Dominated by Bots: An Empirical Analysis of the Effect of Twitter Bots on Cryptocurrency Price Movements[†]

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Abstract

This dissertation examines the impact of Twitter on five major cryptocurrencies by exploring the relationship between tweets and cryptocurrency returns, trading volume, and volatility. Tweets are first classified into bot tweets and human tweets before their key features are extracted using methods including a hybrid sentiment analysis approach. The impact of these features on the cryptocurrency market is then evaluated using linear regression and VAR models. A novel finding is that bot tweets relating to cryptocurrencies do not systematically impact the market, but cryptocurrency-specific relationships exist. Separately, human tweet volume is strongly associated with trading volume and volatility in hourly data but less so in daily data. Finally, higher human tweet sentiment is found to drive returns at lower frequencies. Results from this paper provide evidence that the relationships identified between Twitter and cryptocurrencies in previous studies are largely driven by human tweets rather than bot tweets.

Word count: 9,999

[†]This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the preface and specified in the text. It is not substantially the same as any work that has already been submitted before for any degree or other qualification except as declared in the preface and specified in the text. It does not exceed the prescribed word limit of 10,000 words.

1 Introduction

Since the introduction of Bitcoin in 2008, cryptocurrencies have emerged from their niche communities to become a widely discussed topic in 2022. Believers are excited by the decentralised nature of cryptocurrencies and their possible use cases; sceptics are worried that very few people truly understand how they work and the potential for foul play by bad actors (e.g. ponzi schemes). Nevertheless, cryptocurrencies are now firmly in the mainstream: there are over 10 thousand traded cryptocurrencies with a total market capitalisation of around $1 trillion as of June 2022 (CoinMarketCap, 2022). The rise of fintech brokerages such as Binance that allow investors easy access to the market with low commission fees has also made investing in cryptocurrencies accessible for many. As of late 2021, survey found that more than 10% of people in the U.S. invested in cryptocurrencies, highlighting their growing adoption as an investment instrument (Rodriguez, 2021).

Despite the huge interest and attention on cryptocurrencies, they are still relatively new and poorly understood. They have properties that make them comparable to traditional financial assets (e.g. stocks); but unlike traditional financial assets, they do not have any 'fundamentals' that are related to the real economy (Naeem et al., 2021; Guégan and Renault, 2021).[1] This naturally leads to the question: how are cryptocurrencies priced?

Leveraging from frameworks in behavioural finance, we conjecture that social media play an important role in the determination of the cryptocurrency market. Due to a lack of fundamentals, cryptocurrencies are largely speculative in nature and their value determined by the opinions and sentiments of the market. To obtain information about the market and other investors, investors go to social media sites where they can observe opinions of other market players. They then make decisions based on what they observe, which in turn affects the cryptocurrency market. Our paper focuses on the relationship between social media site Twitter and cryptocurrencies; we are particularly interested in understanding this relationship separately for bot and non-bot (human) tweets. To our knowledge, our study is the first to investigate links between bot tweets and the cryptocurrency market; we also use a novel methodology for sentiment analysis that may be used as a framework for future studies in which sentiment extraction from text is necessary.

To identify the effect of tweets on the cryptocurrency market, we design linear regression and VAR models and evaluate impact of various tweet features on cryptocurrency prices, trading volume, and volatility. We find that human tweet volume is positively associated with trading volume and volatility in the next hour, before having a reversal effect after a few hours. In daily data, returns are positively associated with human tweet sentiments for most cryptocurrencies, while the relationships between human attention and trading volume/volatility are less robust. Separately, we find that bot tweets generally do not affect the market for most cryptocurrencies tested. We did find that for specific cryptocurrencies such as ETH and SOL, higher bot tweet volume is associated with higher trading volume. For ADA, the first lag of bot sentiment and sentiment dispersion are negatively associated with returns. In lower frequency data, bot sentiment and sentiment dispersion are both positively associated with trading volume and volatility for BTC. Altogether, we view these findings as evidence that the links between Twitter and cryptocurrency prices are mostly driven by human tweets rather than bot tweets.

[1] Our paper is interested in cryptocurrencies that are not stablecoins. Stablecoins are cryptocurrencies designed to be either pegged to an asset (e.g. the U.S. dollar), or to have an in-built algorithm to moderate coin supply (Grobys et al., 2021). Therefore, they have a target value by design. It falls beyond the scope of our paper to investigate the relationship between tweets and such assets, as separate modelling is likely required.

2 Literature Review

The explosion in popularity of cryptocurrencies as an investment instrument in recent years has led to increased research to better understand the pricing mechanisms behind them. Many researchers, including Su et al. (2021) and Mai et al. (2018), have argued that cryptocurrencies are largely speculative in nature, and their value is determined by the expectations of a future resale value. Consequently, frameworks from behavioural finance have been leveraged to explore how investor behaviour and emotions may drive cryptocurrency prices.

2.1 Relationship between Social Interactions and Cryptocurrencies

It is well documented that social interactions can affect investors' decisions. Conceptually, peers can be regarded as a source of information, driving investors to make decisions based on social interactions (Golub and Jackson, 2010; Bikhchandani et al., 1998; Banerjee, 1992). Also known as 'herding', individuals within these models disregard their own information and make decisions based on what others do once a certain threshold is reached. Empirically, studies such as Hvide and Östberg (2015) found that individual investment behaviour is strongly associated to that of her coworkers. Similarly, Ivković and Weisbenner (2007) found that a household's stock purchases at the industry level is positively connected to its neighbours' holdings of stocks in the same industry, and a significant share of this relationship can be attributed to word-of-mouth effects.

Clearly, investment behaviour at an individual level is affected by social interactions. However, whether these individual actions lead to a noticeable impact on the market is a separate question. With the emergence of social media platforms, recent studies are able to quantify the impact of social interactions on the market through data collected from such platforms. This is especially relevant for cryptocurrencies, because investors of cryptocurrencies are generally educated, young, and digitally savvy retail investors (Auer and Tercero-Lucas, 2021). These individuals therefore are more likely to be exposed to social media platforms and have their investment decisions affected by information on the sites (Naeem et al., 2021). Earlier research has largely focused on Bitcoin, the largest cryptocurrency by market capitalisation (CoinMarketCap, 2022). For example, Baig et al. (2019) and Eom et al. (2019) find that sentiment extracted from Google Trends explains volatility clustering in Bitcoin, and can help explain changes in volatility in the future. Guégan and Renault (2021) used OLS and Granger-causality tests to evaluate the impact of investor sentiment on StockTwits on intraday Bitcoin returns, finding a statistically significant relationship between investor sentiment and Bitcoin returns for high frequency data. As for Twitter, Garcia and Schweitzer (2015) used Granger-causality tests to find that instances where opinions are polarised on Twitter are associated with increased returns for Bitcoin, while Shen et al. (2019) argued that the number of previous day tweets are significant drivers of Bitcoin realised volatility and trading volume. More recently, many papers have expanded their analysis to a few major cryptocurrencies such as BTC, ETH, XRP, ADA, LTC. Naeem et al. (2021) and Kraaijeveld and De Smedt (2020) conducted Granger-causality testing and found that Twitter sentiment is a strong predictor for returns of a number of major cryptocurrencies. However, Kyriazis (2021) contradicts the notion, having found that Twitter uncertainty exhibits a very weak impact on cryptocurrency returns. It is not surprising that the results of these papers do not always reconcile with each other. Beyond the obvious differences in timeframe, choice of social media platform, and type of cryptocurrency investigated, a major difference across papers is the way sentiment is extracted from text data.

2.2 Extracting Sentiment from Text Data

There are two types of methodologies for extracting sentiment from text data. The first is machine learning modelling and the second is lexicon-based methods (Shapiro et al., 2022; Giachanou and Crestani, 2016). Machine learning modelling requires the development of a classifier model that detects sentiment based on trained examples. For the model to perform well, it needs to be trained on a high-quality and sufficiently large training dataset, which is often costly to obtain in practice (Suardi et al., 2022). Meanwhile, lexicon-based methods usually involve using a ready-made dictionary containing a list of positive and negative words to quantify the sentiment of a text document (Shapiro et al., 2022).

The papers mentioned in Section 2.1 generally extract sentiment from text data (e.g. tweets, messages on forums, Google Trends) using lexicon-based methods. However, different papers have used significantly different dictionaries and approaches as there is no clear consensus on the 'best' approach. For example, Naeem et al. (2021) uses the Twitter Happiness sentiment, which evaluates the sentiments of around 10,000 randomly selected Twitter posts to construct an overall happiness score.[2] The drawback of such an approach is that the score is a reflection of the overall sentiment across Twitter, which may not be the same as the sentiment of actual cryptocurrency investors. Any relationship established between sentiment and cryptocurrencies using this approach may therefore be spurious. The Twitter-based Market Uncertainty ("TMU") Index, employed by Kyriazis (2021), suffers from the same critique since the TMU is constructed using all tweets rather than tweets related to cryptocurrencies.[3] Furthermore, dictionaries are usually domain specific — using a general sentiment lexicon to score documents from a specific domain may yield potentially inaccurate results (Kannan et al., 2016). Loughran and Mcdonald (2011) showed that a general sentiment lexicon heavily misclassified common words in a financial context. Therefore, general sentiment lexicons may be ill-suited for any analysis concerning cryptocurrencies.

A popular dictionary for sentiment analysis in a financial context is the Loughran-McDonald corpus.[4] The Loughran-McDonald corpus is a manually constructed, finance-oriented lexicon suitable for sentiment analysis in the financial domain (Loughran and Mcdonald, 2011). This corpus is usually used in tandem with the bag-of-words method to extract sentiments: terms in the text data are matched to corresponding sentiments in the corpus, and all other textual information are discarded (Shapiro et al., 2022). The researcher can then aggregate the sentiments of individual terms to a single sentiment measure using their formula of choice. In fact, Kraaijeveld and De Smedt (2020) takes it one step further by using a combination of the Loughran-McDonald corpus, manually compiled cryptocurrency lexicon, and Valence Aware Dictionary and Sentiment Reasoner ("VADER") algorithm to evaluate sentiments from Twitter (Hutto and Gilbert, 2014). VADER is a rule-based lexicon model that can process internet slangs and emoticons, making it useful for deployment in microblog-like contexts such as Twitter (Hutto and Gilbert, 2014). Given the established importance of domain-relevance when analysing sentiments, this hybrid methodology —if done correctly— will likely have superior performance compared to using only the Loughran-McDonald corpus and bag-of-

[2]See `http://hedonometer.org/index.html` for more information.
[3]See `https://www.policyuncertainty.com/twitter_uncert.html` for more information.
[4]See Kraaijeveld and De Smedt (2020), Karalevicius et al. (2018), and Li et al. (2014).

words approach. However, when pre-processing its tweet data, Kraaijeveld and De Smedt (2020) appears to remove many of the important heuristics that the VADER algorithm uses to identify sentiment intensity (e.g. capitalisation, punctuation). This would inevitably lead to inaccurate sentiment scores and potentially biased results. Moreover, it is not clear how the authors can effectively use the VADER algorithm on the Loughran-McDonald corpus, as sentiment in the latter is defined in an entirely different way from that of VADER's native dictionary.[5] As such, we propose a more robust hybrid methodology that avoids these pitfalls. Specifically, we first combine the VADER lexicon and our own set of manually compiled cryptocurrency lexicon to generate sentiments using VADER's algorithm; then, for those observations with ambiguous sentiments, we pass them through the Loughran-McDonald corpus using the bag-of-words approach to determine their sentiments.[6]

2.3 Twitter and the Impact of Bots

Twitter's popularity within the cryptocurrency community cannot be understated. Given the large user base and ease of information dissemination, Twitter has become a popular channel for cryptocurrency discussions. Almost all cryptocurrencies will have an official account, and there are many accounts that provide news, updates, and opinions about the cryptocurrency market (Aharon et al., 2022). Twitter's deep connections with the cryptocurrency community likely explain why there are many studies that are able to establish a significant link between the two.[7]. On Twitter, there are some accounts which produce automated messages based on computer algorithm, also known as 'bots'. Generally, bots can be divided into two categories. The first is 'legit' bots — they are used to automate tasks such as sharing news and providing customer service; the second is 'malicious' bots — they are designed with the purpose to "mislead, exploit, and manipulate social media discourse with rumours, spam, malware, misinformation, slander, or even just noise" (Ferrara et al., 2016).

Of course, these malicious bots would not be an issue if they do not achieve their purpose of causing harm. However, there is evidence that bots are widespread and could potentially cause real damage to society. Twitter bots produced around 20% of all tweets about the U.S. election in 2016 in the month leading up to the election (Bessi and Ferrara, 2016), 25% of all tweets around the topic of climate change (Marlow et al., 2021), and up to 14% of all tweets posted on cryptocurrencies (Kraaijeveld and De Smedt, 2020). While existing research has not further segmented these figures into the number of legit and malicious bots, the high number of overall bot tweets, combined with findings that humans are unable to consistently identify bot content, suggest that bad actors could potentially exploit users to their advantage (Wang et al., 2018; Everett et al., 2016; Edwards et al., 2014). For example, Silva and Proksch (2021) uses an episode of Twitter's purge of bots in 2018 as identification and found that extreme right wing politicians benefit more from bots than other party families in the EU. Voting outcomes in specific events —where the margins were tight— such as the 2016 U.S. election and the Brexit referendum were also found to have been affected by bots (Gorodnichenko et al., 2018). In the context of the financial markets, Fan et al. (2020) finds evidence that bot tweets relating to FTSE 100 companies are associated with stock returns, volatility, and trading volume. Therefore, bad actors may deploy malicious bots to spread misinformation and drive investors to act in a

[5] Terms in the Loughran-McDonald corpus fall in one of six sentiment categories, while sentiment in VADER's dictionary is defined on a numeric scale.

[6] We explain this methodology in detail in Section 3.1.2.

[7] See Baig et al. (2019), Eom et al. (2019), Philippas et al. (2019), Shen et al. (2019), and Karalevicius et al. (2018).

certain way in order to profit off this behaviour at the expense of investors.

2.4 Methods to Detect Bots

Unfortunately, studies on how bots affect real world outcomes, particularly in cryptocurrencies, is an under-researched area. There is also no easy way of accurately identifying bots — even Twitter highlighted that they are unable to identify all false or spam accounts (Twitter, 2022). Regardless, there have been efforts made by researchers to identify bots in a systematic way. In general, bot detection techniques can be grouped into three classes: network-based, crowdsourcing, and machine learning methods (Adewole et al., 2017; Ferrara et al., 2016).[8]

Network-based (also known as graph-based) methods involve using social graph properties to first investigate the 'friendship circle' (i.e. links) of each user, then a metric is produced to quantify the likelihood of the user being a bot. For example, building on the assumption that bots are usually well connected to other bots and not real users, Cao et al. (2012) developed the tool "SybilRank" to rank users according to their perceived likelihood of being a bot. However, such methods are heavily driven by assumptions, so a misspecification of assumptions may lead to sub-optimal results (Alothali et al., 2018). Even if assumptions are accurately specified, such algorithms may also be bypassed by a sophisticated bad actor, who could have their bot accounts mimic the features of actual users' friendship circles (Ferrara et al., 2016).

Crowdsourcing involves employing humans to identify bots. Due to the high time and financial costs associated with this process, it is most effective if adopted when the social network platform does not have too many users (Wang et al., 2011). With Twitter's current scale, this method is unlikely to be very feasible.

Machine learning methods use algorithms to identify properties of bots to differentiate bots from actual users. The majority of existing research on bot detection uses machine learning methods because they are highly flexible (Adewole et al., 2017). We will not list the various supervised and unsupervised learning algorithms available; instead, we focus on the most popular algorithms: Bayes theorem-based[9] and random forest[10] (Alothali et al., 2018). Despite their popularity, these algorithms are not without drawbacks. Performance of Bayes theorem-based algorithms suffer significantly when working with high-dimensional data, which is the case with a data rich environment like Twitter. Meanwhile, random forest often suffers from the difficulty in producing output that is easily interpretable. That said, the benefits of the random forest are clear — good performance accuracy and reduced risk of overfitting (Adewole et al., 2017). Without the resources to create a custom training dataset, a random forest algorithm that has a strong tested performance, such as the "Botometer" might fit the purposes of our study (Sayyadiharikandeh et al., 2020). The Botometer generates, for each Twitter account, a corresponding score as to how likely it is to be a bot. The algorithm is able to do so based on training data collected by various researchers over the years, and is tested to be highly effective in identifying bots (Yang et al., 2019). We will therefore use the Botometer to identify bots in this paper.

Our paper makes three key contributions to the literature that document the relationship between social

[8] Here we focus on techniques for the detection of *Twitter* bots.

[9] See Derhab et al. (2021), Alarifi et al. (2016), and Chu et al. (2012).

[10] See Sayyadiharikandeh et al. (2020), Igawa et al. (2016), and Aggarwal et al. (2012).

media and cryptocurrency price movements. First, we further the current research into understanding how tweets originating from bots are related to the cryptocurrency market — to our knowledge, this work is the first to investigate a link between bots and cryptocurrencies. Unlike many earlier papers, we also expand the scope of cryptocurrencies studied beyond Bitcoin to the top five cryptocurrencies by market capitalisation. Second, our approach to quantifying sentiment through a two-step hybrid methodology is distinct from extant literature that usually uses only one rule-based method to define sentiment. Finally, we also provide an updated set of manually compiled cryptocurrency lexicon relevant for 2022 that may be useful for future studies in this area.

3 Data and Methods

In this section, we first describe the tweets datasets related to the five cryptocurrencies. We illustrate how the tweet data is processed, outline how sentiment is extracted, and explain how bot accounts are identified. Second, we describe the cryptocurrency price datasets. Finally, we detail the empirical methodology for analysis.

3.1 Tweets Data

The primary data for our analysis comes from Twitter, where all publicly available tweets posted by users around the world can be viewed. We obtained tweets dated between 1 January 2022 and 30 April 2022 (inclusive) for BTC, ETH, XRP, ADA, and SOL. As explained above, we consider the five largest cryptocurrencies by market capitalisation that are non-stablecoins.[11] For each cryptocurrency, we identify the relevant tweets by using a keyword search for tweets containing its hashtag or ticker symbol. For example, if a tweet contains either "#eth" or "$eth", it would be considered as a relevant Ether tweet.[12] We further filter for English tweets, as our chosen sentiment lexicons are English-based. We then extract tweets using the scraper tool "Snscrape" in Python.[13] Snscrape is relatively new but has already seen applications in recent papers relating to sentiment and text analysis.[14] Applying this scraping procedure to the five cryptocurrencies yielded five datasets with a total of 5,423,842 public tweets. The collected information contains the tweet content ("tweet"), account name, date and time of tweet, location, number of following, and number of followers.

The total number of tweets for each cryptocurrency highly correlates with its market capitalisation relative to others. Bitcoin has the most tweets while XRP the least. We provide an overview of the unprocessed tweets data in the first two columns of Table 2.

[11] See footnote 1.

[12] The keyword search is not case sensitive. Notice we *do not* search for the underlying blockchain technology that the cryptocurrency runs on (e.g. "Ethereum"), as they may contain information irrelevant to the specific cryptocurrency. This approach is in line with Suardi et al. (2022), Shen et al. (2019), and Matta et al. (2015).

[13] See `https://github.com/JustAnotherArchivist/snscrape` for more information.

[14] See Abednego et al. (2022) and Ong et al. (2022).

3.1.1 Processing Tweets

Since tweets are free texts and unstructured in nature, the raw data needs to be processed before any analysis can be conducted. A fine balance needs to be achieved — noise should be removed without compromising the content integrity of tweets. Adapting from the approaches in Suardi et al. (2022) and Kraaijeveld and De Smedt (2020), we process tweets in three main steps. First, we remove website links (“`http`”, “`https`”, “`www`”), excess white spaces, user identifiers (“@”), ticker symbols (“$”), and hashmarks (“#”). We do not remove entire hashtags as they may contain relevant information. Instead, we remove only the hashmarks. It is worth highlighting here that emoticons, emojis, and punctuation are not removed as they convey additional sentiment information. Second, we expand contractions (e.g. “I’ve” to “I have”). Finally, we remove tweets with less than four words as they are too short for accurate sentiment identification (Kraaijeveld and De Smedt, 2020). We illustrate in Table 1 how a sample tweet is processed.

We are left with 5,360,481 tweets after the three processing steps. Summary statistics of the processed tweet data is reported in columns 3–6 of Table 2. Interestingly, there is quite a large divergence in the average number of tweets posted per user during the study period across coins. An average user who posts about ADA would tweet more than twice in frequency compared to a user who posts about SOL. In the first instance, this may be evidence suggesting that there are more bots pumping out posts for ADA compared to other cryptocurrencies.

Table 1: Example of Tweet Processing

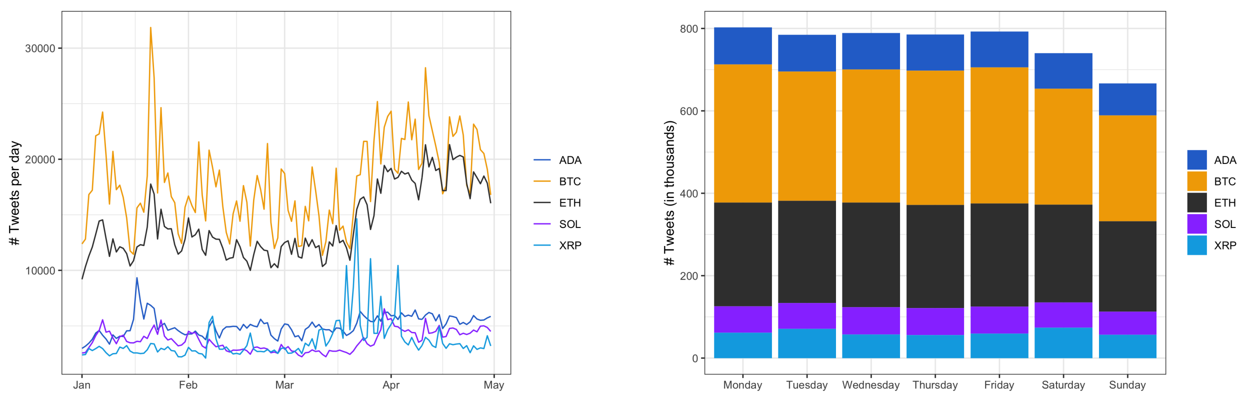
	Processing step	Result
0.	Original tweet	*What will I do if #Crypto Capitulates? I’ll buy the crap out of $ADA and grab more @adaGOATS #LFGoat https://t.co/dL1QmvlvwR*
1.	Remove website links, excess white spaces, user identifiers, ticker symbols, and hashmarks	*What will I do if Crypto Capitulates? I’ll buy the crap out of ADA and grab more adaGOATS LFGoat*
2.	Expand contractions	*What will I do if Crypto Capitulates? I will buy the crap out of ADA and grab more adaGOATS LFGoat*
3.	Remove tweets if less than four words	*What will I do if Crypto Capitulates? I will buy the crap out of ADA and grab more adaGOATS LFGoat*

Table 2: Tweets Data: Overview

	Pre-Processing		Post-Processing			
	# Tweets	# Unique Users	# Tweets	Average Tweets per day	# Unique Users	Average Tweet/User
ADA	608,567	62,715	605,921	5,092	62,014	9.77
BTC	2,202,849	243,230	2,166,438	18,205	238,674	9.08
ETH	1,722,870	237,246	1,710,084	14,370	234,177	7.30
SOL	447,350	99,801	443,249	3,725	98,524	4.50
XRP	442,206	70,512	434,789	3,654	69,587	6.25

To better understand the dynamics of tweets, we plot the number of tweets over time for each coin in Figure

1a. The number of tweets posted relating to BTC and ETH see a general upward trend from mid-March onwards, possibly due to increased discussions online relating to their sustained fall in prices during this period. There are also spikes in tweets corresponding to major news events, for example during the BTC price crash in late January and SEC's legal case against XRP between February and March. When we segment tweets into the day of posting in Figure 1b, we see that for all coins, the number of tweets posted everyday is largely stable on weekdays. Consistent with general trends across Twitter, we observe that tweet figures are lower on weekends due to lower engagement and less time spent on the site by users.



(a) Number of Relevant Tweets over Time

(b) Number of Relevant Tweets: Day of Week

Figure 1: Tweets Data: Summary Charts

3.1.2 Extracting Sentiment

As previewed in Section 2.2, the VADER lexicon combines (i) vocabulary from several well-established sentiment word banks and (ii) other words or symbols common to sentiment expression such as emoticons and internet slangs (Hutto and Gilbert, 2014).[15] Each item in this lexicon is then mapped to a 'sentiment valence' between -4 (most negative) and 4 (most positive), while 0 represents a neutral sentiment.

Our sentiment extraction process is a two-step hybrid approach. In our first step, we combine the VADER lexicon with our manually compiled dictionary, creating a 'combined lexicon'. Our manually compiled dictionary consists of 43 terms popular in the cryptocurrency community; each term is mapped to a corresponding sentiment valence using the same scale as in VADER.[16] Then, for each tweet i, VADER's algorithm is used with the combined lexicon to calculate the 'Compound Score', defined by

$$\text{Compound Score}_i = \frac{x_i}{\sqrt{x_i^2 + \alpha}},$$

where x_i is the sum of the valence scores of each word in the tweet, adjusted according to five heuristic rules.[17] The adjustment parameter α is set to 16, which approximates the maximum expected value of x_i.[18]

[15] These word banks are: Linguistic Inquiry Word Count, General Inquirer, and Affective Norms for English Words.

[16] Detailed information on this dictionary is available in Appendix D.

[17] The five heuristic rules are: (i) punctuation, (ii) capitalisations, (iii) degree modifiers, (iv) contrastive conjunctions, and (v) tri-gram polarity negations (Hutto and Gilbert, 2014).

[18] We set α as the 95th percentile of x_i in our data to exclude outliers. We conduct additional checks and confirm that the

The Compound Score rests between -1 and 1, where a higher score corresponds to a tweet that is more positive in sentiment. Each tweet can then be grouped into one of three sentiment types:

1. Positive sentiment if Compound Score$_i \geq 0.05$,
2. Neutral sentiment if $-0.05 <$ Compound Score$_i < 0.05$, and
3. Negative sentiment if Compound Score$_i \leq -0.05$.

These thresholds are selected as they are empirically shown to have better performance than individual human raters in Hutto and Gilbert (2014). Of the 5,360,481 total tweets, 2,673,984 are classified as positive and 768,725 negative.

Our second step uses the Loughran-McDonald ("LM") corpus and the bag-of-words method to classify tweets that are non-neutral in sentiment, but were not classified as so in step one. This can happen because the vocabulary used in these tweets are not found in the combined lexicon, so by construction these tweets would have a Compound Score of 0. Naturally, there may also be tweets that are correctly classified as neutral because they contain words of both positive and negative sentiments. To ensure that we are not double-classifying tweets that were already correctly classified in step one, we only apply step two to neutral tweets for which *all* words in the tweet were not found in the combined lexicon. As per Karalevicius et al. (2018), we then generate, for each tweet i, an overall sentiment score defined as

$$\text{LM Score}_i = \frac{P_i - N_i}{P_i + N_i},$$

where P_i and N_i are the number of words with positive sentiment and negative sentiment in tweet i respectively. Since the bag-of-words approach does not consider any contextual characteristics of the words within each tweet —and therefore weaker in identifying subtler emotions— we adopt a more stringent criteria when grouping tweets into the three sentiment types:

1. Positive sentiment if $\text{LM}_i \geq 0.20$,
2. Neutral sentiment if $-0.20 < \text{LM}_i < 0.20$, and
3. Negative sentiment if $\text{LM}_i \leq -0.20$.

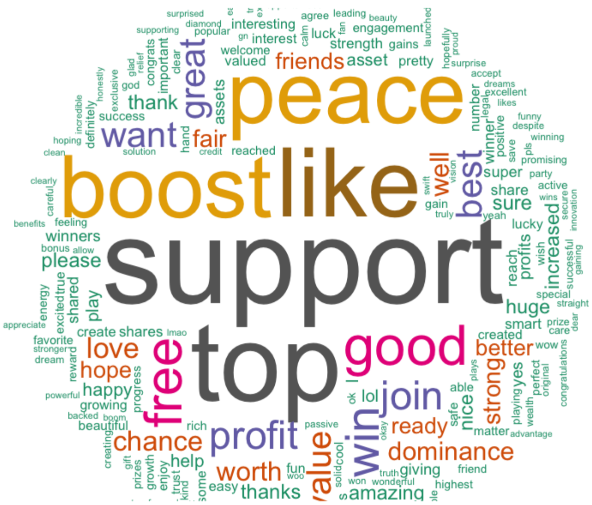
In effect, we are only classifying those tweets that are highly emotive, otherwise we leave them as neutral. From this second step, we obtain a further 2,905 positive tweets and 68,980 negative tweets. We obtain many more negative tweets because the LM dictionary contains many more words relating to negative sentiment in a financial context.

Figure 2 lists some of the more common emotive words identified by our combined lexicon and LM dictionary. Words such as "support", "boost", and "top" are usually used to express a favourable view of a certain cryptocurrency. Meanwhile, many of the commonly used words with negative sentiments are associated with price crashes (e.g. "drop", "low", "crash"). We notice that the proportion of positive tweets as a fraction of total tweets for each cryptocurrency except ADA hovers around 50%; interestingly, this proportion is significantly higher for ADA (see Figure 3a) — this is possibly driven by bot tweets with extremely positive sentiments relating to ADA.[19] We also see in Figure 3b that there is an overall sharp dip in sentiment for

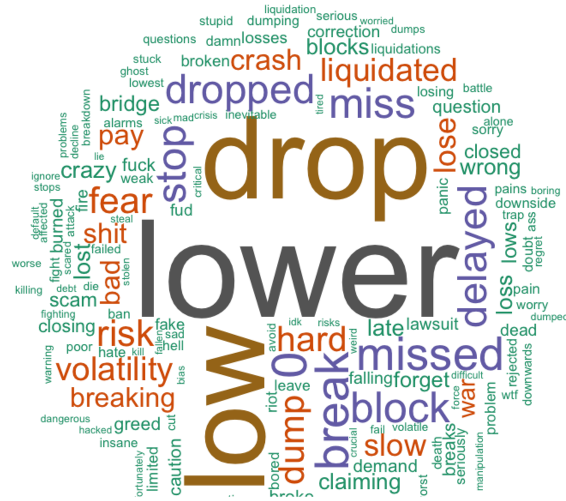
sentiment classifications do not change significantly at other parameter values between 15 (algorithm default) and 19 (99th percentile).

[19] We explore this in Section 3.1.3.

all five cryptocurrencies in late-March, likely corresponding to the major price crash during that period.

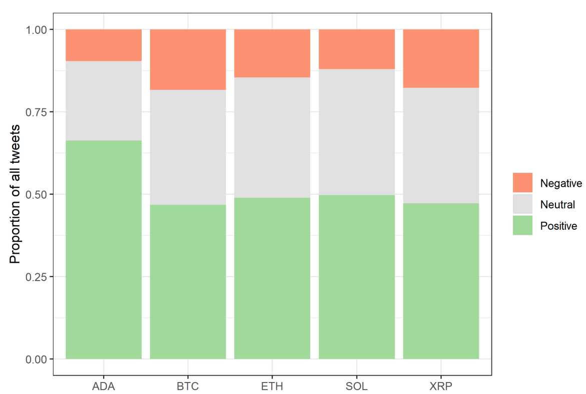


(a) Commonly used Positive Words

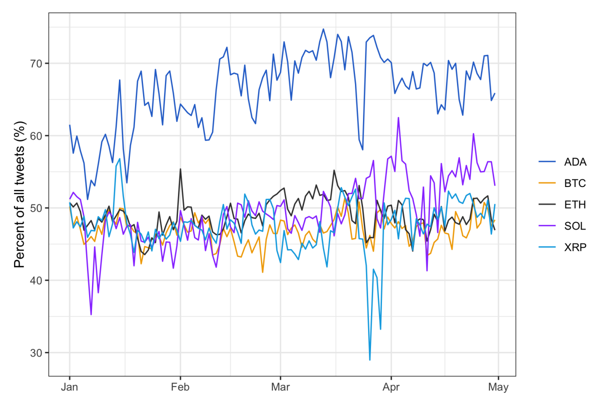


(b) Commonly used Negative Words

Figure 2: Word Clouds: Top Words in Tweet Data



(a) Proportion of Tweets in Each Sentiment Class



(b) Percent of Positive Tweets over Time

Figure 3: Tweet Sentiments Split by Cryptocurrency

3.1.3 Detecting Bots

From the processed dataset in Section 3.1.1, we obtain the set of account names ("handles") that has posted at least one tweet over the study period. Once we feed these handles through Botometer's API, its classification algorithm will generate a score for each handle. The classification algorithm pulls, for each handle, over 1,000 features from Twitter and groups them into six classes: user data, friend data, retweet and mention network structure, content and language, sentiment, and temporal features (Yang et al., 2019). The information within each class is compared to that of actual bots identified in training datasets, before a final score between 0 and 1 is generated. An account with a score closer to 1 suggests it behaves similar to a bot, while a score closer to 0 suggests otherwise. As the algorithm considers information in addition to how 'bot-like' user tweets are, it is able to detect more sophisticated bots that, for instance, tweet like humans but have a bot-like network structure. We show the corresponding account bot scores for all tweets in Figure 4a. For more mature cryptocurrencies with higher market capitalisation (e.g. BTC, ETH, XRP), the scores appear to be lower in general. As suspected, there does appear to be a large number of bot tweets relating to ADA: the median bot score for its tweets is 0.55, which is higher than the third quartile for the other four cryptocurrencies.

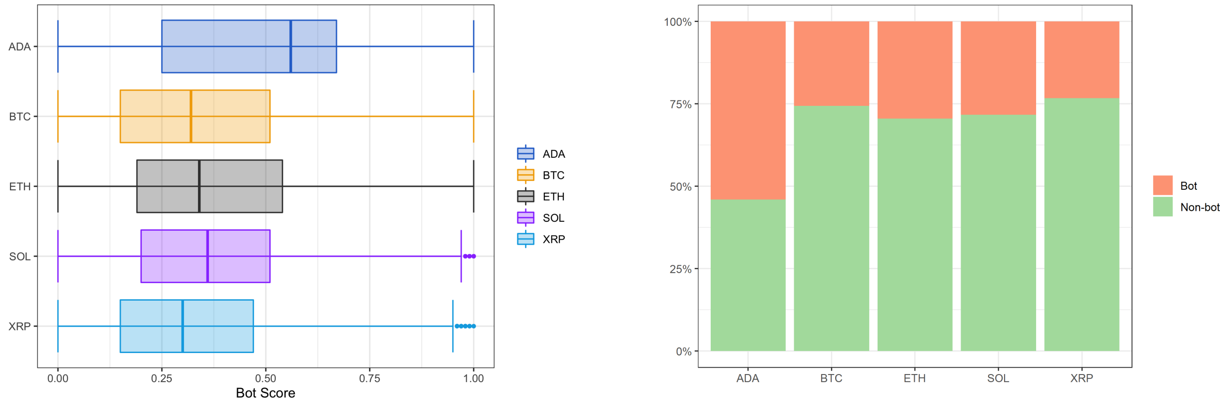
Varol et al. (2017) conducted large-scale evaluations and suggested that the optimal threshold that maximises classification accuracy is between 0.43 and 0.49.[20] As there are many official cryptocurrency accounts that post standardised tweets, we adopt the higher bound threshold of 0.49 in our study so that the probability of mistakenly categorising these official accounts as bots is reduced. More concretely, we show examples of what tweets look like at various bot scores in Table 3. Consistent with what we would expect, tweets with low bot scores look less like automated messages. For the tweet that originated from an account with a bot score of 0.49, we see the power of the Botometer at work — from just looking at the tweet, it is not immediately clear to us that it originated from a bot. However, because the other features of this account such as its friend data and temporal features were highly similar to those of a bot, it was given a relatively high score of 0.49. Therefore, the probability of misclassifying sophisticated bots is minimised and this step sets a strong foundation for our subsequent analysis. On the whole, we find that 17% of handles are categorised as bots. Unsurprisingly, bots generate an outsized 30% of all tweets, suggesting that bots tweet more often than humans. In particular, we see in Figure 4b that bot tweets account for more than 50% of all tweets for ADA. These observations, which are consistent with findings in Kraaijeveld and De Smedt (2020), highlight the importance of having a better understanding of the relationship between bots and cryptocurrencies.

Table 3: Sample Tweets with Corresponding Bot and Sentiment Scores

Tweet	Bot Score	Classification	Sentiment Score
Still just range-bound but $BTC definitely lookin weak. Yesterday daily gave us a bearish engulfing of those closing lows and price keeps getting rejected by the 30/60 on the 4H. If we get a 4H close below the range, I'd recommend preparing for the worst.	0	Human	-0.94 (Negative)
The #NFT market in #Solana has not yet fully exploded. Just calm, hodl and wait. #NFTCommunity #SOL	0.49	Bot	0.68 (Positive)
Consistent growth has been in stablecoins. So to capture the growth must create stablecoin. Back it with $BTC. BTC becomes reserve currency of the digital world.	1	Bot	0.74 (Positive)

We show three sample tweets of varying bot scores in this table: one from a handle with the minimum score of 0, one from a handle with the bot threshold score of 0.49, and one from the maximum score of 1. We also report their corresponding sentiment score and class for completeness.

[20] Accuracy is defined as the number of correct predictions over the total number of predictions. We choose accuracy as the evaluation metric (as opposed to precision, for example) because we think it is equally important to correctly classify bots and non-bots.



(a) Overview of Bot Scores for All Tweets

(b) Identified Bot Tweets Split by Cryptocurrency (%)

Figure 4: Bot Scores and Classifications

For each cryptocurrency we plot what is commonly known as a box plot in Panel (a). The 'box' consists of the first, second (median), and third quartiles of the data; the distance between the first and third quartiles is the interquartile range ("IQR"). The 'whiskers', which extend horizontally to the left and right of the box, illustrate the values that are within 1.5 IQR of the first and third quartiles respectively. 'Maximum' and 'minimum' values are shown by vertical lines at the end of the whiskers. Finally, 'outliers' are depicted by the points beyond the maximum and minimum.

3.2 Cryptocurrency Price Data

Financial data of cryptocurrencies can usually be obtained from two channels: 'coin-ranking' websites or cryptocurrency spot exchanges. Coin-ranking websites (e.g. CoinMarketCap) are often used by researchers because of their ease of accessibility and wide data scope.[21] However, prices on these websites are usually non-traded prices, which are constructed from *inferred* trading volumes from cross-rates against other cryptocurrencies, stablecoins, and fiat rates (Vidal-Tomás, 2022). Consequently, the non-traded prices reflected may differ by up to 10% from actual prices faced by investors (Alexander and Dakos, 2020). Therefore, similar to Choi et al. (2022) and Vidal-Tomás (2021), we use price data from Binance taken from the aggregator site CryptoDataDownload.[22] We choose to use data from Binance because it is the largest cryptocurrency spot exchange by volume as of May 2022 (CoinMarketCap, 2022).

Data is downloaded for the period between 1 January 2022 and 30 April 2022. For each cryptocurrency, the opening price, high price, low price, closing price, trading volume, and trade count (i.e. number of unique trades) are recorded in hourly intervals. Since we are interested in how cryptocurrencies respond to investor sentiment, we use the closing price when calculating returns. A caveat with Binance price data is that it does not trade in USD but instead uses Tether ("USDT"), a stablecoin which is *theoretically* pegged one-to-one to the U.S. dollar. This relationship is however not always true and it is therefore necessary to convert the USDT values to USD for comparability with fiat currencies. Conversion is done using equivalent hourly USD to USDT rates from CryptoDataDownload.

We denote r_{jt} as the logarithmic ("log") return of cryptocurrency j at time t and v_{jt}^{trade} as the log trading volume of cryptocurrency j at time t.[23] For price volatility, we refer to Parkinson (1980) and construct a

[21] See Naeem et al. (2022), López-Martín et al. (2022), and Kraaijeveld and De Smedt (2020).

[22] `https://www.cryptodatadownload.com/`

[23] The approaches for these measures are consistent with standard finance literature.

consistent (albeit inefficient) estimator:

$$vol_{jt} = \frac{100}{2\sqrt{\ln 2}}\left(p_{jt}^{\text{high}} - p_{jt}^{\text{low}}\right), \quad \text{where} \begin{cases} p_{jt}^{\text{high}} = \text{log of high price of cryptocurrency } j \text{ at } t\text{, and} \\ p_{jt}^{\text{low}} = \text{log of low price of cryptocurrency } j \text{ at } t. \end{cases}$$

We plot in Figure 5 the log price p_{jt} and returns r_{jt} for the five cryptocurrencies. Consistent with stylised facts, prices appear to be non-stationary while returns stationary and centered around zero. As with standard finance literature, we use returns instead of prices when conducting our analysis. We also note that the evolution of prices across cryptocurrencies is quite similar, especially between BTC and ETH, suggesting a close relationship between different cryptocurrencies. We also include charts depicting the evolution of trading volume and volatility across time in Appendix A. XRP appears to be the most volatile while BTC the least. As with prices, there appears to be some correlation between the various cryptocurrencies for both volume and volatility.

3.3 Empirical Methodology for Analysis

3.3.1 Defining Variables of Interest

From our obtained Twitter data, we generate, for each cryptocurrency, three variables that capture the main features of tweets.

'Tweet sentiment' measures the overall sentiment of tweets at a point in time, and can be used to proxy the market sentiment. Based on Antweiler and Frank (2004), we define tweet sentiment as

$$S_t = \ln\left(\frac{1+M_t^+}{1+M_t^-}\right), \quad \text{where} \begin{cases} M_t^+ = \text{Number of positive tweets at } t\text{, and} \\ M_t^- = \text{Number of negative tweets at } t. \end{cases}$$

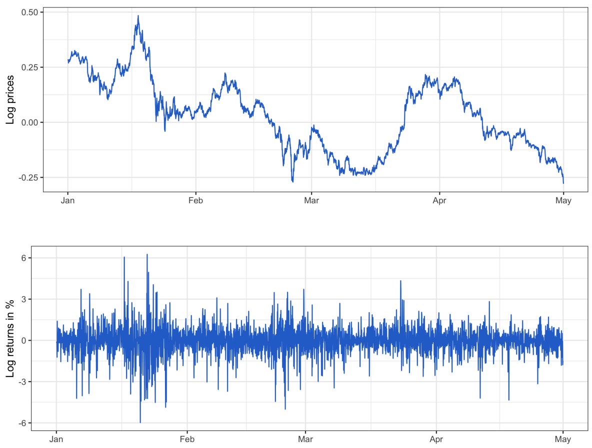
This simple measure aggregates the sentiments of all tweets during a specific time window: a higher proportion of positive sentiment tweets to negative sentiment tweets at t results in a higher S_t. If there are equally as many positive and negative sentiment tweets at t, S_t would be 0.

'Sentiment dispersion' captures the uncertainty amongst investors. Based on a similar measure proposed by Suardi et al. (2022), we define sentiment dispersion as

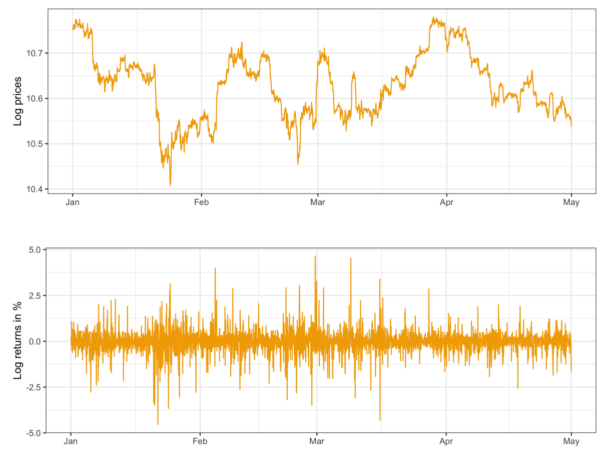
$$SD_t = \sqrt{\frac{1}{N_t - 1}\sum_{i=1}^{N_t}(x_{it} - \mu_t)^2}\ ,$$

where x_{it} records the sentiment of tweet i at time t, μ_t is the average sentiment score across all i at t, and N_t reports the total number of tweets at t. The sentiment dispersion value is weakly positive and a higher value at a specific time signals more variation in opinions across the market.

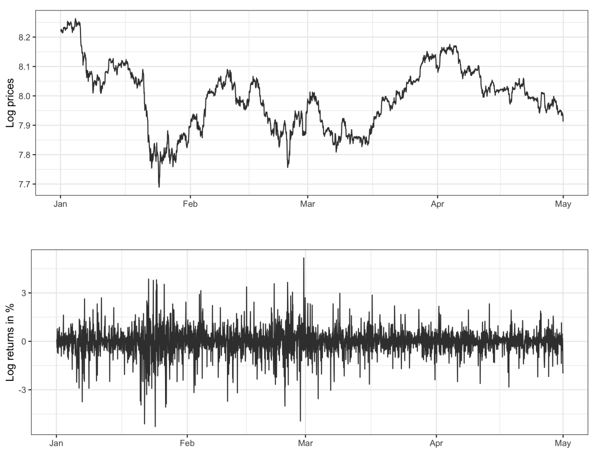
The amount of 'attention' a cryptocurrency receives at time t is proxied by the volume of relevant tweets and defined as $v_t^{\text{mes}} = \ln(1 + N_t)$. We take logs of the total number of tweets plus one for better statistical properties.



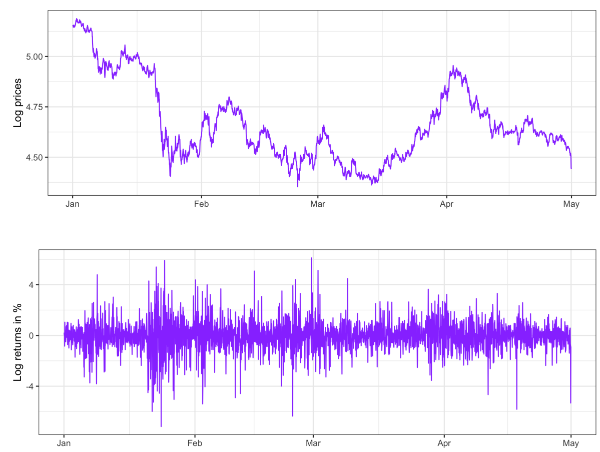
(a) ADA



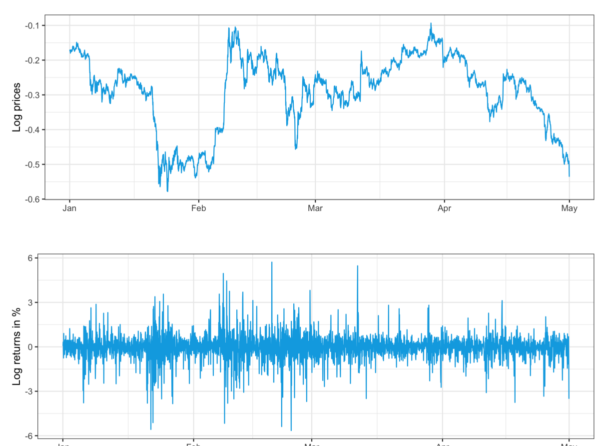
(b) BTC



(c) ETH



(d) SOL



(e) XRP

Figure 5: Price and Returns Split by Cryptocurrency

3.3.2 Empirical Modelling

Below we detail the models used to measure the impact of Twitter sentiment on various cryptocurrencies. We first define a linear regression of the form

$$y_t = \alpha + \sum_{\tau=1}^{5} \boldsymbol{x}'_{t-\tau}\boldsymbol{\beta}_\tau + \sum_{k=1}^{p} \delta_k y_{t-k} + \boldsymbol{c}'_t\boldsymbol{\Gamma} + \varepsilon_t. \tag{1}$$

This is similar to the approach taken in Guégan and Renault (2021), Fan et al. (2020), and Piñeiro-Chousa et al. (2018) and serves as our baseline specification. For each cryptocurrency j, the model is run separately for each of returns r_{jt}, trading volume v_{jt}^{trade}, and volatility vol_{jt} as the dependent variable y_t.[24] The 3×1 vector $\boldsymbol{x}_{t-\tau}$ contains our variables of interest: tweet sentiment S, sentiment dispersion SD, and attention v^{mes} at date $t-\tau$. Hourly data is used and the variables are lagged up to 5 periods prior to t because we are interested in finding the predictive power of past x values at various lag lengths on y (Piñeiro-Chousa et al., 2018). We also include a set of exogenous variables $\boldsymbol{c}_t$ that contemporaneously affect y_t. Referencing existing studies in the literature, stock market returns (S&P 500 index), stock market volatility (VIX index), U.S. dollar quotations (dollar-euro and dollar-sterling exchange rates) are selected (Reboredo and Ugolini, 2018; Dyhrberg, 2016). Lastly, α is a constant and ε_t the mean-zero error term. The model parameters are estimated using ordinary least squares ("OLS") and we use Newey-West heteroskedasticity and autocorrelation consistent ("NW-HAC") standard errors to adjust for potential autocorrelation and heteroskedasticity. As the model specified in (1) has valid inferences *iff* all series in the regression are stationary, we conduct Augmented Dickey-Fuller ("ADF") tests on the variables and ensure that they are indeed I(0). The results of these tests are reported in Appendix B. Consistent with stylised facts, we find that returns, trading volume, and volatility are highly persistent and exhibit serial correlation, so we also include the appropriate number of lags p based on the Akaike Information Criterion ("AIC"). AIC is used instead of Schwarz Bayesian Information Criterion ("SBIC") because it is less parsimonious, so we are less likely to miss significant lag terms.

As we are interested in identifying the relationship between bot tweets and cryptocurrencies, we further specify a model that allows us to disaggregate the overall effect into effects from bot tweets and effects from non-bot tweets:

$$y_t = \alpha + \sum_{\tau=1}^{5} \boldsymbol{x}_{t-\tau}^{NB}{}'\boldsymbol{\beta}_\tau^{NB} + \sum_{\tau=1}^{5} \boldsymbol{x}_{t-\tau}^{B}{}'\boldsymbol{\beta}_\tau^{B} + \sum_{k=1}^{p} \delta_k y_{t-k} + \boldsymbol{c}'_t\boldsymbol{\Gamma} + \varepsilon_t. \tag{2}$$

This model is largely similar to the baseline specification; the only difference is that the variables of interest are now separately quantified for bot tweets ($\boldsymbol{x}^B$) and non-bot tweets ($\boldsymbol{x}^{NB}$). Therefore, $\boldsymbol{\beta}_\tau^B$ captures how the three features (tweet sentiment, sentiment dispersion, and attention) from bot tweets are associated with y. As before, we conduct ADF tests in Appendix B and confirm all variables of interest are stationary. We then use AIC to determine p, OLS with NW-HAC standard errors to estimate the parameters, and run the model separately for each cryptocurrency and each metric.

[24] We run 15 regressions in total (five cryptocurrencies, three metrics for each cryptocurrency).

However, Suardi et al. (2022) found that there are lead-lag relationships between cryptocurrency returns, trading volume, and volatility. If this is true, then (1) and (2) cannot effectively model the dynamics of the various series. This can then lead to biased estimates and incorrect conclusions. When variables are endogenously determined, a vector autoregression ("VAR") may be a more appropriate approach for analysis. A VAR allows for different series to be linked, and also allows for correlation between equation errors. This approach is popular in existing papers that investigate the links between financial assets (or cryptocurrencies) and investor sentiment or attention.[25] Specifically, for each cryptocurrency, we can define a VAR(p) model as:

$$\boldsymbol{Y}_t = \boldsymbol{A} + \sum_{s=1}^{p} \boldsymbol{\Phi}_s \boldsymbol{Y}_{t-s} + \boldsymbol{\Theta} \boldsymbol{C}_t + \boldsymbol{u}_t, \tag{3}$$

where $\boldsymbol{Y}_t = [r_t \quad v_t^{\text{trade}} \quad vol_t \quad S_t^B \quad SD_t^B \quad v_t^{B\text{mes}} \quad S_t^{NB} \quad SD_t^{NB} \quad v_t^{NB\text{mes}}]'$ and $\boldsymbol{C}_t$ is a matrix containing a set of exogenous variables that contemporaneously affect $\boldsymbol{Y}_t$. For consistency, we use the same set of variables as in (1) and (2). The 9×9 matrix $\boldsymbol{\Phi}_s$ captures the cross-equation linkages at lag s.[26] Lastly, $\boldsymbol{A}$ is a vector of constants and $\boldsymbol{u}_t$ is a vector of mean-zero errors. The optimal number of lags, p, is determined using AIC. As before, we require all series in the VAR to be stationary for valid inferences. We can then conduct Granger-causality tests to determine if our variables of interest Granger-cause returns, trading volume, and volatility. We say that if y_2 helps to forecast y_1, then y_2 Granger-causes y_1 (Granger, 1969). We highlight here that Granger-causality does *not* establish causality in an economic sense, but simply finds a statistically significant relation in lagged values of x and y. For example, to test if tweet sentiment from bots S^B Granger-causes the returns of a cryptocurrency r, we would test the following hypothesis:

$$H_0: \ \phi_{14}^1 = \phi_{14}^2 = \cdots = \phi_{14}^p = 0 \qquad [S^B \text{ does not Granger-cause } r]$$

$$H_1: \ \phi_{14}^s \neq 0, \quad s = 1, 2, \ldots, p \qquad [S^B \text{ Granger-causes } r]$$

4 Results

4.1 Baseline Model

In Table 4 we summarise results of our baseline model with log returns (r_{jt}) as the dependent variable. We find that the coefficients of interest are largely insignificant across the five cryptocurrencies, suggesting a lack of relationship between tweets and cryptocurrency returns in general. The exception is with SOL, where we find that tweet sentiment at lags 2 to 5 is weakly significant. While we would expect that higher sentiment from investors drives more purchases for a cryptocurrency, in turn leading to higher returns, we do not consistently see this in our results. This is not surprising: the model fit is poor as the R^2 is below 0.022 for all five cryptocurrencies. Therefore, even though some terms are statistically significant, they are unlikely to have any meaningful economic interpretations. What we are observing here is likely driven by

[25] See Suardi et al. (2022), Shen et al. (2019), Piñeiro-Chousa et al. (2018), and Reboredo and Ugolini (2018).

[26] For the avoidance of doubt, ϕ_{jk}^s captures the effect of series y_k on series y_j at lag s.

statistical variation in the data rather than a depiction of a fundamental relationship between variables, and the terms are unlikely to have any predictive power in an economic sense. Our results are a generalisation of the findings in Suardi et al. (2022), where investor attention is found to poorly predict BTC returns. In contrast to Guégan and Renault (2021) however, we do not find a relationship between sentiment and returns, likely because sentiment is only impactful at higher frequencies (i.e. up to 15 minute intervals), while we have used hourly data here. Furthermore, they have also highlighted the difficulty in using their results to craft a profitable trading strategy because the estimates are of a small magnitude.

Table 4: Log Returns r_{jt}, Baseline Regression, Hourly Data

Parameter estimates	(1) ADA	(2) BTC	(3) ETH	(4) SOL	(5) XRP
Tweet Sentiment$_{t-2}$	0.178**	0.047	0.107	0.119*	-0.039
	(0.08)	(0.077)	(0.104)	(0.069)	(0.048)
Tweet Sentiment$_{t-3}$	-0.053	0.046	0.012	-0.156**	-0.12**
	(0.084)	(0.078)	(0.082)	(0.068)	(0.052)
Tweet Sentiment$_{t-4}$	0.076	-0.014	-0.002	0.133*	0.042
	(0.08)	(0.075)	(0.099)	(0.07)	(0.051)
Tweet Sentiment$_{t-5}$	-0.088	-0.105	0.065	-0.122*	0.004
	(0.076)	(0.075)	(0.092)	(0.065)	(0.048)
Sentiment Dispersion$_{t-1}$	-3.246**	1.056	0.186	-1.495	-0.51
	(1.451)	(1.102)	(1.343)	(1.29)	(0.699)
Sentiment Dispersion$_{t-4}$	1.191	2.401*	0.27	-0.059	-0.401
	(1.433)	(1.232)	(1.372)	(1.223)	(0.757)
Attention$_{t-2}$	-0.029	-0.085	-0.301*	-0.049	0.027
	(0.12)	(0.133)	(0.175)	(0.16)	(0.072)
Attention$_{t-3}$	0.178	0.089	0.252*	0.101	0.045
	(0.112)	(0.112)	(0.151)	(0.165)	(0.082)
# Lags (dependent variable)	4	2	1	1	11
Controls?	✓	✓	✓	✓	✓
Heteroscedastic robust standard errors?	✓	✓	✓	✓	✓
N	2,874	2,874	2,874	2,874	2,868
R^2	0.009	0.009	0.01	0.01	0.022

We only present variables that are statistically significant at the 10% level for at least one cryptocurrency. NW-HAC standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Significant positive and negative estimates are highlighted in shades of green and red respectively. Higher statistical significance is highlighted in darker shades. # Lags determined based on AIC.

We present a summary of our baseline model with trading volume (v_{jt}^{trade}) as the dependent variable in Table 5. A clear pattern emerges from our results: we find that greater attention is strongly associated with higher immediate trading volume, before having reversal effects in later periods. Specifically, we find that a 1% increase in number of tweets at t is associated with a 0.1–0.7% increase in trading volume in the next hour, followed by a decrease of about 0.1–0.3% in trading volume after three to five hours. We postulate that greater attention from investors leads to an immediate increase in trading activity from usual trading levels, but this increase is not sustained as investors have a short attention span and therefore the trading levels revert to long run levels after a few hours. Using ETH as example, we find that the initial spike in trading volume is succeeded by reversals that essentially bring trading volume back to original levels after five hours. Here, we build on the results from Shen et al. (2019), who found that tweet numbers were a significant driver for daily trading volume for BTC.

Table 5: Trading Volume v_{jt}^{trade}, Baseline Regression, Hourly Data

Parameter estimates	(1) ADA	(2) BTC	(3) ETH	(4) SOL	(5) XRP
Tweet Sentiment$_{t-1}$	-0.001	-0.112*	-0.082*	0.009	-0.018
	(0.032)	(0.061)	(0.045)	(0.025)	(0.029)
Tweet Sentiment$_{t-2}$	0.015	-0.025	0.038	0.031	0.055*
	(0.033)	(0.062)	(0.047)	(0.028)	(0.029)
Sentiment Dispersion$_{t-1}$	1.284**	-0.247	0.587	0.334	-0.082
	(0.546)	(0.888)	(0.802)	(0.487)	(0.414)
Sentiment Dispersion$_{t-3}$	-0.302	-0.778	-0.156	0.25	0.794*
	(0.623)	(0.85)	(0.807)	(0.472)	(0.437)
Sentiment Dispersion$_{t-5}$	-0.616	-0.666	-1.738**	0.137	-0.865**
	(0.574)	(0.876)	(0.776)	(0.475)	(0.402)
Attention$_{t-1}$	0.25***	0.714***	0.559***	0.323***	0.095**
	(0.047)	(0.091)	(0.077)	(0.057)	(0.041)
Attention$_{t-3}$	-0.029	-0.135	-0.262***	-0.126*	0.009
	(0.049)	(0.106)	(0.093)	(0.065)	(0.046)
Attention$_{t-4}$	-0.102*	-0.206**	-0.035	0.01	-0.023
	(0.053)	(0.098)	(0.089)	(0.062)	(0.047)
Attention$_{t-5}$	-0.112**	-0.085	-0.256***	-0.308***	-0.098***
	(0.049)	(0.061)	(0.076)	(0.055)	(0.038)
# Lags (dependent variable)	12	4	9	11	9
Controls?	✓	✓	✓	✓	✓
Heteroscedastic robust standard errors?	✓	✓	✓	✓	✓
N	2,867	2,874	2,870	2,868	2,870
R^2	0.598	0.501	0.526	0.592	0.566

We only present variables that are statistically significant at the 10% level for at least one cryptocurrency. NW-HAC standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Significant positive and negative estimates are highlighted in shades of green and red respectively. Higher statistical significance is highlighted in darker shades. # Lags determined based on AIC.

Lastly, we report in Table 6 our baseline model with price volatility (vol_{jt}) as the dependent variable. As with price returns and trading volume, we find that sentiment dispersion is largely not useful in predicting volatility. Interestingly, we find that tweet sentiment has strong negative short-run effects for BTC and ETH: higher sentiments for these two cryptocurrencies drives down their price volatility. Our finding here is similar to Eom et al. (2019), in which investor sentiment is found to predict future volatility of BTC. Similar to trading volume, we also find that the first lag of attention is positive and highly significant across all five cryptocurrencies. However, the reversal effects are less pronounced, so we only observe a downward effect on volatility after the third and fifth hour for ETH, SOL and XRP. Our estimates for attention could be linked to what we observe for trading volume, as it is sensible to expect higher volatility accompanying higher trading volume. It would therefore be useful to explore the VAR model in Section 4.3 where we can include additional terms to control for potential cross-equation linkages.

Table 6: Volatility vol_{jt}, Baseline Regression, Hourly Data

Parameter estimates	(1) ADA	(2) BTC	(3) ETH	(4) SOL	(5) XRP
Tweet Sentiment$_{t-1}$	-0.001	-0.094**	-0.118***	-0.015	-0.001
	(0.036)	(0.041)	(0.042)	(0.031)	(0.026)
Tweet Sentiment$_{t-5}$	0.047	0.072*	-0.027	-0.003	0.035
	(0.038)	(0.042)	(0.041)	(0.029)	(0.026)
Sentiment Dispersion$_{t-1}$	0.725	-0.547	-0.007	0.986*	-0.003
	(0.671)	(0.635)	(0.648)	(0.597)	(0.372)
Attention$_{t-1}$	0.158***	0.348***	0.388***	0.32***	0.072**
	(0.049)	(0.065)	(0.066)	(0.067)	(0.033)
Attention$_{t-3}$	-0.008	-0.029	-0.151*	0.015	0.013
	(0.052)	(0.073)	(0.08)	(0.077)	(0.041)
Attention$_{t-5}$	-0.039	-0.082	-0.061	-0.143**	-0.061**
	(0.051)	(0.059)	(0.062)	(0.062)	(0.03)
# Lags (dependent variable)	10	9	10	12	11
Controls?	✓	✓	✓	✓	✓
Heteroscedastic robust standard errors?	✓	✓	✓	✓	✓
N	2,869	2,870	2,869	2,867	2,868
R^2	0.377	0.288	0.353	0.375	0.307

We only present variables that are statistically significant at the 10% level for at least one cryptocurrency. NW-HAC standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Significant positive and negative estimates are highlighted in shades of green and red respectively. Higher statistical significance is highlighted in darker shades. # Lags determined based on AIC.

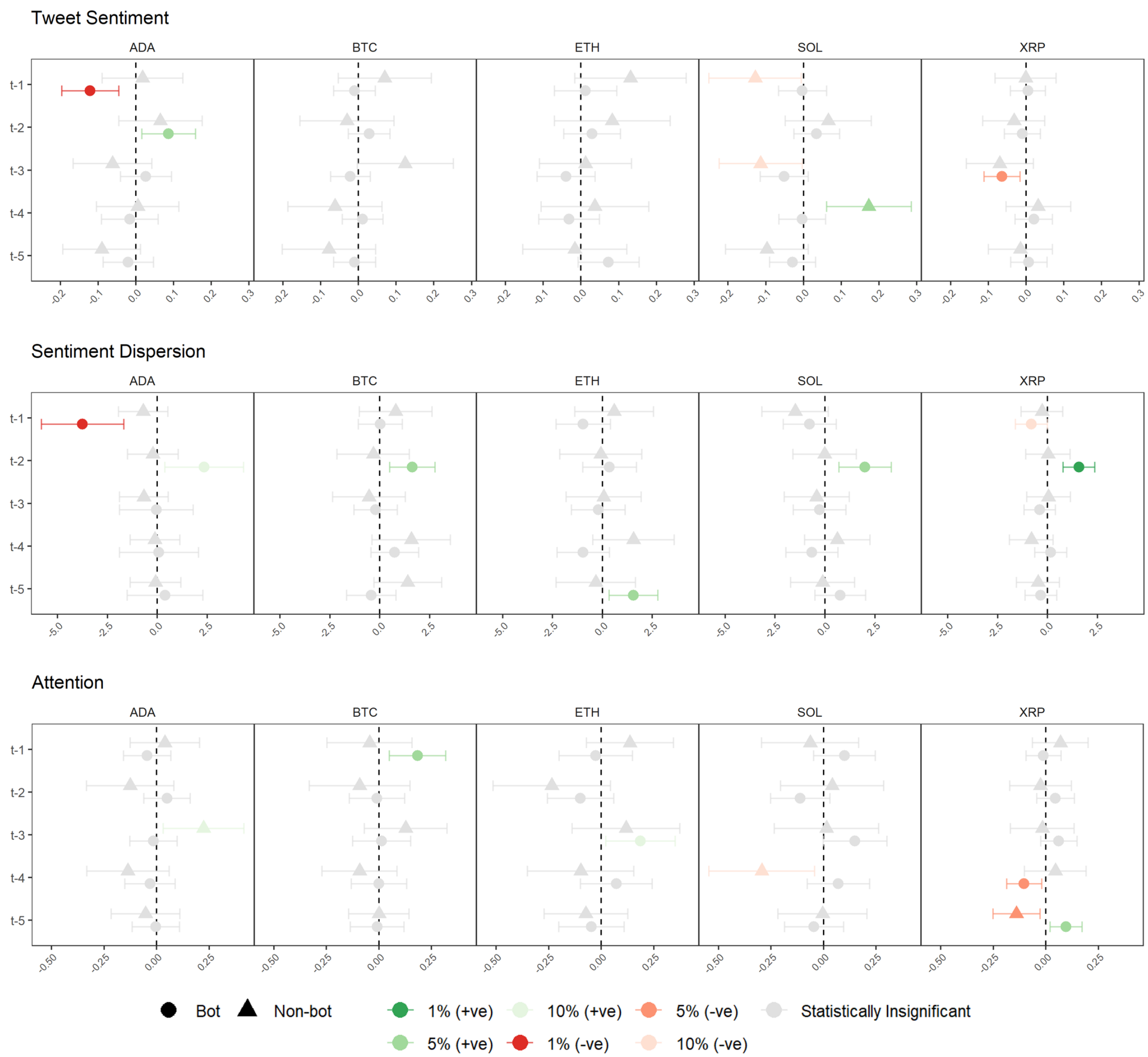
4.2 Bot and Non-bot Split Linear Regression

Estimating the effects of our variables of interest on cryptocurrency prices using regression (1) provide a rough understanding of their general impact on the market. As highlighted in Section 2, we contribute to the literature by treating bot tweets separately from non-bot tweets, and then evaluating their relationships with various cryptocurrencies. Doing so can help better inform the impact of bots on the market and the scope of policies required for them.

We run regression (2) and summarise our results in Figures 6, 7, and 8. For returns, our findings are largely similar to that in the baseline model. It appears that returns are poorly fitted by the three tweet features, regardless of whether they originated from bots or humans. That said, for ADA, the first lag of both tweet sentiment and sentiment dispersion for bot tweets are negative and significant at the 1% level. We hypothesise the following. When there is a large number of positive bot tweets relative to all bot tweets, they mechanically drive up bot sentiment and reduce sentiment dispersion. If such positive bot tweets constitute a majority of all tweets during a specific time period, they would flood the Twitter feeds of investors. This might lead investors to suspect that the tweets originated from bots, thus becoming 'numb' to these large swamps of bot tweets or even treat them as unreliable or malicious. This is the case for ADA, for which the number of bot tweets as a fraction of all tweets is especially high and overwhelmingly positive.[27] Consequently, investors may view these tweets as a negative signal on the strength of the cryptocurrency,

[27] See Figures 3a and 4b.

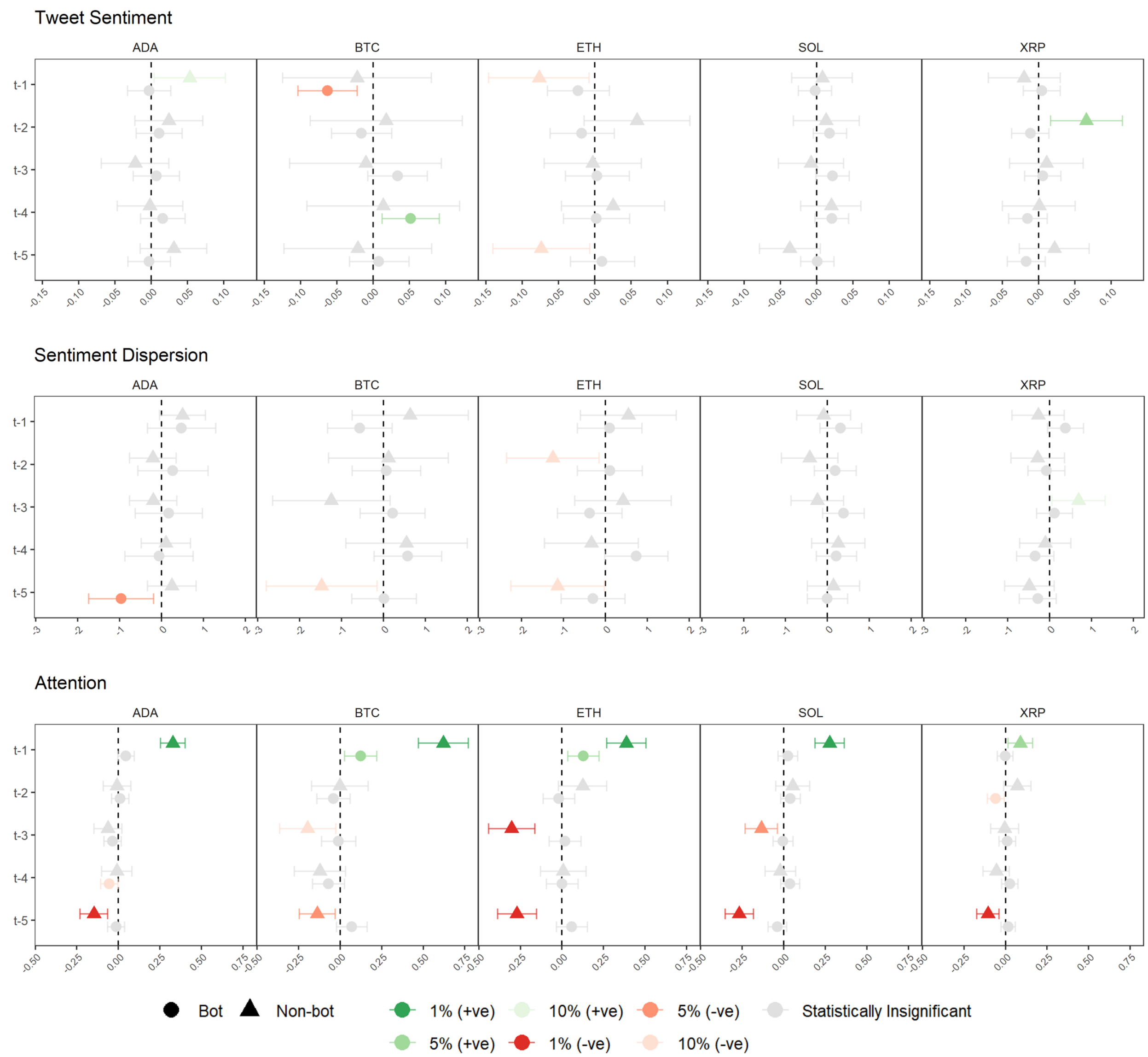
thereby selling the asset and driving down prices (and correspondingly returns). This conceptual framework is also mentioned in Fan et al. (2020), who argued that investors are less likely to act on repeated tweets such as those spread by bots. Separately, while we also find that several coefficients of interest for the other four cryptocurrencies are weakly significant, we do not think there are any systematic relationships that can be derived from these results. Overall, we observe similar trends for cryptocurrencies as with traditional stocks in Fan et al. (2020): sentiment dispersion and attention —regardless from human or bots— are not useful in predicting returns. While they find that tweet sentiment has a significant effect on stock returns, we think the larger fraction of bot tweets for cryptocurrencies help to explain the difference in findings.



Significant positive and negative estimates are highlighted in shades of green and red respectively. Higher statistical significance is highlighted in darker shades. 90% confidence interval for each coefficient estimate is plotted (NW-HAC standard errors).

Figure 6: Log Returns r_{jt}, Bot and Non-bot Split Regression, Hourly Data

In Figure 7, we obtain a clearer picture of what drives the earlier baseline model results for trading volume. It appears that human attention drives trading volume rather than bot attention. The first lag of non-bot attention is positive and highly significant for all five cryptocurrencies (XRP is significant at 5%, the others at 1%), while the same is either non-significant or only weakly significant at 10% for bot attention. Similarly, the later reversal effects are driven by non-bot attention. For example, a 1% increase in the number of non-bot tweets relating to ETH at t is associated with a 0.3% decrease in trading volume at $t + 3$ and $t + 5$; increases in bot attention at t does not lead to any effects on trading volume in later periods.

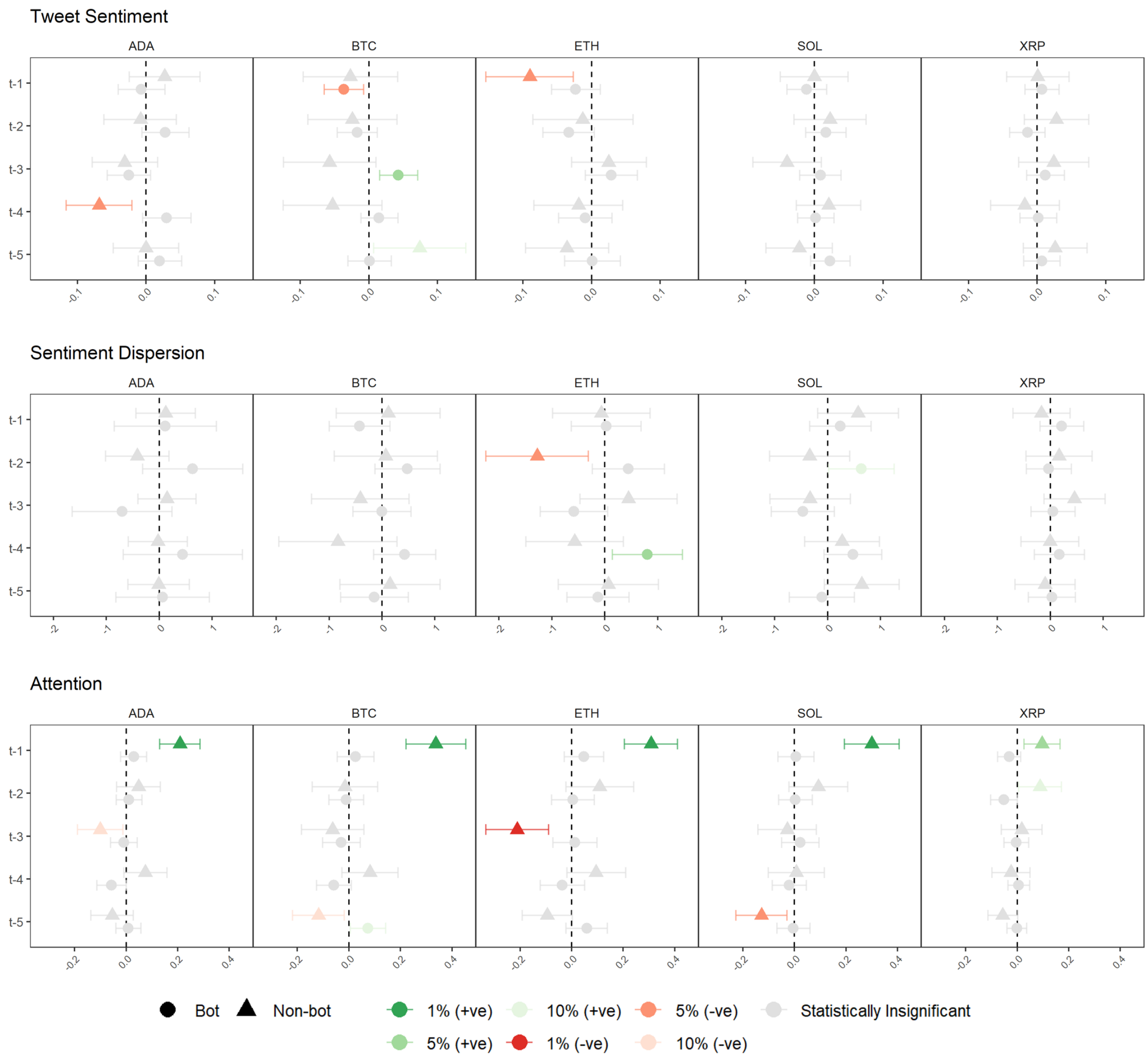


Significant positive and negative estimates are highlighted in shades of green and red respectively. Higher statistical significance is highlighted in darker shades. 90% confidence interval for each coefficient estimate is plotted (NW-HAC standard errors).

Figure 7: Trading Volume v_{jt}^{trade}, Bot and Non-bot Split Regression, Hourly Data

We find this comforting as it does not appear that anyone can stimulate trading activity by simply pumping out large numbers of bot tweets. Nevertheless, these results are a departure from the findings in Fan et al. (2020), which found that tweet sentiment, sentiment dispersion, and attention of both bot and non-bots are all associated with trading volume of stocks. Beyond the fundamental difference between stocks and cryptocurrencies, we also think their empirical model is likely underspecified and their estimates might have absorbed some effects from omitted relevant variables (e.g. lagged terms of trading volume). Their paper also only include one lag of the variables of interest, which we believe is insufficient to capture their dynamic effect on trading volume (i.e. increase then reversal).

Figure 8 shows that our results from the baseline model for price volatility still holds. Here, we find that the relationship between attention and volatility only exists for non-bot attention. In fact, since all but one lag of bot attention are insignificant, we view this as compelling evidence that bot attention has little impact on price volatility, and that our previous full-sample results are purely driven by non-bot attention. Meanwhile, tweet sentiments are generally negatively associated with volatility. However, the estimates are weakly significant and no obvious patterns are detected from these estimates.



Significant positive and negative estimates are highlighted in shades of green and red respectively. Higher statistical significance is highlighted in darker shades. 90% confidence interval for each coefficient estimate is plotted (NW-HAC standard errors).

Figure 8: Volatility vol_{jt}, Bot and Non-bot Split Regression, Hourly Data

In contrast, while Fan et al. (2020) also found a positive association between human attention and volatility, their bot attention and sentiment measures were statistically significant. That said, the same critique we highlighted for trading volume applies. In particular, stock returns have been consistently shown to exhibit volatility persistence and it is therefore necessary to include lags of volatility in their empirical model to minimise bias in estimates.

4.3 Granger-causality Results

Our final piece of analysis revolves around using a VAR to quantify the effect of tweets on the various cryptocurrencies. We first specify a VAR as in equation (3) for each cryptocurrency before conducting Granger-causality tests for our variables of interest on returns, trading volume, and volatility. We report the results of our tests in Figure 9. The findings here are largely confirms our results from the linear regression models. We see that there is no variable in the model that can help predict returns for all five cryptocurrencies. While we find in Figure 6 that the first lag of bot sentiment is negative and highly significant for ADA, bot sentiment does not Granger-cause returns in general.[28] There also appears to be some forecasting power in tweet sentiment and attention for ETH and SOL, driven by significant coefficient estimates between lags 5 to 8. These findings hint at potential longer-term effects of our variables of interest on cryptocurrencies, which we will further explore in Section 4.4. However, given that the models remain poorly fitted with low R^2 values ($< 5\%$), the statistically significant estimates here are unlikely to hold strong forecasting powers. Our findings are largely consistent with Kraaijeveld and De Smedt (2020), who proposed that Twitter does not Granger-cause cryptocurrency returns, but only reacts to them.

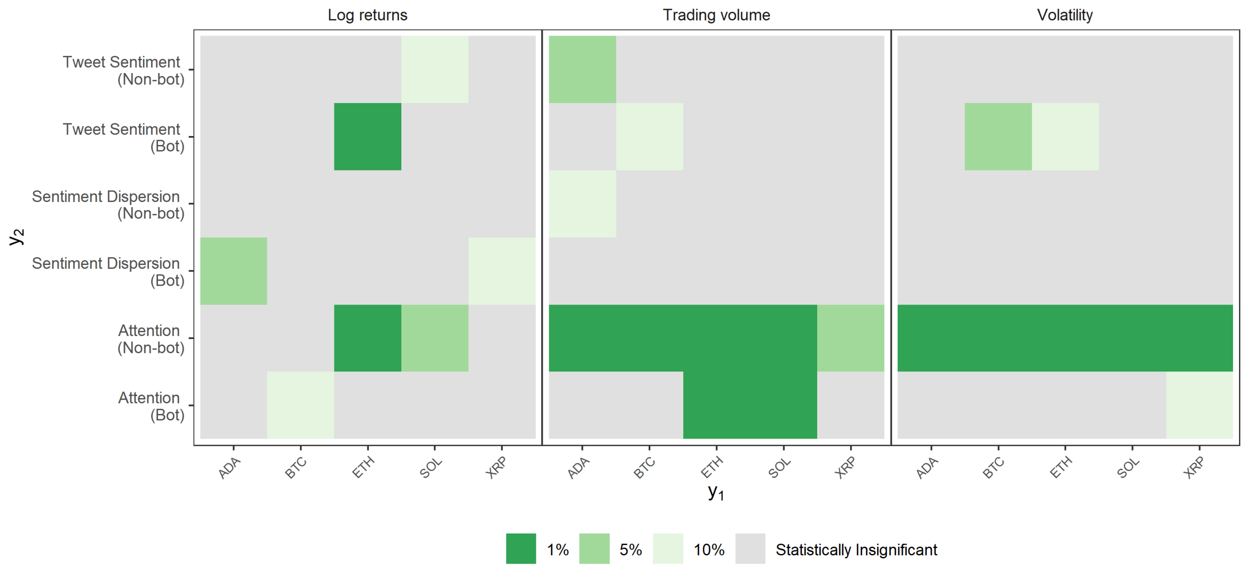
For trading volume and volatility, non-bot attention has forecasting powers across all coins. We even find that for ETH and SOL, there is evidence that bot attention can also help predict trading volume. These results are driven by significant estimates at later lags, providing further evidence that there may be longer-term effects from our variables of interest.

Overall, we believe that the VAR provides a more representative estimation of the relationship between our variables of interest and the various cryptocurrencies because the additional cross-equation terms —which may be correlated with our variables of interest— allows for us to reduce noise and obtain more efficient estimates. In support of this, we do find that returns, trading volume, and volatility have bilateral Granger-causality for a majority of the cryptocurrencies tested.[29] These empirical findings are backed by Suardi et al. (2022), who find a close relationship between returns, trading volume, and volatility.

Regardless, the three empirical models that we use produced largely similar results for every cryptocurrency tested. Beyond the similar results across models, the relationships extracted between the variables of interest and each cryptocurrency are also largely similar across all five cryptocurrencies. These observations and build confidence in our results. Taken together, our models suggest that bot tweets have little impact on the returns of most cryptocurrencies within a shorter timeframe ($<$ 5 hours). There may be some predictability in returns in lower frequency data for specific cryptocurrencies such as ETH and SOL, which we explore in Section 4.4. For trading volume and volatility, non-bot attention is a key driver in predicting future values

[28] We specify a VAR(8) model for ADA. The first lag of bot sentiment remains negative and statistically significant at the 1% level, but later lags are not statistically significant. Detailed results available in Table 9.

[29] See Appendix C.1.



Each cell in the heat map is the conclusion from testing against the null hypothesis that y_2 does not Granger-cause y_1. For ease of interpretability, we only report Granger-causality results for our three variables of interest, split by bot and non-bot tweets. Higher statistical significance is highlighted in darker shades of green. Detailed results are available in Appendix C.1.

Figure 9: Granger-causality, VAR Model, Hourly Data

of these metrics. Finally, it does not appear that sentiment dispersion has any major effects on the five cryptocurrencies.

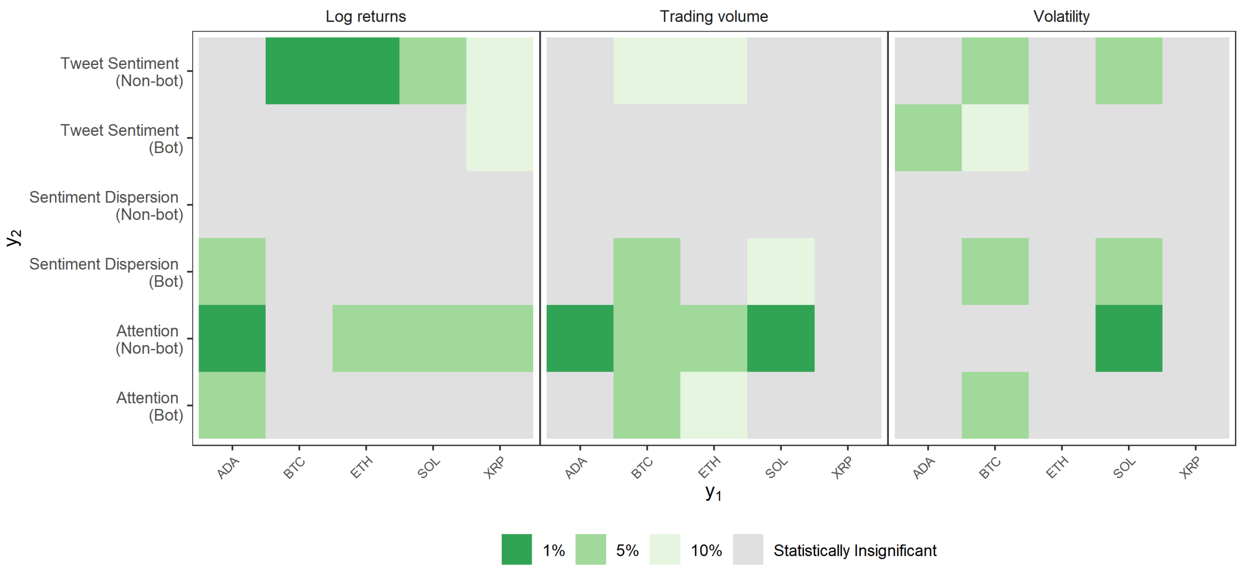
4.4 Low Frequency Data Analysis

Since Twitter is a real-time social media site, we believe a higher frequency analysis (i.e. hourly intervals) is more representative when measuring the relationship between Twitter and cryptocurrencies. Nevertheless, as we observed from the VAR model, there may exist a strong link between the two at a lower frequency. Therefore, as a supplementary exercise, we conduct the VAR and Granger-causality analysis as per (3) on daily data for the same study period.[30]

Figure 10 summarises results of the Granger-causality tests using daily data. We are able to uncover separate trends that appear to be present only in lower frequency data. For returns, we observe that human tweet sentiment appear to have forecasting power for BTC, ETH, and SOL. Specifically, the first lag of human tweet sentiment is positive and significant for all but ADA, while the third lag is usually negative. Furthermore, we observe that human attention also carries predictive power for returns for all but BTC. This suggests that information diffusion from Twitter is slower and the market impact is only experienced at lower frequencies for returns. For trading volume, the conclusions from the high frequency data largely persists, though with smaller significance and weaker magnitude: higher human attention still appears to drive trading volume at the daily level. In particular, only the first lag (previous day) of human attention is positively associated

[30]We do not conduct the analysis on data with even lower frequency (e.g. weekly) because the model would eat up too many degrees of freedom and overfit the data, leading to non-useful results.

with trading volume for all cryptocurrencies, suggesting that human attention is largely a short-term driver of trading volume. The trends for volatility here are quite different from that found in high-frequency data: human attention no longer Granger-causes volatility with daily frequency data for all but SOL. Even then, only the first lag of human attention is significant for SOL. Similar to trading volume, it appears that the impact of human attention on volatility is mostly short-term. Overall, bot tweets do not appear to have any significant impact on the cryptocurrencies except BTC.



Each cell in the heat map is the conclusion from testing against the null hypothesis that y_2 does not Granger-cause y_1. For ease of interpretability, we only report Granger-causality results for our three variables of interest, split by bot and non-bot tweets. Higher statistical significance is highlighted in darker shades of green. Detailed results are available in Appendix C.2.

Figure 10: Granger-causality, VAR model, Daily Data

5 Discussion

While we have taken careful steps in our empirical modelling and analysis, limitations still exist. In this section, we discuss the potential limitations of our research, steps taken to address these limitations, and suggest avenues for future research.

5.1 Classification of Bots

A crucial step in our analysis is to separate tweets into those that are bot tweets and those that are human tweets. To this end, we used the Botometer API to score each Twitter handle, before selecting a threshold to differentiate between humans and bots. Since Botometer uses the 200 most recent tweets of a handle for analysis, the Botometer score can change over time; the transient nature of bot scores is also empirically shown in Yang et al. (2022). As we are conducting the bot classification activity up to five months after the initial tweet, the Botometer scores may be inaccurate. Furthermore, our selected threshold value of 0.49

may be too high, leading to many false negatives (i.e. actual bots being classified as humans). It is therefore reasonable to expect that the classification process —from both the API scoring and our threshold value— may lead to some incorrect classification of tweets.

As per Yang et al. (2022), we followed the best practice of conducting the bot classification exercise immediately after the data collection process to mitigate the issue of inaccurate bot scores. Separately, we conducted robustness checks on the threshold value for bot classification. In addition to our primary threshold of 0.49, we also tested other threshold values of 0.43 and 0.46.[31] The corresponding results from these additional threshold values are reassuringly similar to that from the primary threshold value, building confidence in our findings. Ultimately, we believe this issue is likely to affect only very few accounts: if an account starts as a human or bot, then it is likely to remain the same over time in most cases. Only the difficulty in identifying whether it is a bot may change a little as bots become more sophisticated over time; however, we think the above robustness checks and the short duration of this study sufficiently mitigate this concern.

5.2 'Bot Effect' Interpretation

In Section 4, we found that there are some limited effects from bot tweets on specific cryptocurrencies. However, we cannot definitively conclude that malicious bots originating from bad actors are the ones driving these relationships. It may be possible that non-malicious bots, such as those that report cryptocurrency transactions and news, aid in the transfer of information and help to make the market more transparent. The total 'bot effect' may be purely driven by these non-malicious bots, while malicious bots do not actually have any effects on prices. Therefore, even though bot sentiment dispersion and attention forecast BTC trading volume and volatility (for example), we cannot argue that any bad actors can simply manipulate the market by flooding Twitter with bot tweets. Likewise, for those cryptocurrencies with non-significant relationships with bot tweets, it could be that non-malicious bots may have a positive effect on returns, while malicious bots are more obvious to detect for humans and, for reasons that we mention in Section 4.2, may have a negative effect. Aggregated together, the total effect then would be around zero.

Prior research has highlighted that bots, regardless of type, are difficult to identify. As such, malicious bots could behave like a non-malicious bot (or even human). Given the difficulty in accurately separating malicious bots from non-malicious ones, we do not further segment bot tweets into these categories. We believe our results are nonetheless informative in providing an insight into the relationship between bots in general and the various cryptocurrencies.

5.3 Structural Breaks in Cryptocurrency Prices

It is well-established that cryptocurrency prices are highly volatile and investors can experience large swings in returns in a short period of time. Bouri et al. (2019) have argued that the dynamics of BTC exhibits structural breaks, and accounting for these breaks is necessary for valid inferences. While there is no clear consensus if these 'breaks' are truly structural or are simply shocks that can be explained by appropriate

[31] As mentioned in Section 3.1.3, the recommended optimal threshold value is between 0.43 and 0.49. We therefore test values that lie within this range. We even explored thresholds outside of this range at 0.3 and 0.6. However, the classification accuracy at these thresholds appear to be very low based on our anecdotal inspections.

factors, we chose to restrict our sample period to five months to minimise the likelihood of capturing any structural breaks while still obtaining a large enough sample for our empirical models. That said, we believe one should still practice caution when extrapolating our findings for long horizons.

5.4 Extensions

Market-beating trading strategy. Our findings above indicate that a sophisticated trader could potentially exploit the forecasting power of tweets to beat the market. We believe tweet features such as human tweet sentiments and attention measures could potentially be used to create profitable trading strategies. A simple strategy could be the following. Every day, rank all cryptocurrencies (excluding ADA) by the change in previous day's non-bot sentiment measure. Based on these rankings, one can form value-weighted portfolios and hold the position for one day, before rebalancing the portfolio on the following day.

Heterogeneous impact of tweets. We have made a clear distinction between human and bot tweets in our paper. However, we treat all tweets in our data equally. We recognise that the effect of a tweet originating from different users may not be the same — content originating from popular accounts (e.g. celebrities and influencers) have been shown to have better reach, engagement, and can influence audience behaviour because they are seen to have higher credibility (Zaheer, 2018). For example in 2020, Tesla's CEO Elon Musk —who had over 33m followers then— tweeted that the Tesla stock is too high in his view.[32] On that same day, share price of Tesla dropped as much as 12%, stemming from a massive sell-off (Bursztynsky, 2020). Therefore, we believe an extension to our research could treat regular and popular users (both humans and bots) differently and then evaluate the potentially heterogeneous impact of their tweets on the market.

Lead-lag relationship between cryptocurrencies. As we have explored in Section 3.2, the evolution of returns, trading volume, and volatility appear to be similar across several cryptocurrencies.[33]. We observe in the stock market that lead-lag effects are commonly found, so we might expect these effects given the similarities between stocks and cryptocurrencies.[34] Given the dominance of BTC and ETH in terms of market capitalisation, we may expect these bigger cryptocurrencies to drive smaller ones. As such, a simple extension to our existing analysis is to include lags of other cryptocurrencies in the linear regression models to better control for these relationships. A bigger VAR can also be considered given a sufficiently large dataset.

Natural experiments to identify causal effects. While we have included in our empirical models lagged variables of interest and a set of controls, we cannot claim that the estimated effects from our models are necessarily causal. For instance, significant Granger-causality results are only interpreted as having forecasting significance. For researchers interested in a causal effect of tweets on cryptocurrencies, they may want to exploit an exogenous shock to Twitter and observe how that shock affected cryptocurrency prices. For example, one could compare the difference in cryptocurrency market behaviour during a Twitter outage to non-outage periods. This exact approach is used to identify Twitter's causal impact on stock market activity in Rakowski et al. (2021), while Kuchler et al. (2022) used Hurricane Sandy as their natural

[32] See `https://twitter.com/elonmusk/status/1256239815256797184`.

[33] See Figures 5, 11, and 12.

[34] See Parsons et al. (2020) for geographic lead-lags, Cohen and Frazzini (2008) for customer-supplier lead-lags, and Moskowitz and Grinblatt (1999) for industry lead-lags.

experiment to identify the effect of geographical proximity on liquidity provision from investors.

6 Conclusions

Analysing the features of human and bot tweets of related cryptocurrencies provide an informative view of how they are interconnected to the cryptocurrency market. Previous research in this area have explored relationships between various social media sites and cryptocurrencies. They explored how attention, sentiment, and sentiment dispersion on these sites affected cryptocurrency prices, mostly with a focus on BTC. Similarly, there is also research exploring the relationship between Twitter and the stock market. Such studies play an important role in helping social media sites and regulators better understand the interplay of social media and asset prices. They can inform policy decisions and help set legal frameworks as to how and what to regulate. For retail and institutional investors, these studies can also help shape their trading strategies to exploit potential market inefficiencies and earn abnormal profits.

While previous research highlights the links between cryptocurrencies and tweets in general, they do not distinguish between bot and human tweets. Many of the sentiment analysis done also used a less sophisticated or less context-relevant dictionary, leading to potentially erroneous results. We bridge the gap in the existing literature by (i) treating bot and human tweets as separate and evaluating their effects separately, and (ii) employing a two-step hybrid methodology with a manually compiled cryptocurrency lexicon in our paper. To that end, we developed two linear regression models and a VAR model to quantify the relationships. We then studied the coefficient estimates in the linear regression models and conducted Granger-causality tests on the VAR model.

Our paper finds that human tweet volume is positively associated with trading volume and volatility in the next hour, before having a reversal effect after a few hours. With daily data, returns are positively associated with human tweet sentiments for most cryptocurrencies, while the relationships between human attention and trading volume/volatility become less robust. In contrast, bot tweets have, in general, very little impact on cryptocurrency returns, trading volume, and volatility regardless of data frequency. However, we have uncovered bot tweets and cryptocurrency-specific relationships. For hourly data, ETH and SOL bot tweet volume have forecasting powers for their trading volume, and the first lag of bot sentiment and sentiment dispersion are negatively associated with returns for ADA. For daily data, bot sentiment dispersion and attention predict both trading volume and volatility for BTC. All in all, we view our findings as evidence that the links between Twitter and cryptocurrency prices are largely driven by human tweets rather than bot tweets; while bot tweets may impact some specific cryptocurrencies, they appear to be largely 'filtered out' by investors and thereby do not drive returns, trading volume, or volatility.

Our findings may prove useful for social media companies and policymakers alike. We think that the lack of effect from bot tweets on cryptocurrencies suggests that no bad actors can easily manipulate the market by flooding Twitter with bot tweets of a certain sentiment. With the limited amount of regulation on cryptocurrencies at current, this issue does not appear to be one that needs to be immediately addressed. Regardless, the threat of bot tweets and potential market manipulation still exists: we know that bots are getting more sophisticated over time and individuals are finding it increasingly difficult to differentiate between bots and humans. If bad actors are able to effectively mask bot tweets as real tweets, undesirable market outcomes can still occur. As such, social media companies should still allocate resources to identifying bots and flagging these accounts accordingly. Furthermore, since we also find real relationships between human tweets and cryptocurrencies, this research is also useful for traders who might be able to utilise this knowledge to beat the market. Finally, our novel approach to extracting sentiment from tweets can serve as a framework for future research on sentiment extraction from Twitter.

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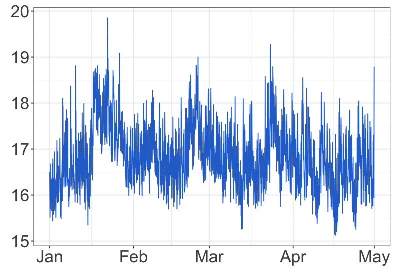
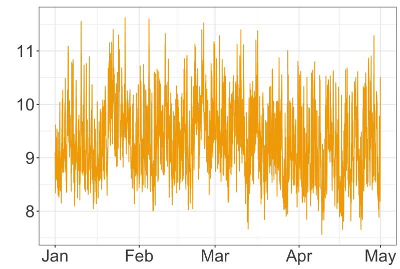
A Trading Volume and Volatility



(a) ADA



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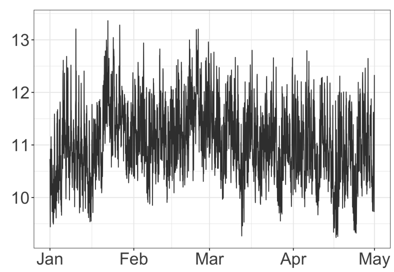
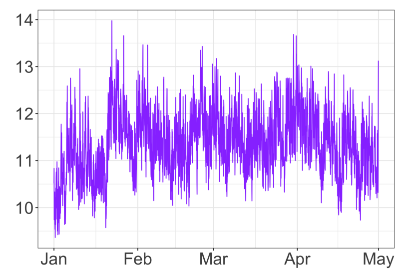
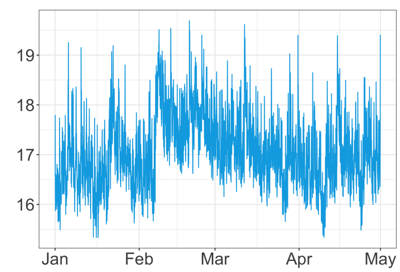


(c) ETH



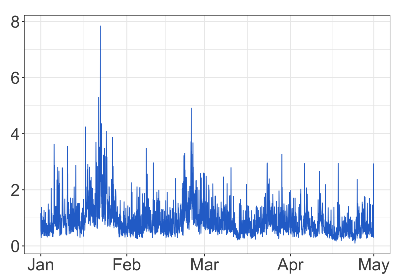
(d) SOL



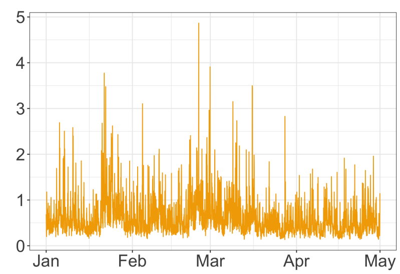
(e) XRP

Figure 11: Trading Volume Split by Cryptocurrency

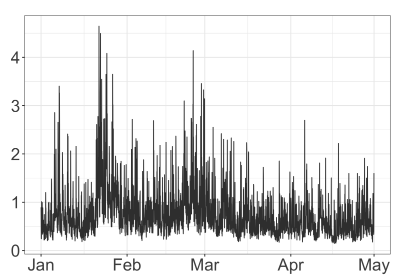
Trading volume, denoted by v_{jt}^{trade}, is the log trading volume of cryptocurrency j at time t.



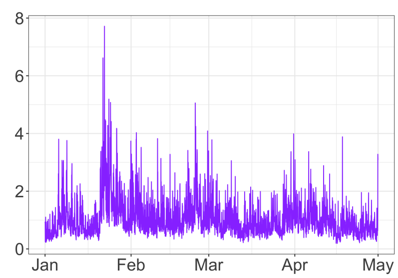
(a) ADA



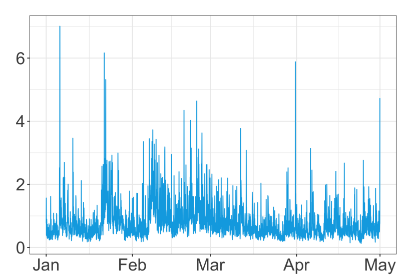
(b) BTC



(c) ETH



(d) SOL



(e) XRP

Figure 12: Volatility Split by Cryptocurrency

Volatility is defined as $vol_{jt} = \frac{100}{2\sqrt{\ln 2}}\left(p_{jt}^{\text{high}} - p_{jt}^{\text{low}}\right)$, where p_{jt}^{high} = log of high price of cryptocurrency j at t and p_{jt}^{low} = log of low price of cryptocurrency j at t.

B ADF Tests

Table 7: ADF Tests: Variables of Interest

Cryptocurrency	Sample	Series	Lags	Test Statistic	Decision (at 1%)
ADA	Full Sample	Tweet Sentiment	11	-11.43	
		Sentiment Dispersion	12	-6.75	No Unit Root
		Attention	11	-10.95	
	Non-bot	Tweet Sentiment	12	-9.98	
		Sentiment Dispersion	11	-10.30	No Unit Root
		Attention	12	-10.78	
	Bot	Tweet Sentiment	8	-10.31	
		Sentiment Dispersion	12	-4.08	No Unit Root
		Attention	12	-8.41	
BTC	Full Sample	Tweet Sentiment	8	-9.42	
		Sentiment Dispersion	6	-10.61	No Unit Root
		Attention	11	-11.72	
	Non-bot	Tweet Sentiment	11	-7.99	
		Sentiment Dispersion	11	-8.03	No Unit Root
		Attention	12	-11.58	
	Bot	Tweet Sentiment	11	-10.19	
		Sentiment Dispersion	8	-12.20	No Unit Root
		Attention	11	-8.77	
ETH	Full Sample	Tweet Sentiment	12	-8.39	
		Sentiment Dispersion	12	-9.22	No Unit Root
		Attention	12	-11.50	
	Non-bot	Tweet Sentiment	12	-7.60	
		Sentiment Dispersion	12	-9.52	No Unit Root
		Attention	12	-11.97	
	Bot	Tweet Sentiment	12	-8.10	
		Sentiment Dispersion	12	-7.60	No Unit Root
		Attention	12	-9.16	
SOL	Full Sample	Tweet Sentiment	6	-14.00	
		Sentiment Dispersion	6	-14.49	No Unit Root
		Attention	12	-8.35	
	Non-bot	Tweet Sentiment	6	-14.43	
		Sentiment Dispersion	6	-15.12	No Unit Root
		Attention	12	-8.91	
	Bot	Tweet Sentiment	6	-14.89	
		Sentiment Dispersion	12	-7.90	No Unit Root
		Attention	12	-7.98	
XRP	Full Sample	Tweet Sentiment	5	-13.80	
		Sentiment Dispersion	11	-8.43	No Unit Root
		Attention	2	-13.47	
	Non-bot	Tweet Sentiment	8	-11.36	
		Sentiment Dispersion	12	-8.14	No Unit Root
		Attention	9	-12.30	
	Bot	Tweet Sentiment	5	-18.25	
		Sentiment Dispersion	11	-9.57	No Unit Root
		Attention	11	-9.55	

The constant with time trend model is used based on a visual inspection of the time series plot of the corresponding series. Lag length is determined based on AIC. Decision is arrived after comparing the Test Statistic to the appropriate MacKinnon's Critical Value.

Table 8: ADF Tests: Dependent Variables

Cryptocurrency	Series	Lags	Test Statistic	Decision (at 1%)
ADA	Log returns	3	-25.42	
	Log trading volume	11	-7.58	No Unit Root
	Price volatility	12	-7.64	
BTC	Log returns	1	-36.55	
	Log trading volume	3	-15.45	No Unit Root
	Price volatility	8	-12.24	
ETH	Log returns	0	-53.72	
	Log trading volume	4	-13.73	No Unit Root
	Price volatility	9	-10.18	
SOL	Log returns	0	-54.68	
	Log trading volume	10	-8.76	No Unit Root
	Price volatility	12	-7.65	
XRP	Log returns	10	-16.43	
	Log trading volume	12	-7.18	No Unit Root
	Price volatility	12	-8.14	

The constant, no trend model is used based on a visual inspection of the time series plot of the corresponding series. Lag length is determined based on AIC. Decision is arrived after comparing the Test Statistic to the appropriate MacKinnon's Critical Value.

C Full Empirical Results

C.1 VAR and Granger-causality Tests, Hourly Data

Table 9: Granger-causality Tests and VAR Coefficient Estimates, Hourly Data, ADA

Equation	Excluded	Test statistic	p	Lag Number							
				1	2	3	4	5	6	7	8
Log returns	Trading volume	1.154	8	-0.088	0.067	-0.055	0.129*	-0.126*	-0.014	0.132*	-0.044
	Volatility	2.281**	8	0.068	-0.139**	0.195***	-0.093	0.062)	-0.021	-0.053	-0.021
	Attention (Bot)	0.453	8	-0.044	0.061	-0.02	-0.005	0.03	-0.002	-0.025	-0.101
	Attention (Non-bot)	0.78	8	0.101	-0.108	0.078	-0.14	-0.099	0.12	0.14	-0.125
	Sentiment Dispersion (Bot)	2.327**	8	-4.022***	2.319*	-0.277	-0.049	-0.617)	1.904	0.944	-1.256
	Sentiment Dispersion (Non-bot)	0.348	8	-0.903	-0.057	-0.688	-0.14	-0.036	-0.057	0.509	-0.328
	Tweet Sentiment (Bot)	1.453	8	-0.124***	0.08*	0.038	-0.018	-0.048	0.041	0.009	-0.011
	Tweet Sentiment (Non-bot)	0.512	8	0.016	0.069	-0.05	0.021	-0.081	-0.042	0.06	-0.003
Trading volume	Log returns	1.948**	8	-0.009	-0.02**	0	-0.007	-0.015*	-0.005	0.008	0.013
	Volatility	1.054	8	0.023	0.003	-0.021	-0.028	-0.044	0.003	-0.011	-0.021
	Attention (Bot)	1.035	8	0.048	0.01	-0.038	-0.055	-0.019	-0.003	0.047	-0.007
	Attention (Non-bot)	7.974***	8	0.271***	-0.018	-0.062	0.018	-0.081	-0.024	-0.047	-0.043
	Sentiment Dispersion (Bot)	1.129	8	0.233	0.048	0.083	-0.1	-0.898*	-0.546	0.385	1.048**
	Sentiment Dispersion (Non-bot)	1.699*	8	0.532	-0.223	-0.16	0.147	0.383	-0.364	-0.893**	-0.456
	Tweet Sentiment (Bot)	0.849	8	-0.008	0.005	0.005	0.015	-0.003	-0.008	-0.025	0.041**
	Tweet Sentiment (Non-bot)	2.089**	8	0.063**	0.024	-0.025	-0.006	0.03	0.016	-0.088***	-0.019
Volatility	Log returns	4.562***	8	-0.022**	-0.022**	-0.019**	-0.018**	-0.028***	-0.016*	0.01	0.011
	Trading volume	5.194***	8	0.167***	-0.086**	-0.018	-0.046	0.036)	0.035	0.004	0.053*
	Attention (Bot)	0.728	8	0.009	-0.008	-0.004	-0.044	-0.004	-0.044	0.043	0.041
	Attention (Non-bot)	3.715***	8	0.168***	0.047	-0.086	0.069	-0.057	0.029	-0.067	-0.023
	Sentiment Dispersion (Bot)	1.476	8	0.365	0.443	-0.789	0.207	0.077	-0.135	0.737	0.151
	Sentiment Dispersion (Non-bot)	0.594	8	0.255	-0.521	0.199	0.096	0.176	-0.315	-0.339	-0.264
	Tweet Sentiment (Bot)	1.171	8	0.01	0.023	-0.028	0.022	0.018	0.009	-0.017	0.019
	Tweet Sentiment (Non-bot)	1.076	8	0.041	-0.015	-0.024	-0.059*	0.004	0.008	-0.042	-0.014

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 10: Granger-causality Tests and VAR Coefficient Estimates, Hourly Data, BTC

Equation	Excluded	Test statistic	p	Lag Number							
				1	2	3	4	5	6	7	8
Log returns	Trading volume	0.645	8	-0.062	0.023	-0.054	0.064	-0.047	0.023	-0.025	-0.004
	Volatility	1.967**	8	0.146**	-0.038	0.11*	-0.11*	0.078	0.001	-0.003	0.069
	Attention (Bot)	1.926*	8	0.152*	0.005	-0.029	-0.013	-0.068	0.154*	0.124	-0.079
	Attention (Non-bot)	1.495	8	-0.094	-0.046	0.136	-0.015	0.035	-0.33**	0.228	-0.129
	Sentiment Dispersion (Bot)	1.374	8	0.183	1.644**	-0.191	0.847	-0.334	-0.189	-0.667	0.549
	Sentiment Dispersion (Non-bot)	0.834	8	0.705	-0.342	-0.47	1.339	1.891	-1.04	0.394	0.38
	Tweet Sentiment (Bot)	0.305	8	-0.017	0.032	-0.033	0.011	-0.005	0.018	0.017	-0.024
	Tweet Sentiment (Non-bot)	1.013	8	0.084	-0.02	0.154*	-0.059	-0.024	-0.156*	-0.019	-0.001
Trading volume	Log returns	1.104	8	-0.019	-0.025*	-0.004	0.001	-0.01	-0.018	-0.007	0.022
	Volatility	3.242***	8	-0.039	-0.115**	-0.096**	-0.041	0.008)	-0.007	-0.059	0.077*
	Attention (Bot)	1.167	8	0.154***	-0.017	0.002	-0.033	0.058	-0.06	-0.041	-0.036
	Attention (Non-bot)	11.305***	8	0.603***	0.034	-0.151	-0.039	-0.147	-0.005	-0.072	-0.074
	Sentiment Dispersion (Bot)	0.685	8	-0.542	-0.019	0.043	0.404	0.057	-0.434	0.856*	-0.033
	Sentiment Dispersion (Non-bot)	1.362	8	0.171	-0.133	-1.514*	0.467	-0.74	0.042	-1.618*	1.603*
	Tweet Sentiment (Bot)	1.904*	8	-0.052**	-0.014	0.03	0.047*	-0.009	0.055**	-0.016	-0.016
	Tweet Sentiment (Non-bot)	0.39	8	-0.022	0.008	-0.042	-0.001	0.045	0.008	-0.049	-0.054
Volatility	Log returns	1.669	8	-0.001	-0.022**	-0.02*	-0.008	-0.014)	-0.016	0.009	0.011
	Trading volume	1.738*	8	0.006	0.014	0.016	0.008	0.008	0.045*	0.008	0.014
	Attention (Bot)	1.018	8	0.05	-0.012	-0.026	-0.051	0.084*	-0.066	-0.026	0.048
	Attention (Non-bot)	5.499***	8	0.325***	-0.047	-0.077	0.053	-0.098	0.021	0.054	-0.089
	Sentiment Dispersion (Bot)	0.862	8	-0.311	0.528	-0.001	0.51	-0.107	-0.21	0.36	0.059
	Sentiment Dispersion (Non-bot)	1.232	8	-0.221	-0.029	-0.556	-0.822	0.091	0.84	-0.907	1.232**
	Tweet Sentiment (Bot)	2.144**	8	-0.028	-0.018	0.041**	0.014	-0.013	0.045**	-0.02	-0.022
	Tweet Sentiment (Non-bot)	0.704	8	-0.021	0	-0.048	-0.056	0.067	0.045	-0.012	-0.001

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 11: Granger-causality Tests and VAR Coefficient Estimates, Hourly Data, XRP

Equation	Excluded	Test statistic	p	Lag Number					
				1	2	3	4	5	6
Log returns	Trading volume	1.245	6	-0.058	-0.037	-0.048	-0.009	0.107*	-0.034
	Volatility	2.87***	6	0.143**	-0.032	0.145**	0.002	-0.099*	-0.023
	Attention (Bot)	1.476	6	-0.013	0.058	0.064	-0.088	0.116**	-0.047
	Attention (Non-bot)	0.788	6	0.038	0.019	-0.069	0.064	-0.107	-0.037
	Sentiment Dispersion (Bot)	2.076*	6	-0.878*	1.523***	-0.337	0.136	-0.282	-0.019
	Sentiment Dispersion (Non-bot)	0.479	6	-0.284	0.122	0.011	-0.791	-0.419	-0.269
	Tweet Sentiment (Bot)	1.069	6	-0.001	-0.001	-0.069**	0.025	0.002	-0.018
	Tweet Sentiment (Non-bot)	0.46	6	-0.003	-0.021	-0.071	0.044	-0.013	-0.02
Trading volume	Log returns	0.763	6	0.009	-0.005	0.016	-0.003	0.008	-0.004
	Volatility	2.628**	6	0.026	-0.029	-0.008	-0.066**	-0.036	-0.031
	Attention (Bot)	0.914	6	0	-0.059*	0.011	0.019	0.019	-0.022
	Attention (Non-bot)	2.773**	6	0.063	0.07	-0.004	-0.027	-0.048	-0.06
	Sentiment Dispersion (Bot)	0.662	6	0.375	-0.048	0.122	-0.25	-0.218	-0.086
	Sentiment Dispersion (Non-bot)	1.041	6	-0.342	-0.264	0.719*	-0.008	-0.376	-0.362
	Tweet Sentiment (Bot)	0.544	6	0	-0.012	0.006	-0.015	-0.018	0.008
	Tweet Sentiment (Non-bot)	1.1	6	-0.026	0.063**	0.007	0.006	0.02	0.007
Volatility	Log returns	1.976*	6	-0.001	-0.024**	-0.008	-0.024**	0.004	-0.008
	Trading volume	4.963***	6	0.125***	-0.034	-0.03	0.025	0.009	0.033
	Attention (Bot)	1.873*	6	-0.041	-0.052*	-0.001	-0.005	0	-0.015
	Attention (Non-bot)	3.352***	6	0.07	0.09*	0.02	-0.013	-0.026	-0.039
	Sentiment Dispersion (Bot)	0.555	6	0.307	-0.06	0.025	0.24	0.114	0.144
	Sentiment Dispersion (Non-bot)	0.426	6	-0.22	0.175	0.467	-0.064	-0.132	-0.318
	Tweet Sentiment (Bot)	1.033	6	0.005	-0.014	0.013	0.001	0.004	0.034**
	Tweet Sentiment (Non-bot)	0.635	6	-0.001	0.04	0.02	-0.015	0.019	-0.034

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 12: Granger-causality Tests and VAR Coefficient Estimates, Hourly Data, ETH

Equation	Excluded	Test statistic	p	Lag Number											
				1	2	3	4	5	6	7	8	9	10	11	12
Log returns	Trading volume	1.404	12	-0.094*	0.062	-0.131**	0.097*	-0.002	-0.013	0.008	0.023	-0.04	0.021	-0.054	0.137***
	Volatility	3.277***	12	0.169***	-0.112*	0.23***	-0.088	-0.021	-0.087	0.003	0.016	0.192***	-0.069	0.052	-0.058
	Attention (Bot)	1.215	12	-0.069	-0.093	0.087	0.01	-0.095	0.155	0.239**	0.056	0.009	-0.075	0.043	-0.206**
	Attention (Non-bot)	3.313***	12	0.021	-0.179	0.145	-0.024	0.179	-0.304*	0.12	-0.246	-0.517***	0.519***	-0.222	0.151
	Sentiment Dispersion (Bot)	1.175	12	-0.933	0.029	-0.09	-0.75	1.249	1.828**	-0.318	0.009	-0.538	-1.63*	0.957	-0.192
	Sentiment Dispersion (Non-bot)	1.172	12	0.152	-0.039	0.027	1.304	-0.256	-1.306	1.474	2.966**	1.221	-0.661	-1.662	-0.151
	Tweet Sentiment (Bot)	2.199***	12	0.027	0.051	-0.023	-0.008	0.089*	0.112**	-0.075	-0.128***	-0.077	-0.024	0.009	0.006
	Tweet Sentiment (Non-bot)	1.256	12	0.073	0.097	-0.01	0.05	0.006	-0.023	0.001	0.169**	0.033	0.086	-0.063	-0.003
Trading volume	Log returns	2.523***	12	-0.037***	-0.028**	-0.008	-0.015	-0.015	-0.014	-0.02*	0.006	-0.007	0.015	-0.016	0.004
	Volatility	1.467	12	0.037	-0.039	-0.059	-0.059	-0.002	-0.016	-0.005	0.044	0.092**	0.012	-0.006	-0.054
	Attention (Bot)	2.336***	12	0.103*	-0.023	0.009	-0.008	0.056	0.09	0.082	-0.088	-0.033	-0.112*	-0.087	0.185***
	Attention (Non-bot)	6.174***	12	0.294***	0.118	-0.236***	0.069	-0.095	0.093	-0.205**	0.01	-0.302***	0.044	0.048	0.033
	Sentiment Dispersion (Bot)	0.708	12	0.221	0.135	-0.429	0.889*	-0.124	-0.443	0.057	0.259	-0.744	-0.11	0.214	0.442
	Sentiment Dispersion (Non-bot)	0.948	12	0.363	-1.362*	0.544	-0.229	-0.434	-1.221*	-0.511	0.424	0.126	-0.226	0.378	0.382
	Tweet Sentiment (Bot)	1.264	12	-0.022	-0.021	-0.007	0.009	0.004	0.035	-0.076***	0.025	0.005	-0.041	0.048*	0.016
	Tweet Sentiment (Non-bot)	1.293	12	-0.085*	0.065	0.007	0.032	-0.054	0.042	0.037	0.041	-0.013	0	-0.068	-0.082*
Volatility	Log returns	4.198***	12	-0.036***	-0.032***	-0.03***	-0.018*	-0.022**	-0.015	-0.005	0.012	-0.015	0.006	-0.004	-0.005
	Trading volume	0.939	12	0.054**	-0.059**	0.035	0.021	-0.024	-0.019	0.011	0.016	-0.008	0.018	0.004	0.001
	Attention (Bot)	0.815	12	0.026	0.017	0.014	-0.044	0.071	0.019	0.06	-0.029	-0.032	-0.064	-0.049	0.069
	Attention (Non-bot)	4.732***	12	0.234***	0.118	-0.213***	0.107	0.023	0.094	-0.201***	0.054	-0.189**	0.076	0.034	-0.027
	Sentiment Dispersion (Bot)	0.855	12	0.182	0.514	-0.52	0.84**	-0.102	0.002	-0.006	-0.381	0.118	0.111	-0.544	0.375
	Sentiment Dispersion (Non-bot)	1.092	12	-0.215	-1.417**	0.68	-0.501	0.642	-0.522	0.065	0.04	0.015	0.534	-0.624	-0.48
	Tweet Sentiment (Bot)	1.675*	12	-0.015	-0.035	0.023	-0.005	-0.008	0.016	-0.067***	0.016	0.018	-0.04*	0.051**	0.012
	Tweet Sentiment (Non-bot)	1.469	12	-0.084**	0.006	0.053	-0.003	-0.01	0.017	0.017	0.059	-0.02	0.006	-0.058	-0.078**

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 13: Granger-causality Tests and VAR Coefficient Estimates, Hourly Data, SOL

Equation	Excluded	Test statistic	p	Lag Number											
				1	2	3	4	5	6	7	8	9	10	11	12
Log returns	Trading volume	2.364***	12	-0.072	0.067	-0.17**	0.035	-0.123	0.123	0.067	-0.034	-0.146*	0.2**	-0.034	0.206***
	Volatility	3.2***	12	0.031	-0.083	0.184***	0.044	0.064	-0.111*	-0.068	-0.031	0.154**	-0.22***	0.129**	-0.119*
	Attention (Bot)	0.8	12	0.099	-0.135	0.176*	0.06	0.013	-0.054	0.075	-0.061	-0.066	0.057	0.021	0.017
	Attention (Non-bot)	1.963**	12	0.074	0.033	-0.114	-0.355**	0.015	0.102	-0.106	0.002	-0.171	0.375**	-0.423***	0.112
	Sentiment Dispersion (Bot)	1.335	12	-0.892	1.805**	-0.367	-0.232	0.559	0.051	-0.219	0.732	-0.287	-0.113	2.262***	0.092
	Sentiment Dispersion (Non-bot)	0.605	12	-1.024	0.295	-0.35	1.136	-0.174	-1.469	-0.16	-0.68	-1.126	0.949	-0.253	-0.415
	Tweet Sentiment (Bot)	1.22	12	-0.007	0.046	-0.055	0.014	-0.038	0.05	-0.032	-0.045	-0.066*	0.025	0.011	0.076**
	Tweet Sentiment (Non-bot)	1.723*	12	-0.125*	0.066	-0.108	0.21***	-0.12	-0.068	0.069	-0.032	-0.008	0.074	0.005	-0.118*
Trading volume	Log returns	0.863	12	-0.003	-0.018**	0.004	-0.003	-0.002	0.004	-0.003	-0.001	0.009	0.006	0.003	-0.005
	Volatility	1.181	12	0.041*	-0.037	-0.047*	-0.017	-0.006	0.001	-0.021	-0.012	0.009	0.033	-0.01	0.018
	Attention (Bot)	2.566***	12	-0.004	0.02	-0.01	0.024	-0.03	-0.025	0.103***	0.035	-0.103***	-0.017	0.008	0.122***
	Attention (Non-bot)	8.247***	12	0.222***	0.126**	-0.088	0.045	-0.104*	-0.172***	-0.057	-0.133**	-0.094	0.068	-0.073	0.149***
	Sentiment Dispersion (Bot)	1.375	12	0.331	0.106	0.368	0.375	0.068	-0.437	-0.013	0.393	0.471	-0.141	-0.674**	0.2
	Sentiment Dispersion (Non-bot)	0.368	12	-0.061	-0.312	0.02	0.348	0.403	-0.343	-0.019	-0.275	-0.35	0.15	0.196	-0.014
	Tweet Sentiment (Bot)	0.918	12	-0.004	0.013	0.019	0.023	0.004	-0.013	-0.008	0.024*	0.004	-0.004	-0.005	0.008
	Tweet Sentiment (Non-bot)	1.158	12	0	-0.001	-0.002	0.026	-0.043	0.067**	-0.009	-0.03	-0.048*	0.002	0.036	-0.013
Volatility	Log returns	3.819***	12	-0.025***	-0.036***	-0.013	-0.022**	-0.02**	0.011	-0.01	-0.011	-0.002	-0.007	-0.004	-0.015*
	Trading volume	2.154**	12	0.104***	-0.012	0.045	-0.008	0.025	-0.001	-0.009	0.028	0.029	-0.036	-0.001	-0.035
	Attention (Bot)	1.409	12	-0.031	-0.024	0.015	-0.041	-0.02	0.004	0.063	0.086*	-0.082*	-0.018	0.029	0.092**
	Attention (Non-bot)	4.398***	12	0.254***	0.125*	-0.011	0.055	-0.038	-0.12	0.001	-0.076	-0.106	0.129*	-0.123*	0.115*
	Sentiment Dispersion (Bot)	1.371	12	0.354	0.702*	-0.323	0.603	0.047	-0.586	-0.049	0.763**	0.088	-0.302	-0.18	0.027
	Sentiment Dispersion (Non-bot)	0.603	12	0.51	-0.352	-0.283	0.27	0.744	-0.219	0.446	-0.299	-0.543	-0.203	0.124	0.03
	Tweet Sentiment (Bot)	1.027	12	-0.006	0.018	0.01	0.003	0.024	-0.016	-0.005	0.021	0.026	-0.002	0.012	0.012
	Tweet Sentiment (Non-bot)	0.946	12	0.007	0.012	-0.032	0.016	-0.032	0.071**	-0.029	-0.018	-0.036	-0.038	0.003	-0.01

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

C.2 VAR and Granger-causality Tests, Daily Data

Table 14: Granger-causality Tests and VAR Coefficient Estimates, Daily Data, ADA

Equation	Excluded	Test statistic	p	Lag Number		
				1	2	3
Log returns	Trading volume	0.177	3	-0.447	-0.705	-0.527
	Volatility	0.271	3	-0.685	1.106	0.162
	Attention (Bot)	3.084**	3	-5.905*	-2.52	-4.475
	Attention (Non-bot)	4.436***	3	12.084***	-5.761	-0.473
	Sentiment Dispersion (Bot)	2.924**	3	-59.886	26.297	-33.37
	Sentiment Dispersion (Non-bot)	0.493	3	-48.488	-52.025	45.247
	Tweet Sentiment (Bot)	0.27	3	0.329	1.318	-0.884
	Tweet Sentiment (Non-bot)	0.371	3	5.07	-2.546	-2.479
Trading volume	Log returns	1.538	3	0.025*	0.002	0.016
	Volatility	1.258	3	-0.314*	-0.061	0.023
	Attention (Bot)	0.745	3	-0.392	-0.249	0.291
	Attention (Non-bot)	4.764***	3	1.446***	-0.851*	0.451
	Sentiment Dispersion (Bot)	0.05	3	1.285	-0.707	-0.937
	Sentiment Dispersion (Non-bot)	0.664	3	-2.98	6.392	6.801
	Tweet Sentiment (Bot)	0.857	3	0.154	0.113	0.025
	Tweet Sentiment (Non-bot)	1.704	3	-0.591	-0.907	1.079*
Volatility	Log returns	1.186	3	0.019	-0.002	0.016
	Trading volume	3.86**	3	0.421**	-0.025	0.364**
	Attention (Bot)	1.589	3	-0.64	-0.283	0.399
	Attention (Non-bot)	0.384	3	0.412	-0.271	0.164
	Sentiment Dispersion (Bot)	1.032	3	4.397	-3.275	3.401
	Sentiment Dispersion (Non-bot)	1.715	3	6.699	4.623	9.503
	Tweet Sentiment (Bot)	2.764**	3	0.274	0.018	0.279
	Tweet Sentiment (Non-bot)	0.789	3	-0.205	-0.531	0.874

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 15: Granger-causality Tests and VAR Coefficient Estimates, Daily Data, BTC

Equation	Excluded	Test statistic	p	Lag Number		
				1	2	3
Log returns	Trading volume	2.135	3	2.962**	0.46	-1.555
	Volatility	3.074**	3	-4.331**	-0.639	3.145*
	Attention (Bot)	0.171	3	-0.436	-2.074	2.73
	Attention (Non-bot)	1.538	3	2.784	-4.304	-3.876
	Sentiment Dispersion (Bot)	0.738	3	-3.212	-10.855	40.447
	Sentiment Dispersion (Non-bot)	0.948	3	-37.537	78.208	27.83
	Tweet Sentiment (Bot)	1.541	3	-2.788	-2.049	1.922
	Tweet Sentiment (Non-bot)	7.383***	3	14.171***	-4.483	-10.162**
Trading volume	Log returns	2.505*	3	0.049***	0.008	0.003
	Volatility	1.201	3	0.378	-0.014	-0.366
	Attention (Bot)	3.657**	3	-0.312	0.246	1.599**
	Attention (Non-bot)	3.587**	3	1.194**	-0.993*	-0.704
	Sentiment Dispersion (Bot)	3.367**	3	14.887***	-4.171	-2.138
	Sentiment Dispersion (Non-bot)	1.063	3	-11.704	7.126	-9.612
	Tweet Sentiment (Bot)	1.722	3	0.575*	0.151	-0.377
	Tweet Sentiment (Non-bot)	2.546*	3	-1.124**	-0.805	1.006
Volatility	Log returns	2.603*	3	0.035***	0.011	0.006
	Trading volume	3.479**	3	-0.152	0.217	0.4***
	Attention (Bot)	3.008**	3	-0.028	0.09	0.997**
	Attention (Non-bot)	1.711	3	0.45	-0.511	-0.394
	Sentiment Dispersion (Bot)	3.368**	3	9.896***	0.256	-4.6
	Sentiment Dispersion (Non-bot)	1.228	3	-9.337	3.74	-6.084
	Tweet Sentiment (Bot)	2.271*	3	0.386*	0.146	-0.415**
	Tweet Sentiment (Non-bot)	3.147**	3	-0.737*	-0.824*	0.787*

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 16: Granger-causality Tests and VAR Coefficient Estimates, Daily Data, ETH

Equation	Excluded	Test statistic	p	Lag Number		
				1	2	3
Log returns	Trading volume	3.518**	3	3.415***	1.888	-0.119
	Volatility	2.928**	3	-3.533**	-1.942	1.174
	Attention (Bot)	0.276	3	-2.042	3.892	0.425
	Attention (Non-bot)	3.24**	3	-0.827	-10.649*	-1.455
	Sentiment Dispersion (Bot)	0.533	3	44.308	-12.818	14.694
	Sentiment Dispersion (Non-bot)	0.915	3	-32.46	62.524	36.527
	Tweet Sentiment (Bot)	2.072	3	1.858	-5.482**	0.631
	Tweet Sentiment (Non-bot)	7.362***	3	13.557***	2.509	-9.811***
Trading volume	Log returns	0.043	3	-0.003	0.002	-0.004
	Volatility	0.963	3	0.207	-0.253	0.207
	Attention (Bot)	2.539*	3	-0.006	1.529*	0.058
	Attention (Non-bot)	3.456**	3	1.602**	-2.163**	-0.3
	Sentiment Dispersion (Bot)	0.254	3	4.88	-3.168	-1.579
	Sentiment Dispersion (Non-bot)	0.393	3	0.347	1.892	-8.683
	Tweet Sentiment (Bot)	0.167	3	-0.103	0.102	-0.193
	Tweet Sentiment (Non-bot)	2.402*	3	-1.42**	0.947	-0.194
Volatility	Log returns	0.057	3	-0.001	0.003	0.004
	Trading volume	2.429*	3	-0.039	0.382**	0.217
	Attention (Bot)	2.09	3	-0.029	1.041	0.206
	Attention (Non-bot)	1.983	3	0.737	-1.436**	-0.079
	Sentiment Dispersion (Bot)	0.387	3	4.886	0.29	-1.663
	Sentiment Dispersion (Non-bot)	1.193	3	-6.271	0.298	-8.727
	Tweet Sentiment (Bot)	0.847	3	-0.045	0.244	-0.412
	Tweet Sentiment (Non-bot)	2.035	3	-1.08**	0.297	-0.109

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 17: Granger-causality Tests and VAR Coefficient Estimates, Daily Data, SOL

Equation	Excluded	Test statistic	p	Lag Number		
				1	2	3
Log returns	Trading volume	1.205	3	3.089*	-0.381	-0.275
	Volatility	1.925	3	-2.389	2.872*	0.646
	Attention (Bot)	0.546	3	-2.456	6.437	-3.106
	Attention (Non-bot)	3.071**	3	3.947	-14.942**	-3.765
	Sentiment Dispersion (Bot)	1.53	3	18.256	-1.227	114.487**
	Sentiment Dispersion (Non-bot)	2.01	3	97.077	56.745	-168.039**
	Tweet Sentiment (Bot)	0.696	3	-0.006	-2.485	0.543
	Tweet Sentiment (Non-bot)	2.971**	3	11.123**	-2.072	-8.437*
Trading volume	Log returns	1.914	3	0.02	-0.017	-0.011
	Volatility	1.837	3	-0.291*	-0.128	-0.121
	Attention (Bot)	0.167	3	-0.138	-0.109	-0.105
	Attention (Non-bot)	4.881***	3	2.314***	-0.471	0.056
	Sentiment Dispersion (Bot)	2.162*	3	-10.703*	-7.02	-1.977
	Sentiment Dispersion (Non-bot)	1.534	3	5.423	4.059	13.312
	Tweet Sentiment (Bot)	0.515	3	-0.126	0.024	0.203
	Tweet Sentiment (Non-bot)	1.436	3	-0.163	-0.147	0.962*
Volatility	Log returns	1.352	3	-0.001	-0.024*	-0.008
	Trading volume	1.593	3	0.092	0.072	0.353*
	Attention (Bot)	1.413	3	-0.966*	-0.124	0.373
	Attention (Non-bot)	5.24***	3	2.129***	0.369	-0.12
	Sentiment Dispersion (Bot)	2.815**	3	-16.208**	-2.7	2.875
	Sentiment Dispersion (Non-bot)	1.033	3	-5.471	0.954	15.445*
	Tweet Sentiment (Bot)	0.132	3	-0.115	0.039	0.06
	Tweet Sentiment (Non-bot)	2.913**	3	-1.071**	0.425	1.07**

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

Table 18: Granger-causality Tests and VAR Coefficient Estimates, Daily Data, XRP

Equation	Excluded	Test statistic	p	Lag Number		
				1	2	3
Log returns	Trading volume	0.583	3	0.468	-0.903	-0.974
	Volatility	1.708	3	-1.026	0.592	2.293*
	Attention (Bot)	0.407	3	-2.749	1.008	1.092
	Attention (Non-bot)	3.494**	3	8.776***	-3.455	-4.778
	Sentiment Dispersion (Bot)	1.401	3	-60.48	-22.706	37.421
	Sentiment Dispersion (Non-bot)	0.261	3	-25.857	44.462	-2.791
	Tweet Sentiment (Bot)	2.655*	3	-2.873	-3.676*	2.048
	Tweet Sentiment (Non-bot)	2.617*	3	8.596***	-0.857	0.092
Trading volume	Log returns	0.621	3	0.008	0.016	0.02
	Volatility	0.33	3	0.05	-0.028	-0.166
	Attention (Bot)	0.165	3	-0.233	0.179	0.105
	Attention (Non-bot)	1.396	3	0.997**	-0.343	0.148
	Sentiment Dispersion (Bot)	0.877	3	-3.732	-6.067	-3.355
	Sentiment Dispersion (Non-bot)	1.202	3	6.205	7.305	13.444
	Tweet Sentiment (Bot)	1.765	3	-0.145	-0.591**	-0.037
	Tweet Sentiment (Non-bot)	0.431	3	0.354	-0.226	-0.403
Volatility	Log returns	0.221	3	-0.001	-0.008	0.009
	Trading volume	1.646	3	-0.283	0.153	0.254
	Attention (Bot)	0.51	3	-0.287	0.058	0.394
	Attention (Non-bot)	0.588	3	0.577	0.014	-0.191
	Sentiment Dispersion (Bot)	0.86	3	-1.824	-6.145	-3.871
	Sentiment Dispersion (Non-bot)	1.305	3	2.053	8.421	12.598
	Tweet Sentiment (Bot)	1.094	3	-0.118	-0.451	0.079
	Tweet Sentiment (Non-bot)	1.58	3	0.372	0.222	-0.969**

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # Lags determined based on AIC.

D Cryptocurrency Dictionary for Sentiment Analysis

Table 19: Manually-compiled Cryptocurrency Dictionary

Term	**Sentiment Valence**	**Term**	**Sentiment Valence**	**Term**	**Sentiment Valence**
bullish	2	scamcoin	-2	degen	-3
hodl	2	rugpull	-2	moonbois	-1
bull	2	rugged	-2	moonboys	-1
bear	-2	noob	-1	boomer	-1
bearish	-2	newb	-1	boomercoin	-1
rocket	2	wgmi	3	pleb	-1
moon	3	wagmi	3	nuke	-2
mooning	3	ngmi	-3	bagholder	-1
fud	-3	bearwhale	-2	flippening	1
shill	-2	nocoiner	-1	flip	1
rekt	-4	apes	-1	vaporware	-3
whale	1	aping	-1	btd	3
shitcoin	-2	hsbaf	2	btfd	3
dust	-1	cryptojacking	-2		
ath	1	lfg	4		

Our manually compiled lexicon consists of 43 terms popular in the cryptocurrency community. These terms are selected by us from online cryptocurrency articles, and we mapped each term to a corresponding sentiment valence using the same scale as in VADER. As with any user-made dictionary, we note that the valence score for each term is quantified based on our interpretation and understanding of the term.