.4246***	Ho: Volume does not Granger Cause IA	19.7989***

Note: Panel A reports the Granger causality results obtained from a VAR(7) model. 'IA' denotes investor attention which is the first difference of the logarithm of the 30-day moving average of cleaned tweets volume. 'Return' is the first difference of logarithm of the closing price. 'Volatility' is the Parkinson extreme value estimator measure of volatility. 'Volume' is the first difference of the logarithm of the trading volume. The lag length of 7 is selected based on the AIC information criterion. Appendix B shows the VAR coefficient estimates. *, ** and *** indicate significance at the 10%, 5% and 1% significance levels, respectively.

is deemed adequate in characterising the volatility of bitcoin returns. The Ljung-Box test for serial correlation in the squared standardised residuals with 15 lags shows no systematic pattern can be exploited to improve the model. The jump intensity parameter λ is 0.4196, and it is statistically significant at the 5% level. The Ljung Box test statistic for ε_t (the jump intensity residuals) also indicates that it does not exhibit any systematic pattern and that they are independent. This implies that the constant intensity jump model is adequate in characterising the discrete changes in bitcoin returns. The coefficient estimate $\widehat{\varphi}$ is positive and statistically significant at the 1% level, suggesting that sentiment dispersion positively contributes to bitcoin returns volatility. Thus, the result supports Hypothesis 1.

4.2. Investor attention, returns, volatility and trading volume (Hypothesis 2)

Table 4 reports the Granger causality test performed on the VAR(7) model. The estimation results of the VAR(7) model is reported in Appendix B. It can be seen that the IA has predictive power on trading volume over the whole sample period. The H2a and H2b are rejected at the conventional significance levels, but we fail to reject H2c because the results show that IA Granger causes bitcoin trading volume. The predictive power of IA on bitcoin trading volume is consistent with that of Shen et al. (2019) despite having used a different approach where the four variables are estimated jointly in the VAR, and we use the refined investor attention measure. Our results also align with the findings of Urquhart (2018), who find that attention offers no significant predictive power for realised volatility or returns. Likewise, Figà-Talamanca and Patacca (2020) find their market attention measures fail to predict returns, although both the trading volume and the internet search intensity positively affect bitcoin volatility. However, we do not find that trading volume and IA positively affect bitcoin volatility. These differences in results could stem from several factors. First, the construction of investor attention is based on different databases. Our study uses Twitter data, while Urquhart (2018) and Figà-Talamanca and Patacca (2020) employ Google trend data. Urquhart (2018) uses the search term "Bitcoin'' to measure retail investors' attention. Specifically, the Google search volume index (SVI) is utilised by Urquhart (2018) and Figà-Talamanca and Patacca (2020) as a measure of investors' attention. In contrast, we rely on the *VADER* processed Twitter dataset to quantify sentiments and construct the attention variable. Urquhart (2018) also uses the realised volatility measure of Andersen et al. (2003), which computes the 5-min squared intraday log-price changes of bitcoin before aggregating them to daily frequency. Figà-Talamanca and Patacca (2020) measure of the bitcoin returns volatility is based on the Exponential GARCH model. Contrasting these measures, we compute the volatility of bitcoin returns using the Parkinson (1980) extreme value estimator from daily data.

There is evidence that bitcoin returns Granger causes volatility, while past volatility and returns both Granger cause trading volume. Taken together, our results support the joint estimation of the 4-variable VAR model instead of the bivariate model commonly adopted in the literature as it is essential to capture lead-lag relationships between trading volume, volatility and returns in the bitcoin market.

Table 5
Attention-induced Trading Strategy vs. Passive Buy-and-Hold Trading Strategy.

Panel A		Summary Statistics					
Rebalance	Strategy	Mean	SD	Min	Max	Obs	
Daily	Active	0.00%	4.04%	−18.59%	59.20%	1795	
	Passive	0.16%	4.03%	−59.20%	20.30%	1795	
Weekly	Active	0.85%	9.63%	−27.14%	46.94%	255	
	Passive	1.51%	9.45%	−31.95%	32.58%	255	
Monthly	Active	5.95%	25.77%	−35.17%	73.03%	58	
	Passive	9.26%	24.56%	−37.01%	73.03%	58	
Panel B		Trading Strategies					
		Daily Rebalance		Weekly Rebalance		Monthly Rebalance	
		Active strategy	Passive strategy	Active strategy	Passive strategy	Active strategy	Passive strategy
2016	Return	−14.79%	79.17%	−5.65%	86.62%	14.68%	83.56%
	SD	−2.26%	2.27%	5.74%	5.75%	14.03%	12.51%
	Sharpe Ratio	6.70	34.82	−1.04	15.01	1.02	6.66
2017	Return	28.35%	217.16%	148.22%	210.18%	186.19%	299.70%
	SD	5.02%	4.90%	11.83%	11.64%	34.37%	28.32%
	Sharpe Ratio	5.46	44.10	12.45	17.97	5.39	10.55
2018	Return	−98.97%	−169.16%	42.12%	−61.35%	160.76%	−92.08%
	SD	4.24%	4.34%	10.90%	10.73%	26.93%	21.96%
	Sharpe Ratio	−23.80	−39.39	3.69	−5.90	5.90	−4.28
2019	Return	−12.62%	45.60%	−41.86%	58.06%	69.24%	82.34%
	SD	3.53%	3.52%	8.25%	8.61%	22.01%	22.15%
	Sharpe Ratio	−4.16	12.38	−5.33	6.51	3.05	3.62
2020	Return	99.35%	107.42%	72.80%	92.22%	−85.94%	163.28%
	SD	4.47%	4.41%	9.74%	8.64%	22.86%	24.77%
	Sharpe Ratio	22.16	24.27	7.43	10.63	−3.77	6.58
Full Sample	Return	0.00%	0.16%	0.85%	1.51%	5.95%	9.26%
	SD	4.04%	4.03%	9.63%	9.45%	25.77%	24.56%
	Sharpe Ratio	−0.28	−0.24	−0.03	0.04	0.19	0.33

The Bai-Perron (1998) sequential structural break test that allows for a minimum of 5 breaks on the mean returns from the returns regression on an intercept yield a test statistic of 6.88, which is lower than the critical value of 8.58. We fail to reject the null Hypothesis of no break in the mean bitcoin returns. Given the lack of evidence that bitcoin mean returns have experienced a structural break, we do not proceed with the sub-sample analyses for Granger causality.

4.3. *IA-induced trading strategy performance (Hypothesis 3)*

Table 5 shows the results of the active trading strategy constructed based on the investor attention (IA) factor and the passive trading strategy, which follows a passive buy-and-hold trading strategy.

Panel A of Table 5 illustrates the summary statistics of the active and passive trading strategies. Over the whole sample period, the passive buy-and-hold strategy shows greater mean returns and lower standard deviations than those of the active IA-induced trading strategy. Panel B shows the yearly returns, standard deviation and the Sharpe ratio for both strategies with daily, weekly and monthly rebalancing frequencies for the whole sample period. Interestingly, the active IA-induced trading strategies outperform the passive buy-and-hold strategies in 2018. The active strategy generates better returns than the passive strategy, yielding higher Sharpe ratios in 2018. However, the active strategy underperforms the passive strategies in other years during the sample period. Thus, on balance, the results are not strong enough for failing to reject Hypothesis 3 because the attention-induced trading strategy does not achieve superior performance compared to the passive buy-and-hold trading strategy over the entire sample period. Nonetheless, as the active IA-induced trading strategy can provide superior performance in the short term, such as in 2018, it indicates that investor attention can be a useful trading parameter for active investors in the short term.

5. Conclusion

This paper proposes a novel investor sentiment dispersion measure using an innovative lexicon-based sentiment analysis method and a comprehensive Twitter data set. We argue that sentiment dispersion proxies uncertainty in the bitcoin market, so we examine the relationship between uncertainty, proxied by investor sentiment dispersion, and bitcoin returns volatility. The results show a positive relationship between them, suggesting that bitcoin investors are exposed to greater risk with a higher level of uncertainty in the market. Using a comprehensive Twitter dataset, we propose a refined investor attention factor for bitcoin and revisit its predictive power on bitcoin return, volatility and trading volume following Shen et al. (2019). After removing the noisy signals from the investor attention factor, we find that the refined investor attention factor only predicts bitcoin trading volume, but not bitcoin returns and volatility using a 4-variable VAR model. Lastly, we show that the investor attention-induced trading strategy performs better than a passive buy-and-hold trading strategy in 2018. Still, the active trading strategy underperforms the passive strategy over the long term implying that using investor attention alone as a trading parameter does not produce superior performance over the long term. Our findings add to the richness of knowledge in bitcoin trading strategy and potentially open up a new research avenue to incorporate investor attention into more advanced trading strategies.

Our findings advance the knowledge on the effects of social media in the bitcoin market by presenting new evidence that dispersion in views through social media explains bitcoin market dynamics. As such, our study has substantial practical implications for bitcoin investors and social media and cryptocurrency market regulators.

CRediT authorship contribution statement

Sandy Suardi: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Atiqur Rahman Rasel:** Data curation, Methodology, Validation, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Bin Liu:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Appendix A

Tweets	VADER Score	Polarity
People need stopping saying HODL annoying Thursday Thoughts crypto trx tron xrp ripple bitcoin	−0.511	Negative
Buffett cryptocurrencies can say almost with certainty that they will come bad ending mgg bitcoin cryptocurrencies	−0.417	Negative
very amazing What feels like earn bitcoin daily basis with Available Google Play money Androidpic	0.840	Positive
The latest The Political Voices Update edition Thanks bitcoin altcoin	0.440	Positive
Just few examples the mainstream media obsession with trying scare people away from cryptos bitcoin crypocurrency MSMpic	−0.681	Negative
When Will the Bitcoin Bubble Pop gold bitcoin Bitcoin BTC ETH LTC BCH	0.000	Neutral
Bitcoin itself cannot scale have every single financial transaction the world broadcast everyone and included the block chain There needs secondary level payment systems which lighter weight and more efficient Hal Finney Dec bitcoin	0.050	Neutral
Which coin will hit first Vote and Retweet please crypto cryptocurrency stellar xlm tron trx verge xvg siacoin sc altcoins bitcoin btc ethereum eth ripple xrp onion deeponion miota iota xem nem eos bytecoin dogecoin tether usdt bcc ico btg kin	0.318	Positive
Please don cash out your retirement fund invest bitcoin What better way increase profit attain wealth Decrease your tax liability less tax	0.896	Positive

Appendix B. Full sample results

	IA	Volume	Return	Volatility
Intercept	0.0001	0.0172**	0.0010	0.0005***
IA_{-1}	0.1419***	0.4437	0.0305	0.0031
IA_{-2}	0.0915***	−0.6594*	−0.0859	0.0056
IA_{-3}	0.0315	0.5438	0.1024	0.0028
IA_{-4}	0.0611**	−1.3047***	0.0122	−0.0072
IA_{-5}	0.0131	−0.0868	−0.0617	0.0017
IA_{-6}	0.0719***	0.5193	−0.0168	−0.0002
IA_{-7}	0.1278***	0.4680	0.0079	0.0051
$Volume_{-1}$	0.0047**	−0.4054***	0.0010	−0.0001
$Volume_{-2}$	0.0030	−0.3392***	0.0056	0.0004
$Volume_{-3}$	−0.0027	−0.3305***	0.0090*	0.0001
$Volume_{-4}$	−0.0015	−0.2205***	0.0089	0.0005
$Volume_{-5}$	0.0001	−0.2074***	0.0027	0.0003
$Volume_{-6}$	0.0007	−0.1047***	0.0054	0.0000
$Volume_{-7}$	0.0031	0.0448**	0.0058	0.0000
$Return_{-1}$	0.0131	0.6257***	−0.0125	−0.0033*
$Return_{-2}$	0.0109	0.3193***	0.0289	0.0006
$Return_{-3}$	0.0168	0.4169***	−0.0114	0.0016
$Return_{-4}$	0.0079	0.3074**	−0.0138	−0.0031
$Return_{-5}$	0.0045	0.2874**	0.0339	−0.0030
$Return_{-6}$	−0.0014	0.0425	0.0111	0.0020
$Return_{-7}$	0.0159	−0.1233	−0.0203	0.0016
$Volatility_{-1}$	0.2171	5.4135***	0.3164	0.4485***
$Volatility_{-2}$	−0.1052	−8.6895***	−0.4590	−0.0928***
$Volatility_{-3}$	0.0025	1.9115	0.2374	0.0924***
$Volatility_{-4}$	0.0160	−0.1887	−0.2253	0.0452
$Volatility_{-5}$	−0.1154	−2.0096	0.3444	−0.0190
$Volatility_{-6}$	0.0127	−0.4560	−0.6765*	0.0964***
$Volatility_{-7}$	−0.0120	−4.8989**	1.4029***	0.332

Note: 'IA' denotes investor attention which is the first difference of the logarithm of the 30-day moving average of cleaned tweets volume. 'Return' is the first difference of logarithm of the closing price. 'Volatility' is the Parkinson extreme value estimator measure of volatility. 'Volume' is the first difference of the logarithm of the trading volume. The lag length of 7 is selected based on the AIC information criterion. *, ** and *** indicate significance at the 10%, 5% and 1% significance levels, respectively.

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