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Do news headlines matter in the cryptocurrency market?

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ABSTRACT

The paper examines the influence of investor sentiment based on news headlines on the Cryptocurrency Market Index and ten individual cryptocurrency returns. We capture investors' sentiment from cryptocurrency-specific news headlines. We use a lexicon-based Natural Language Processing (NLP) technique to construct a unique sentiment indicator, and the sentiment scores are generated using two financial dictionaries: Henry(2008)(HE) and Loughran and Mcdonald(2011) (LM). The findings of the study show that news sentiment has a significant impact on cryptocurrency returns. When the investors' sentiment is optimistic or bullish, the cryptocurrency market experiences herding behaviour, leading to an increase in prices. The diverse and heterogeneous nature of the various cryptocurrencies causes each individual cryptocurrency to respond differently to sentiment. Further, we see that sentiment has a more pronounced impact on young, small, and volatile cryptocurrencies. Our study is among the few studies that use cryptocurrency-specific news headlines rather than news bodies to build a news sentiment indicator. JEL codes: E49, G14, G15

KEYWORDS

Cryptocurrency; news headlines; sentiment; Natural Language Processing; opinion mining

I. Introduction

A cryptocurrency is a digital or virtual currency secured by cryptography, making it nearly impossible to counterfeit. Many cryptocurrencies are decentralized networks based on blockchain technology – a distributed ledger enforced by a network of computers (Dong et al. 2022). A defining feature of cryptocurrencies is that they are generally not issued by any central authority, rendering them theoretically immune to government interference or manipulation (Bunjaku, Gjorgieva-Trajkovska, and Miteva-Kacarski 2017). The cryptocurrency market has witnessed enormous growth in popularity since the introduction of the first cryptocurrency, Bitcoin (Nakamoto 2008). There has been a surge in the number of altcoins available in the market. As of August 2021, there are about 5000+ cryptocurrencies traded in the market. The total market capitalization of cryptocurrencies has rocketed from $1.6 billion in April 2013 to $1.9 trillion in August 2021. The market is dominated by Bitcoin which alone accounts for about 46.7% share of the total market capitalization (www.coinmarketcap.com). As of 2021, there are over 300 million crypto users worldwide. The top five countries in terms of crypto users are India (100 million), USA(27 million), Nigeria(13 million), Vietnam(5.9 million), and the United Kingdom(3.3 million) (www.bloomberg.com). The attractiveness and the demand for cryptocurrency is increasing, with investors' choosing the cryptocurrency for diversification of their portfolios (Subramaniam and Chakraborty 2020).

Some researchers contend that cryptocurrency serves as an alternative to fiat currency (Levulytė and Šapkauskienė 2021; Carrick 2016; Kristoufek 2015); others argue that it has the features of a financial asset (Corbet et al. 2019; Bouri et al. 2017; Baur, Hong, and Lee 2018), and some also attribute cryptocurrency as purely a speculative financial bubble (Chen et al. 2019; Corbet, Lucey, and Yarovaya 2018) with no fundamental value (Cheah and Fry 2015). Due to the lack of clarity on the nature of cryptocurrency, there is no consensus among researchers regarding the factors affecting cryptocurrency prices. Thus, the valuation of cryptocurrencies highly depends upon the perceptions and opinions of the investors. Further, the cryptocurrency market attracts participation

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majorly from individual investors and computer programming enthusiasts (Yelowitz and Wilson 2015; Lui 2013) who may lack sufficient trading knowledge (Naeem, Mbarki, and Shahzad 2021). Thus, the information available in the market plays a critical role in moulding the cryptocurrency investors' sentiments, thereby affecting their trading behaviour.

News media is an essential source of publicly available information, which may significantly impact investor sentiment. Unfavourable news and social media chatter about the cryptocurrency may generate a negative sentiment and reduce its attractiveness to investors. On the other hand, positive news information may lead to positive sentiment and increase attractiveness. Studies in the past literature provide substantial evidence that investor sentiment plays a significant role in cryptocurrency price determination. Karalevicius, Degrande, and De Weerdt (2018) used textual analysis to study the impact of media sentiment and found significant interaction with cryptocurrency. Baig, Blau, and Sabah (2019) used Google trends as a sentiment proxy that significantly impacted Bitcoin price clustering. Kristoufek (2013) measured Bitcoin sentiment through Wikipedia and Google search queries. They found that there is a connection between search queries and Bitcoin prices. Rajput, Soomro, and Soomro (2020) used the Google search volume-based Bitcoin Sentiment Index (BSI) to study the relationship between Bitcoins and the US Dollar and found a positive association between the sentiment and Bitcoin returns and volume. Anamika and Subramaniam (2021) used a novel survey-based sentiment index, and their results suggest that sentiment is a significant predictor of cryptocurrency returns. Kraaijeveld and De Smedt (2020) used Twitter data to capture investor sentiment and found that they significantly impact cryptocurrency returns. Bouoiyour and Selmi (2015) captured investors' attractiveness for Bitcoin using Google trends and found a significant impact on cryptocurrency prices. Shen, Urquhart, and Wang (2019) investigated the impact of investor attention using the number of tweets as a proxy and found that it drives the Bitcoin volatility and volume.

The past literature captured investor sentiment using social media and blogs. There are few studies that captured sentiment using public information available on news media platforms. The cryptocurrency market is driven more by public information (Naeem, Mbarki, and Shahzad 2021). Thus, this paper aims to study whether the investor sentiments generated by public information available in news media can predict the movement in cryptocurrency prices. We capture the investors' sentiment using news headlines data and analyse its impact on the returns of the cryptocurrency market. We build our own unique sentiment indicator based on cryptocurrency-specific news headlines using the Natural language processing (NLP) technique. We obtain news headlines from the Refinitiv Eikon database and use a lexicon-based approach to extract quantifiable sentiment from qualitative text data. We construct the sentiment indicator from January 2010 to June 2021. We examine how sentiment affects the Cryptocurrency Index and a set of ten individual cryptocurrencies for our study, viz. Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Ethereum Classic, Monero, EOS, Dash, and Zcash. We control for potential factors that may impact cryptocurrency prices. We find a significant positive relationship between news sentiment and cryptocurrency returns, implying that investors give importance to public information available in the market, thereby affecting their trading behaviour in the cryptocurrency market.

Our study makes the following contributions to the existing literature: First, we contribute to the strand of behavioural finance literature, which gives importance to the irrational aspect of investors in the price-determination of assets (Tversky and Kahneman 1992; Daniel, Hirshleifer, and Subrahmanyam 1998; Baker and Wurgler 2006). We provide evidence that investors' sentiments driven by news information significantly affect cryptocurrency returns. Past studies used proxies from social media such as Twitter, Wikipedia searches, blogs, Reddit discussions, and Google search trends to capture the sentiment. Given the nature of participants in the cryptocurrency market, the sentiment driven by public information plays a vital role in the valuation of cryptocurrencies. This is one of the few studies that capture the sentiment from news media information, a public domain.

Second, we construct a news sentiment indicator from news headlines. There are few studies that use news article headlines rather than full news stories to capture sentiment through text-mining (Ooi 2020). We prefer the usage of news headlines rather than full news stories for sentiment construction due to two reasons. For starters, news headlines convey vital information about investor attention, which can be monitored and collected effectively using Natural Language Processing (NLP) techniques. Second, the sentiment index derived from news headlines has less noise and irrelevant data, which helps to increase the indicator's dependability (Khadjeh Nassirtoussi et al. 2015). We filter the news headlines which are specific to the cryptocurrency market. It is one of few studies that capture sentiment using cryptocurrency-specific news headlines (Akyildirim et al. 2021).

Finally, very few studies have studied the role of news sentiment on cryptocurrencies other than Bitcoin (Lamon, Nielsen, and Redondo 2017). Several altcoins emerged in the market post the success of Bitcoin. When Bitcoin performs well, the investors become confident that the performance of altcoins will also improve. This kind of behaviour is attributed to representativeness bias, as described by Tversky and Kahneman (1974). In the light of the recent popularity of altcoins among investors, it becomes essential to study altcoins. We, therefore, extend the body of literature by analysing the Cryptocurrency Index and a set of ten individual cryptocurrencies.

The remaining paper is organized as follows: Section II discusses the literature on sentiment and the cryptocurrency market. Section III and IV provide information on the data and methodology, respectively. Section V discusses the empirical findings and results, and Section VI concludes.

II. Literature review

The existing literature has documented that behavioural aspects have a significant role in the cryptocurrency market. Shleifer and Summers (1990) argue that 'noise traders' in financial markets are driven by noise rather than information. They may believe that pseudo-signals, such as advice from brokers, convey important information about future returns. Such information may not be considered substantial in a rational model (Black 1986). Their beliefs about information influence their trading behaviour, thereby causing deviations in prices.

It has been observed that investors have a tendency to chase the trend. They follow a positive feedback strategy: buy stocks when it rises and sell after it falls. The arbitrageurs are unable to counter this 'trend-chasing,' and they also jump on the bandwagon (Shleifer and Summers 1990). This 'bandwagon effect' persistently affects the prices as new investors driven by sentiment keep pouring into the market (De Long et al. 1990). Banerjee (1992) further evidenced that individual investor are characterized by herd behaviour. The individual investor considers the information contained in others' decisions more valuable than their own private information. The 'herding' behaviour is based on positive feedback. This has an important implication for financial markets, suggesting that as investors' participation increases, the prices are likely to go up. As suggested by Naeem, Mbarki, and Shahzad (2021), the cryptocurrency market also exhibits this phenomenon. The market is driven by individual investors who rely on public information and are characterized by herding behaviour.

The news headlines and articles are publicly available sources of information that may impact the investors' sentiment and trading behaviour. Tetlock (2007) study is a seminal work that assessed the possible connections between news media content and stock market activity. Corbet et al. (2020a) developed a news sentiment index by analysing news stories that follow macroeconomic announcements and determined whether it affects Bitcoin returns. Their results show that changes in GDP rates have a significant impact on Bitcoin returns. Štefan et al., 2020 studied whether news related to macroeconomic announcements and regulation and hacking of Bitcoin affect the volatility of Bitcoin. They find that Bitcoin volatility reacts strongly to Bitcoin regulation news and cryptocurrency exchange hacking news. Rognone, Hyde, and Zhang (2020) investigated the impact of unscheduled currency and Bitcoin news on return, volatility, and volume of Bitcoin and traditional currencies. They found that both positive and negative news has a positive impact on Bitcoin, contrary to the results found for traditional currencies. Caferra (2020) investigated the relationship between sentiment derived from worldwide news (GDelt Project) and the return dispersion of 13 cryptocurrencies. They discovered that the dispersion of returns is minimal at times of good news. Their findings show that cryptocurrency pricing is volatile and is influenced by behavioural characteristics. Bouri, Gkillas, and Gupta (2020) studied the role of news-based trade uncertainty measures on Bitcoin returns and found that Bitcoin acts as a hedge against the US stock market during trade uncertainty.

The past literature, as discussed above, have used various measures to capture sentiment and their role in the cryptocurrency market. We aim to capture the investors' sentiment by constructing a sentiment indicator based on news headlines. A few studies have explored the usage of news article headlines rather than news article bodies (Khadjeh Nassirtoussi et al. 2015; Lamon, Nielsen, and Redondo 2017; Cao and Rhue 2019). Our study contributes to this underexplored area of research by using cryptocurrency-specific news headlines and conducting an analysis on the Cryptocurrency Index and a set of ten cryptocurrencies.

III. Data

We examine the role of sentiment on the Cryptocurrency Index sourced from the Bloomberg Terminal. This Cryptocurrency Index (also known as Bloomberg Galaxy Cryptocurrency Index (BGCI)) is a benchmark that measures the performance of the largest cryptocurrencies traded in the USD. As of August 2021, the BGCI constitutes Bitcoin, Ethereum, Bitcoin Cash, Litecoin, and EOS. It serves as a proxy for the broader cryptocurrency market (www.bloomberg.com). We further extend our study to analyse ten individual cryptocurrencies with a market capitalization above $4 billion, viz., Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Ethereum Classic, Monero, EOS, Dash, and Zcash (Please refer to Table 1). We collect daily data on price and volume from www.coinmarketcap.com. The prices are in terms of the USD. The sample period is different for each cryptocurrency depending upon data availability. A detailed description of the sample period for each cryptocurrency is appended in Table A1 in the appendix.

We use the News Monitor application in the Refinitiv Eikon terminal to crawl and download the news headlines relating to cryptocurrency and form a dataset. We enter the topic 'Blockchain and Cryptocurrency,' a predefined topic in the application for filtering the news. We also use the keywords 'crypto' and 'cryptocurrency' to capture maximum news headlines data. The News Monitor app collects news from over 13,000+ newsletters, newspapers, newswire, reports, press releases, magazines, blogs, broadcasts, reports, scholarly journals, trade journals, and web content across seven geographical regions, forty industry sectors, and over 175+ countries in the world.

Table 1. Market statistics of cryptocurrencies as on 13 June 2021.

	Market Cap	Percentage share	Price	Circulating Supply	Volume
Bitcoin	$732,465,659,891.77	46.37%	$39,097.86	18,734,162 BTC	$40,669,112,837.87
Ethereum	$291,673,894,434.50	18.46%	$2,508.39	116,279,249 ETH	$27,092,945,369.98
Ripple	$40,792,805,237.04	2.58%	$0.8832	46,189,574,356 XRP	$3,059,837,086.14
Litecoin	$11,410,049,187.31	0.72%	$170.93	66,752,415 LTC	$2,041,213,334.65
Bitcoin Cash	$11,527,111,106.22	0.73%	$614.35	18,762,950 BCH	$1,578,903,639.97
Monero	$4,683,523,647.83	0.30%	$261.19	17,931,165 XMR	$172,816,270.57
EOS	$4,857,348,724.89	0.31%	$5.09	954,226,578 EOS	$1,220,333,618.67
Ethereum Classic	$6,869,070,967.02	0.43%	$59.06	116,313,299 ETC	$2,644,959,954.35
Dash	$1,758,328,339.37	0.11%	$172.72	10,179,999 DASH	$390,841,392.34
Zcash	$1,594,212,347.69	0.10%	$133.02	11,985,000 ZEC	$322,549,391.92
Others	$472,107,153,727.13	29.89%	-	-	
Total Market Capitalisation	$1,579,739,157,610.77				

This table shows the market capitalization, their percentage share in the total market capitalization, the closing price, the circulating supply, and the traded volume of cryptocurrencies as on 13 June 2021. Source: www.coinmarketcap.com.

Table 2. News headlines count data.

Year	Before duplicates removal (1)	After duplicates removal (2)
2010	20	15
2011	24	23
2012	28	27
2013	86	64
2014	331	282
2015	482	390
2016	543	416
2017	3007	2020
2018	18,967	13,576
2019	6286	4817
2020	6325	4330
2021	5150	4139
Total	41,249	30,100

This table reports the total number of news headlines obtained from the Refinitiv Eikon News Monitor Application. Column (1) reports the number of news headlines before removing the duplicate headlines. Column (2) reports the number of news headlines after removing the duplicates.

The news headlines are collected from 18 January 2010 onwards to 10 June 2021. All the news items were manually scraped. Each of the news headlines was manually examined, and any duplications were removed. The details of the number of headlines collected are presented in Table 2.

We utilize the Economic Policy Uncertainty (EPU) Index of the US as a proxy to control the macro-economic uncertainty (Wang et al. 2019). Based on previous studies, we use gold returns to control for metal market factors (Bouoiyour and Selmi 2015) and the S&P 500 Index to control for financial market factors (Youssef 2020). To control for market microstructure factors, we use the bid-ask spread (Dimpfl and Peter 2020) and volume (Urquhart 2017). EPU is sourced from *www.policyuncertainty.com*. The bid-ask spread, gold price, and S&P 500 index closing value is obtained from Thomson Reuter Eikon Database (Anamika and Subramaniam 2021). The volume of cryptocurrencies is obtained from www.coinmarketcap.com.

The descriptive statistics of cryptocurrency returns, Cryptocurrency Index, and sentiment scores are presented in Table 3. The average returns of all the variables are positive, except for Zcash returns and LM sentiment score. The Cryptocurrency Index returns are moderately skewed. The returns of Bitcoin, Bitcoin Cash, and Monero are symmetrically skewed. The remaining variables exhibit high skewness. All the variables exhibit excess kurtosis and the presence of outliers. The Jarque-Bera test rejects the normality in all variable series. We use Brock, Dechert, Sheinkman, and LeBron (BDS) test to check the linearity of data series, and we find that except for Ethereum, all the other variables exhibit non-linearity. The Augmented Dicky-Fuller linear unit root (ADF) test shows that the variables are stationary. Further, the Kapetanios, Shin, and Snell(KSS) nonlinear unit root test also shows that the variables are stationary (Please refer to Table 4).

IV. Methodology

Data preprocessing

Before we begin to extract sentiment scores from the news headlines, it is imperative to clean the raw news headlines' text data. The raw data is often very noisy, which may reduce its reliability. In Natural language processing (NLP), the raw text corpus is converted into a tidy form to make it suitable for further processing.

Table 3. Descriptive statistics of the returns and sentiment scores.

	Mean	Median	Max	Min	S.D.	Skewness	Kurtosis	Jarque-Bera	p-value	Outliers	BDS
Crypto Index	0.002	0.004	0.198	−0.336	0.054	−0.672	6.89	697.86	0.000***	Yes	0.011***
Bitcoin	0.002	0.002	0.357	−0.465	0.043	−0.54	14.104	15,536.16	0.000***	Yes	0.022***
Ethereum	0.003	0.001	0.412	−1.302	0.068	−3.224	69.735	406,616.2	0.000***	Yes	0.000
Ripple	0.002	−0.002	1.027	−0.616	0.073	1.607	29.381	85,517.02	0.000***	Yes	0.043***
Litecoin	0.001	0.000	0.829	−0.514	0.064	1.207	26.589	70,378.36	0.000***	Yes	0.029***
Bitcoin Cash	0.000	−0.002	0.432	−0.561	0.076	0.151	12.492	5475.292	0.000***	Yes	0.027***
Monero	0.002	0.001	0.585	−0.534	0.069	0.155	11.904	8658.704	0.000***	Yes	0.022***
EOS	0.001	0.000	0.987	−0.503	0.078	1.416	25.326	31,274.39	0.000***	Yes	0.027***
Ethereum Classic	0.002	0.000	1.443	−0.508	0.078	3.389	73.538	381,005.2	0.000***	Yes	0.028***
Dash	0.002	−0.001	1.271	−0.468	0.076	2.591	42.436	178,972.9	0.000***	Yes	0.032***
Zcash	−0.002	−0.002	1.039	−1.269	0.082	−1.596	58.392	221,519.5	0.000***	Yes	0.024***
HE	0.043	0.034	0.388	−0.345	0.059	0.606	8.888	3247.780	0.000***	Yes	0.127***
LM	−0.068	−0.066	0.386	−0.530	0.101	0.078	4.926	335.563	0.000***	Yes	0.124***

This table presents the descriptive statistics of Cryptocurrency Index returns, the returns of ten individual cryptocurrencies, and sentiment scores (LM,HE). The normality of the series is tested using the Jarque-Bera test. Brock,Dechert, Sheinkman and LeBron (BDS) tests the linearity of the series. ***,**, and * denotes rejection of null hypothesis at 1%,5%,and 10%. LM is Loughran and Mcdonald (2011) sentiment score, and HE is Henry (2008) sentiment score.

Table 4. Linear and non-linear stationarity test statistics of returns and sentiment scores.

	1	2	3	4
	ADF t-statistic	p-value	KSS statistic	k
Crypto_Index	−31.646	0.000***	−4.318***	7
Bitcoin	−55.904	0.000***	−9.368***	8
Ethereum	−45.429	0.000***	−6.381***	8
Ripple	−52.108	0.000***	−13.062***	8
Litecoin	−54.654	0.000***	−5.265***	8
Bitcoin Cash	−37.364	0.000***	−4.311***	6
Monero	−53.961	0.000***	−8.005***	8
EOS	−39.046	0.000***	−6.444***	8
Ethereum Classic	−49.642	0.000***	−8.905***	8
Dash	−54.243	0.000***	−4.170***	5
Zcash	−43.56	0.000***	−3.873***	7
LM	−10.311	0.000***	−7.015***	7
HE	−11.923	0.000***	−6.240***	8

This table presents the results of stationarity tests. The Augmented Dicky-Fuller(ADF) linear unit root test checks the stationarity of the series. Column(2) presents the *p*-value of the ADF test. ***,**, and * denotes significance level at 1%, 5%, and 10% respectively. The Kapetanios, Shin, and Snell(KSS) non-linear unit root test tests the null hypothesis $\theta = 0$, i.e. there is a unit root. The KSS test statistics results are presented in Column (3). The lags(k) for the KSS test are presented in Column(4). The critical values of the KSS unit root test are −3.93, −3.40, and −3.13 at 1%, 5%, and 10% significance levels, respectively. LM is Loughran and Mcdonald (2011) sentiment score, and HE is Henry (2008) sentiment score.

The tidying process consists of tokenization and normalization of raw text data. The news headlines text is broken down or tokenized into individual words through the tokenization process. After the tokenization, the text is normalized before it can be processed further. This includes:

- Converting the corpus of text to lower case.
- Removal of special characters such as ‘@,%,$,<, >,/’ from the text.
- Removal of numbers and punctuations.
- Removal of unnecessary whitespaces.
- Removal of common stopwords such as “the, is at, on”
- The last step is stemming. This process reduces the word to its root form.

Next, we use the corpus to build a term-document matrix (Ooi 2020). This matrix enlists the most frequent terms and the number of times they have appeared in the text. This step helps to identify the most popular and trending words/topics. Figure 1 helps to visualize frequent words in the news headlines. As is evident from Figure 1, Bitcoin seems to be the most popular cryptocurrency in the market as it appears in the list of top three words.

A word cloud is also created using common word data to aid in the visualization of qualitative data. It is a visual representation of keywords contained in the text of news headlines. Each word’s size shows how often it appears in the text. The word cloud in Figure 2 indicates that cryptocurrency is the main keyword in all headlines. Furthermore, the terms’ blockchain’ and ‘exchange’ also appeared in many headlines. Apart from Bitcoin, the other popular cryptocurrency which showed frequent presence in headlines is Ethereum.

Extracting sentiment scores

After cleaning the news headlines text data, we convert the qualitative information stored in text data into a quantitative sentiment score. We use a lexicon or dictionary-based method to extract

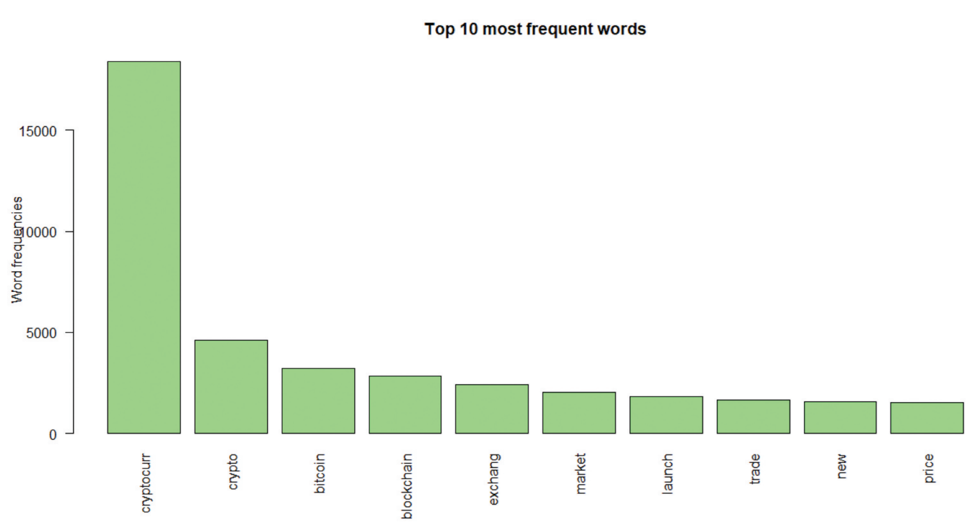

Figure 1. Illustration of the number of occurrences of top ten words in the news headlines text.

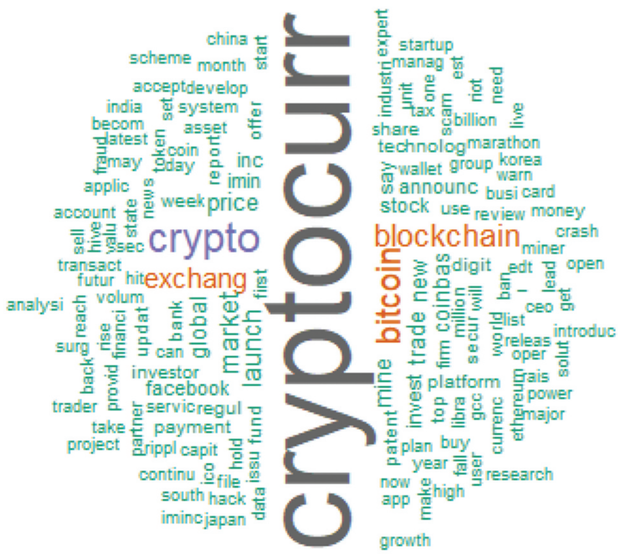

Figure 2. A word cloud of frequent keywords found in news headlines text.

sentiment from text data. A dictionary is a collection of positive, negative, or neutral words that can be used to determine the semantic orientation of a text. Each word in the clean text of the news headline will be matched to words in the dictionary, and the word's polarity will be marked accordingly (Ooi 2020).

General lexicons such as Harvard's General Inquirer (GI) and Diction sentiment word lists misclassify certain financial terms. For example, 'tax', 'capital', 'cost', and 'division' are classified as negative toned words, whereas 'share', 'power', 'respect', and 'company' are classified as positive toned words. In financial terms, these words should be classified as neutral. To prevent such misclassification of words from news headlines text, we utilize domain-specific financial text dictionaries for our study. Henry (2008) and Loughran and Mcdonald (2011) lexicons are based on financial text that captures financial terminology, which may differ from general English words in terms of meaning, tone, and polarity.

Henry (2008) analysed the financial information stored in the earnings announcement press release reports of firms from the telecommunications and computer services industries and related equipment manufacturers from 1998 to 2002. Earnings announcement reports consist of general English and business language that give insights into a firm's performance. They construct a thesaurus/dictionary of keywords specifically related to financial reporting. However, their word list has a collection of limited words. Loughran and Mcdonald (2011) analysed the financial text of all 10-Ks and 10-K405s filings from the EDGAR website (www.sec.gov) from 1994 to 2008 to form a financial news-specific sentiment word list/dictionary that better reflected the most likely interpretation of the word in the business context. Their word list is extensive, covering a wide range of positive and negative toned words.

We utilize Loughran and Mcdonald (2011) (LM) lexicon as it has a broader coverage of financial terminology. We also utilize Henry (2008) (HE) lexicon for robustness purposes to validate our findings. Based on these financial dictionaries, sentiments can be classified as positive, neutral, or negative. The scale for sentiment scores is decimal and ranges from −1 (indicating most negative) to +1(indicating most positive) (Mhatre 2020).

We extract a set of two sentiment scores (LM and HE) for each news headline. There were many cases with multiple news headlines in one day. We averaged the sentiment scores of all the observations of that particular day to calculate an aggregate news sentiment score for that day.

Construction of sentiment indicator

After extracting the sentiment score, we aim to investigate the response of cryptocurrency price movements to news sentiment. Studies in the past show that news may have a delayed response on asset prices (McQueen, Pinegar, and Thorley 1996). Some investors tend to react more quickly to news events, while some take time to retrieve and process news events and thus exhibit delayed reactions to news (Klibanoff, Lamont, and Wizman 1998). The public sentiment on a given day is influenced by a mix of current events and events from the preceding few days (Li et al. 2021). Recent news items receive a higher weighting from investors than older news stories. As a result, fresh news has a more significant effect than older news (Andreassen 1990).

Given this circumstance, we estimate that each news event will have a seven-day impact on investor sentiment and that the impact of news will

Table 5. Linear Granger causality test.

Null Hypothesis	F-statistic/$_{L.M.}$	Causality	F-statistic/$_{HE}$	Causality
PANEL A				
Sentiment do not cause Crypto_Index returns	2.5605*** [6]	Yes	1.9499* [6]	Yes
Crypto_Index Returns do not cause Sentiment	1.6362 [6]	No	3.2914 [6]	No
PANEL B				
Sentiment do not cause Bitcoin returns	0.4739 [6]	No	0.1305 [6]	No
Bitcoin Returns do not cause Sentiment	0.8674 [6]	No	1.4758 [6]	No
Sentiment do not cause Ethereum returns	4.3639*** [2]	Yes	1.2318 [8]	No
Ethereum Returns do not cause Sentiment	4.4197*** [2]	Yes	2.5980*** [8]	Yes
Sentiment do not cause Ripple returns	1.4513 [8]	No	2.5379*** [8]	Yes
Ripple Returns do not cause Sentiment	1.0952 [8]	No	0.3665 [8]	No
Sentiment do not cause Litecoin returns	0.5095 [8]	No	0.4311 [6]	No
Litecoin Returns do not cause Sentiment	1.2413 [8]	No	1.2582 [6]	No
Sentiment do not cause Bitcoin Cash returns	1.2585 [8]	No	2.9976*** [8]	Yes
Bitcoin Cash Returns do not cause Sentiment	1.4054 [8]	No	0.9960 [8]	No
Sentiment do not cause Monero returns	1.5849 [6]	No	0.1130 [6]	No
Monero Returns do not cause Sentiment	1.8136* [6]	Yes	0.9471 [6]	No
Sentiment do not cause EOS returns	1.0890 [8]	No	0.8156 [8]	No
EOS Returns do not cause Sentiment	1.6870* [8]	Yes	4.4064*** [8]	Yes
Sentiment do not cause Ethereum Classic returns	2.0217** [8]	Yes	1.5499 [8]	No
Ethereum Classic Returns do not cause Sentiment	1.4084 [8]	No	1.5499 [8]	No
Sentiment do not cause Dash returns	3.1587** [2]	Yes	1.1338 [2]	No
Dash Returns do not cause Sentiment	4.1043*** [2]	Yes	5.6759*** [2]	Yes
Sentiment do not cause Zcash returns	1.8525* [8]	Yes	0.6724 [8]	No
Zcash Returns do not cause Sentiment	0.9410 [8]	No	3.7847*** [8]	Yes

This table reports the F-statistics of the Granger Causality Test. ***,**, and * denote significance level at 1%,5%, and 10% respectively. Values in square brackets[] report the lags chosen based on Akaike Information Criteria (AIC).

diminish exponentially each day after it is released (Li et al. 2021). Following Li et al. (2021), we create a cumulative sentiment score (CSS). As a result, the cumulative sentiment score on day t is equal to the sum of the sentiment value on that day t plus the sentiment value over the previous six days, as shown below in Equation (1):

$$CSS_t = \sum_{i=1}^{6} e^{-i/7} SV_{t-i} + SV_t \tag{1}$$

CSS_t is the cumulative sentiment score on day t. The exponentially-adjusted sentiment value of day t−i is represented by $e^{-i/7}SV_{t-i,}$ and SV_t denotes the sentiment value of day t.

Granger causality test

To see whether news headlines sentiment has any predictive power in estimating the movement in cryptocurrency prices, we first test the causality in means between two-time series variables. We use the methodology of Granger (1969). The Granger method examines how much of the current variable y is explained by previous values of y and if adding lagged values of x may enhance the explanation. If the lagged coefficient values of x are significant in the prediction of y, the variable y is said to be granger caused by variable x. Granger causality is a type of two-way causation that assesses the role of one variable's information content in predicting the other.

The causality for all possible pairs of (x,y) is tested using the following regressions:

$$y_t = \propto_0 + \sum_{i=1}^{l} \propto_i y_{t-i} + \sum_{i=1}^{l} \beta_i x_{t-i} + e_t \tag{2}$$

$$x_t = \propto_0 + \sum_{i=1}^{l} \propto_i x_{t-i} + \sum_{i=1}^{l} \beta_i y_{t-i} + u_t \tag{3}$$

Equation (2) tests the null hypothesis that 'x does not granger cause y,' while Equation (3) tests the null hypothesis that 'y does not granger cause x.' (3). The variable 'x' stands for news sentiment (LM/HE) in this study, whereas the variable 'y' stands for Cryptocurrency Index returns and individual cryptocurrency returns. The F-statistics reported in Table 5 are the Wald statistics for the joint hypothesis shown in Equation (4):

$$\beta_1 = \beta_2 = \beta_3 = \ldots = \beta_l = 0 \tag{4}$$

If the lagged coefficients are jointly and statistically equal to zero, the null hypothesis is rejected. The Akaike Information Criteria (AIC) is used to determine the appropriate lag for each pair.

Empirical model

Next, we employ the following regression model to analyse the relationship between news sentiment and Cryptocurrency Index returns:

$$CryptoReturns_{i,t} = c + \beta_1 CSS_{j,t} + \sum_n \partial_n Controls^n_{i,t} + e_{i,t} \quad (5)$$

The same model in Equation (5) is utilized to analyse individual cryptocurrencies. *CryptoReturns* is the log of closing price at time t minus the log of closing price at time *t*-1, CSS is cumulative news sentiment score as calculated in Equation (1), j denotes each of the two news sentiments based on LM and HE lexicon, t denotes a day, i denotes Cryptocurrency Index and each of the ten cryptocurrencies, i.e. Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Monero, EOS, Ethereum Classic, Dash and Zcash. The control variables used in the empirical model are cryptocurrency bid-ask spread, change in EPU, log-normalized cryptocurrency volume, S&P 500 Index returns, and gold returns. Equation (5) is estimated using the Robust LS method due to the presence of outliers and heterogeneity.[1]

V. Results and discussion

Granger causality

The results of the Granger Causality test in Panel A of Table 5 report that news sentiment (LM & HE) granger causes Cryptocurrency Index returns. This implies that the information contained in the news headlines can predict the movement of the cryptocurrency market as proxied by the Cryptocurrency Index. The investors in the cryptocurrency market are ‘noise crypto traders’ whose ‘herding’ behaviour is driven by public information. Thus, the valuation of cryptocurrency is driven by opinions and sentiments (Naeem, Mbarki, and Shahzad 2021), as evidenced by our findings. Our results are also in line with the study by Kennis (2018) who found that news sentiment granger causes the price change in Bitcoin. Their results suggested that news is seemingly being used to collect trading intelligence, and thus news sentiment leads to price movements.

The findings for individual ten cryptocurrencies are reported in Panel B of Table 5. There is bidirectional causality between the news sentiment (LM) and returns of Ethereum and Dash. We see unidirectional causality between News sentiment (LM) and the returns of Ethereum Classic and ZCash. Further, the News sentiment (HE) granger causes the returns of Ripple and Bitcoin Cash. Baker and Wurgler (2006) discovered that sentiment has a greater impact on young stocks, small stocks, and highly volatile stocks. Similarly, our findings show that sentiment has a more pronounced impact on young, small, and volatile cryptocurrencies like Ripple, Ethereum, Ethereum Classic, Zcash, Bitcoin Cash, and Dash.

Regression analysis

Table 6 reports the impact of News sentiment (using LM lexicon) on the returns of the Cryptocurrency Index and individual cryptocurrency returns as estimated in Equation (5). Column (2) in Panel A of Table 6 shows that news sentiment has a significant positive impact on the returns of the Cryptocurrency Index. The index is an aggregate measure of the performance of top cryptocurrencies and is representative of the cryptocurrency market (www.bloomberg.com). The finding provides evidence that when the public information available in the market generates bullish sentiment, the cryptocurrency market experiences herding among investors, which further leads to a rise in prices. Our results are in line with the study of Nasekin and Chen (2020) who also found that sentiment can capture the fluctuations in the Cryptocurrency Index.

Column (2) in Panel B of Table 6 reports the impact of News sentiment (LM) on individual cryptocurrencies. The results show that it has a significant positive impact on the returns of Bitcoin, Monero, Ethereum Classic, and Zcash. This implies that when the news sentiment is optimistic, the cryptocurrency prices experience

[1]Please refer to Table A2 in the appendix for heteroscedasticity test results. Further, Table A3 and Table A4 report the serial correlation test results and variation inflation factors.

Table 6. Regression of News Sentiment (LM lexicon) on Cryptocurrency.

	1	2	3	4	5	6	7	8	9
	Constant	LM_t	Crypto $Bidask_t$	EPU_t	GR_t	SPR_t	Crypto $Volume_t$	R^2	Adj. R^2
PANEL A									
Crypto_Index	0.008***	0.051***	-	−0.007***	−0.086	0.641***	-	0.031	0.027
	(0.0022)	(0.019)		(0.003)	(0.155)	(0.105)			
PANEL B									
Bitcoin	−0.000	0.008*	−0.000	−0.001	−0.016	0.167***	0.000	0.004	0.001
	(0.004)	(0.005)	(0.000)	(0.001)	(0.061)	(0.048)	(0.000)		
Ethereum	−0.119***	0.002	0.000*	−0.000	0.028	0.375***	0.005***	0.022	0.017
	(0.026)	(0.015)	(0.000)	(0.002)	(0.125)	(0.084)	(0.001)		
Ripple	−0.073***	0.007	1.562	0.001	0.125	0.383***	0.003***	0.016	0.011
	(0.021)	(0.015)	(1.813)	(0.002)	(0.118)	(0.079)	(0.001)		
Litecoin	−0.081***	0.005	−0.008	0.000	0.069	0.448***	0.004***	0.021	0.016
	(0.024)	(0.017)	(0.007)	(0.002)	(0.136)	(0.091)	(0.001)		
Bitcoin Cash	−0.115***	−0.007	0.001	0.002	0.171	0.445***	0.005***	0.022	0.017
	(0.025)	(0.017)	(0.001)	(0.002)	(0.137)	(0.091)	(0.001)		
Monero	−0.042**	0.031**	0.006	−0.001	0.098	0.517***	0.002***	0.027	0.022
	(0.017)	(0.016)	(0.005)	(0.002)	(0.132)	(0.089)	(0.001)		
EOS	−0.068*	0.003	0.041	0.001	0.138	0.371***	0.003*	0.009	0.004
	(0.038)	(0.017)	(0.140)	(0.002)	(0.135)	(0.090)	(0.002)		
Ethereum	−0.065**	0.030*	0.012	0.003	−0.009	0.371***	0.003***	0.014	0.009
Classic	(0.025)	(0.016)	(0.023)	(0.002)	(0.128)	(0.086)	(0.001)		
Dash	−0.099***	0.001	0.001	0.003	0.217	0.339***	0.005***	0.014	0.009
	(0.029)	(0.017)	(0.001)	(0.002)	(0.133)	(0.088)	(0.001)		
Zcash	−0.112***	0.033**	−0.006	0.001	0.224	0.455***	0.006***	0.025	0.02
	(0.032)	(0.019)	(0.005)	(0.003)	(0.152)	(0.102)	(0.002)		

This table represents the regression results of Equation (5). The standard errors are within parenthesis. ***,**, and * denotes significance level at 1%,5%, and 10% respectively. LM is Loughran and Mcdonald (2011) sentiment score, Crypto Bidask is the bid-ask spread of the cryptocurrencies, EPU is Economic Policy Uncertainty Index, GR is gold returns, SPR is S&P 500 Index returns, and Crypto Volume is the volume of the cryptocurrencies.

an appreciation in price. Our results are in line with Yue, Zhang, and Zhang (2021) who found that positive news sentiment leads to an increase in cryptocurrency returns. Further, Chen et al. (2019) found that investor sentiment derived from messages associated with cryptocurrency's financial discussions has a higher predictive power.

However, sentiment has an insignificant impact on the other cryptocurrency prices such as Ethereum, Ripple, Litecoin, Bitcoin Cash, EOS, and Dash. Due to the diversity and heterogeneity of the cryptocurrency market, not all cryptocurrencies will react to news in the same way. For instance, Bitcoin follows a proof-of-work mechanism to validate block transactions, whereas Ethereum is moving towards a consensus mechanism called proof-of-stake. Corbet et al. (2020b) also argued that digital assets do not always react in an identical manner. Their movement in prices is driven by a combination of factors such as the increase in market capitalization, volatility spillovers, and policy announcements.

We also use the HE lexicon to extract sentiment from News Headlines. The results are reported in Column (2) of Table 7. The results show that News sentiment (based on HE lexicon) has a significant positive impact on Cryptocurrency Index, Ripple, Ethereum Classic, Dash, and Zcash returns. This further reinforces that the returns of young, small, and volatile cryptocurrencies are more prone to sentiment.

Regarding control variables, we find that S&P 500 Index returns have a significantly positive impact on cryptocurrency returns. This implies that the herding in the cryptocurrency market rises as the S&P 500 Index rises (Youssef 2020). van Wijk (2013) stresses that financial indicators such as stock exchanges represent the market expectations of investors regarding the financial development of the economy. When the stock indices reflect a favourable financial investment environment, it may give a fillip to the use of cryptocurrency in trade and exchanges. This will cause a spike in cryptocurrency demand, thereby leading to a positive impact (Ciaian, Rajcaniova, and Kancs 2016).

Table 7. Regression of news sentiment (HE lexicon) on cryptocurrency.

	1	2	3	4	5	6	7	8	9
	Constant	HE_t	Crypto $Bidask_t$	EPU_t	GR_t	SPR_t	Crypto $Volume_t$	R^2	Adj. R^2
PANEL A									
Crypto_Index	−0.001	0.130***	-	−0.007**	−0.071	0.641***	-	0.036	0.032
	(0.002)	(0.036)		(0.003)	(0.154)	(0.104)			
PANEL B									
Bitcoin	−0.000	0.009	−0.000	−0.001	−0.002	0.171***	0.000	0.003	0.001
	(0.003)	(0.007)	(0.000)	(0.001)	(0.061)	(0.048)	(0.000)		
Ethereum	−0.116***	0.023	0.000*	−0.000	0.027	0.372***	0.005***	0.022	0.017
	(0.026)	(0.029)	(0.000)	(0.002)	(0.126)	(0.083)	(0.001)		
Ripple	−0.069***	0.046**	1.565	0.001	0.134	0.384***	0.003***	0.017	0.012
	(0.021)	(0.027)	(1.813)	(0.002)	(0.118)	(0.079)	(0.001)		
Litecoin	−0.079***	0.016	−0.009	0.000	0.072	0.449***	0.004***	0.021	0.016
	(0.024)	(0.032)	(0.007)	(0.002)	(0.137)	(0.091)	(0.001)		
Bitcoin Cash	−0.111***	0.010	0.001	0.002	0.171	0.440***	0.005***	0.022	0.017
	(0.025)	(0.032)	(0.001)	(0.002)	(0.136)	(0.091)	(0.001)		
Monero	−0.044***	0.027	0.006	−0.001	0.099	0.521***	0.002***	0.026	0.021
	(0.017)	(0.030)	(0.005)	(0.002)	(0.132)	(0.089)	(0.001)		
EOS	−0.064*	0.023	0.041	0.001	0.142	0.369***	0.003**	0.01	0.004
	(0.039)	(0.030)	(0.140)	(0.002)	(0.135)	(0.090)	(0.002)		
Ethereum Classic	−0.059***	0.070***	0.014	0.003	−0.005	0.354***	0.003***	0.015	0.01
	(0.025)	(0.029)	(0.022)	(0.002)	(0.128)	(0.086)	(0.001)		
Dash	−0.088***	0.060**	0.001	0.003	0.224	0.328***	0.004***	0.016	0.011
	(0.029)	(0.031)	(0.001)	(0.002)	(0.133)	(0.089)	(0.001)		
Zcash	−0.121***	0.047*	−0.006	0.001	0.225	0.462***	0.006***	0.025	0.019
	(0.032)	(0.035)	(0.005)	(0.003)	(0.152)	(0.102)	(0.002)		

This table represents the regression results of Equation (5). The standard errors are within parenthesis. ***,**, and * denotes significance level at 1%,5%, and 10% respectively. HE is Henry (2008) sentiment score, Crypto Bidask is the bid-ask spread of the cryptocurrencies, EPU is Economic Policy Uncertainty Index, GR is gold returns, SPR is S&P 500 Index returns, and Crypto Volume is the volume of the cryptocurrencies.

We also observe a significant positive impact of cryptocurrency volume on cryptocurrency returns. Due to the lack of valuation models in the cryptocurrency market, the market participants tend to rely on technical analysis to design their trading strategies. The trading volume thus plays an essential role in predicting the returns (Balcilar et al. 2017). Further, Bouri et al. (2019) show that trading volume consists of information that helps in predicting cryptocurrency returns. As the traded volume of cryptocurrencies, the investors' attention towards the market rises. This further adds to the noise and hype and increases the demand for cryptocurrencies, thereby causing an upward push on the prices (Rajput, Soomro, and Soomro 2020).

VI. Conclusion

This study investigates the impact of news sentiment on the cryptocurrency market. We construct a news sentiment indicator based on cryptocurrency-specific news headlines crawled from Refinitiv Eikon News Monitor Application. The indicator is built using a lexicon-based Natural language processing (NLP) technique. The sentiment scores are generated using two financial dictionaries, viz. Henry (2008) and Loughran and Mcdonald (2011). This score serves as a proxy for investor news sentiment on cryptocurrency. We investigate the impact of news sentiment on Cryptocurrency Index returns and the returns of ten individual cryptocurrencies, viz. Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Ethereum Classic, Monero, EOS, Dash, and Zcash. Our results suggest that when the public information generates bullish sentiment, the cryptocurrency market experiences herding behaviour among the investors, leading to a rise in prices. All the cryptocurrencies do not respond to sentiment in an identical manner due to the diverse and heterogeneous nature of the cryptocurrency market. The young and volatile cryptocurrencies are more responsive to sentiments (Baker and Wurgler 2006).

This study contributes to the strand of behavioural finance literature, which gives importance to the irrational aspect of investors in the price-determination of assets. Further, this is one of few studies that constructs a sentiment indicator by capturing sentiment from cryptocurrency-specific news headlines using NLP techniques. The extant literature has primarily focused on analysing Bitcoin. We extend the body of literature by analysing Cryptocurrency Index and cryptocurrencies other than Bitcoin.

Our study will benefit the traders and investors who may gauge the predicted movement in cryptocurrencies by analysing the prevailing investors' sentiment in the news media. It will aid them in designing the trading strategies, especially for newer cryptocurrencies that are more prone to sentiment. It will also help portfolio managers to consider the inclusion of cryptocurrency as one of the alternative assets in the portfolio for a better risk-reward arrangement.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Akyildirim, E., A. F. Aysan, O. Cepni, and S. P. C. Darendeli. 2021. "Do Investor Sentiments Drive Cryptocurrency Prices?" *Economics Letters* 206: 109980. doi:10.1016/j.econlet.2021.109980.

Anamika, C. M., and S. Subramaniam. 2021. "Does Sentiment Impact Cryptocurrency?" *Journal of Behavioral Finance* 0 (0): 1–17. doi:10.1080/15427560.2021.1950723.

Andreassen, P. B. 1990. "Judgmental Extrapolation and Market Overreaction: On the Use and Disuse of News." *Journal of Behavioral Decision Making* 3 (3): 153–174. doi:10.1002/bdm.3960030302.

Baig, A., B. M. Blau, and N. Sabah. 2019. "Price Clustering and Sentiment in Bitcoin." *Finance Research Letters* 29: 111–116. doi:10.1016/j.frl.2019.03.013.

Baker, M., and J. Wurgler. 2006. "Investor Sentiment and the Cross-Section of Stock Returns." *The Journal of Finance* 61 (4): 1645–1680. doi:10.1111/j.1540-6261.2006.00885.x.

Balcilar, M., E. Bouri, R. Gupta, and D. Roubaud. 2017. "Can Volume Predict Bitcoin Returns and Volatility? a Quantiles-Based Approach." *Economic Modelling* 64: 74–81. doi:10.1016/j.econmod.2017.03.019.

Banerjee, A. V. 1992. "A Simple Model of Herd Behavior." *The Quarterly Journal of Economics* 107 (3): 797–817. doi:10.2307/2118364.

Baur, D. G., K. Hong, and A. D. Lee. 2018. "Bitcoin: Medium of Exchange or Speculative Assets?" *Journal of International Financial Markets, Institutions and Money* 54: 177–189. doi:10.1016/j.intfin.2017.12.004.

Black, F. 1986. "Noise." *The Journal of Finance* 41 (3): 528–543. doi:10.1111/j.1540-6261.1986.tb04513.x.

Bloomberg Galaxy Crypto Index | Bloomberg Indices. n.d. "Bloomberg Professional Services." Accessed 10 September 2021. https://www.bloomberg.com/professional/product/indices/bloomberg-galaxy-crypto-index/

Bloomberg.com. 2021. "Bloomberg.Com. from." https://www.bloomberg.com/

Bouoiyour, J., and R. Selmi. 2015. "What Does Bitcoin Look Like?" *Annals of Economics and Finance* 16: 449–492.

Bouri, E., K. Gkillas, and R. Gupta. 2020. "Trade Uncertainties and the Hedging Abilities of Bitcoin." *Economic Notes* 49 (3): e12173. doi:10.1111/ecno.12173.

Bouri, E., C. K. M. Lau, B. Lucey, and D. Roubaud. 2019. "Trading Volume and the Predictability of Return and Volatility in the Cryptocurrency Market." *Finance Research Letters* 29: 340–346. doi:10.1016/j.frl.2018.08.015.

Bouri, E., P. Molnár, G. Azzi, D. Roubaud, and L. I. Hagfors. 2017. "On the Hedge and Safe Haven Properties of Bitcoin: Is It Really More Than a Diversifier?" *Finance Research Letters* 20: 192–198. doi:10.1016/j.frl.2016.09.025.

Bunjaku, F., O. Gjorgieva-Trajkovska, and E. Miteva-Kacarski. 2017. "Cryptocurrencies – Advantages and Disadvantages." *Journal of Economics* 2 (1): 31–39.

Caferra, R. 2020. "Good Vibes Only: The Crypto-Optimistic Behavior." *Journal of Behavioral and Experimental Finance* 28: 100407. doi:10.1016/j.jbef.2020.100407.

Cao, M., and L. Rhue. 2019. "Disposed of Bitcoin? Using the Disposition Effect to Understand Financial News Sentiment and Bitcoin Returns." *AMCIS 2019 Proceedings*. https://aisel.aisnet.org/amcis2019/ebusiness/ebusiness/3

Carrick, J. 2016. "Bitcoin as a Complement to Emerging Market Currencies." *Emerging Markets Finance and Trade* 52 (10): 2321–2334. doi:10.1080/1540496X.2016.1193002.

Cheah, E.-T., and J. Fry. 2015. "Speculative Bubbles in Bitcoin Markets? an Empirical Investigation into the Fundamental Value of Bitcoin." *Economics Letters* 130: 32–36. doi:10.1016/j.econlet.2015.02.029.

Chen, C. Y., R. Despres, L. Guo, and T. Renault. 2019. "What Makes Cryptocurrencies Special? Investor Sentiment and Return Predictability During the Bubble." *SSRN Electronic Journal*. doi:10.2139/ssrn.3398423.

Ciaian, P., M. Rajcaniova, and D. Kancs. 2016. "The Economics of BitCoin Price Formation." *Applied Economics* 48 (19): 1799–1815. doi:10.1080/00036846.2015.1109038.

Corbet, S., C. Larkin, B. M. Lucey, A. Meegan, and L. Yarovaya. 2020a. "The Impact of Macroeconomic News on Bitcoin Returns." *The European Journal of Finance* 26 (14): 1396–1416. doi:10.1080/1351847X.2020.1737168.

Corbet, S., C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya. 2020b. "Cryptocurrency Reaction to FOMC Announcements: Evidence of Heterogeneity Based on Blockchain Stack Position." *Journal of Financial Stability* 46: 100706. doi:10.1016/j.jfs.2019.100706.

Corbet, S., B. Lucey, A. Urquhart, and L. Yarovaya. 2019. "Cryptocurrencies as a Financial Asset: A Systematic Analysis." *International Review of Financial Analysis* 62: 182–199. doi:10.1016/j.irfa.2018.09.003.

Corbet, S., B. Lucey, and L. Yarovaya. 2018. “Datestamping the Bitcoin and Ethereum Bubbles.” *Finance Research Letters* 26: 81–88. doi:10.1016/j.frl.2017.12.006.

Cryptocurrency Prices, Charts And Market Capitalizations | CoinMarketCap. n.d. Accessed 11 September2021. https://coinmarketcap.com/

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. “Investor Psychology and Security Market Under- and Overreactions.” *The Journal of Finance* 53 (6): 1839–1885. doi:10.1111/0022-1082.00077.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. ”Noise Trader Risk in Financial Markets.” *The Journal of Political Economy* 98 (4): 703–738. JSTOR. doi:10.1086/261703.

Dimpfl, T., and F. J. Peter. 2020. “Nothing but Noise? Price Discovery Across Cryptocurrency Exchanges.” *Journal of Financial Markets* 100584. doi:10.1016/j.finmar.2020.100584.

Dong, B., L. Jiang, J. Liu, and Y. Zhu. 2022. “Liquidity in the Cryptocurrency Market and Commonalities Across Anomalies.” *International Review of Financial Analysis* 81: 102097. doi:10.1016/j.irfa.2022.102097.

Economic Policy Uncertainty Index. n.d. Accessed 11 September 2021 https://www.policyuncertainty.com/index.html

Granger, C. W. J. 1969. “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods.” *Econometrica* 37 (3): 424–438. doi:10.2307/1912791.

Henry, E. 2008. “Are Investors Influenced by How Earnings Press Releases are Written?” *The Journal of Business Communication (1973)* 45 (4): 363–407. doi:10.1177/0021943608319388.

Karalevicius, V., N. Degrande, and J. De Weerdt. 2018. “Using Sentiment Analysis to Predict Interday Bitcoin Price Movements.” *The Journal of Risk Finance* 19 (1): 56–75. doi:10.1108/JRF-06-2017-0092.

Kennis, M. A. 2018. “Multi-Channel Discourse as an Indicator for Bitcoin Price and Volume Movements.” ArXiv:1811.03146 [Cs, q-Fin, Stat]. http://arxiv.org/abs/1811.03146

Khadjeh Nassirtoussi, A., S. Aghabozorgi, T. Ying Wah, and D. C. L. Ngo. 2015. “Text Mining of News-Headlines for FOREX Market Prediction: A Multi-Layer Dimension Reduction Algorithm with Semantics and Sentiment.” *Expert Systems with Applications* 42 (1): 306–324. doi:10.1016/j.eswa.2014.08.004.

Klibanoff, P., O. Lamont, and T. A. Wizman. 1998. “Investor Reaction to Salient News in Closed-End Country Funds.” *The Journal of Finance* 53 (2): 673–699. doi:10.1111/0022-1082.265570.

Kraaijeveld, O., and J. De Smedt. 2020. “The Predictive Power of Public Twitter Sentiment for Forecasting Cryptocurrency Prices.” *Journal of International Financial Markets, Institutions and Money* 65: 101188. doi:10.1016/j.intfin.2020.101188.

Kristoufek, L. 2013. “BitCoin Meets Google Trends and Wikipedia: Quantifying the Relationship Between Phenomena of the Internet Era | Scientific Reports.” https://www.nature.com/articles/srep03415?WT.ec_id=SREP-20131210

Kristoufek, L. 2015. “What are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis.” *PLoS ONE* 10 (4): e0123923. doi:10.1371/journal.pone.0123923.

Lamon, C., E. Nielsen, and E. Redondo. 2017. *Cryptocurrency Price Prediction Using News and Social Media Sentiment*. United States: SMU Data Science Review, Dallas TX.

Levulytė, L., and A. Šapkauskienė. 2021. “Cryptocurrency in Context of Fiat Money Functions.” *The Quarterly Review of Economics and Finance* 82: 44–54. doi:10.1016/j.qref.2021.07.003.

Li, Y., S. Jiang, X. Li, and S. Wang. 2021. “The Role of News Sentiment in Oil Futures Returns and Volatility Forecasting: Data-Decomposition Based Deep Learning Approach.” *Energy Economics* 95: 105140. doi:10.1016/j.eneco.2021.105140.

Loughran, T., and B. Mcdonald. 2011. “When is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks.” *The Journal of Finance* 66 (1): 35–65. doi:10.1111/j.1540-6261.2010.01625.x.

Lui, S. 2013. *THE DEMOGRAPHICS OF BITCOIN (PART 1 UPDATED)—SIMULACRUM*. https://simulacrum.cc/en/the-demographics-of-bitcoin/

McQueen, G., M. Pinegar, and S. Thorley. 1996. “Delayed Reaction to Good News and the Cross-Autocorrelation of Portfolio Returns.” *The Journal of Finance* 51 (3): 889–919. doi:10.2307/2329226.

Mhatre, S. 2020, May 13. “Text Mining and Sentiment Analysis: Analysis with R.” *Simple Talk*. https://www.red-gate.com/simple-talk/databases/sql-server/bi-sql-server/text-mining-and-sentiment-analysis-with-r/

Naeem, M. A., I. Mbarki, and S. J. H. Shahzad. 2021. “Predictive Role of Online Investor Sentiment for Cryptocurrency Market: Evidence from Happiness and Fears.” *International Review of Economics & Finance* 73: 496–514. doi:10.1016/j.iref.2021.01.008.

Nakamoto, S. 2008. “Bitcoin: A Peer-To-Peer Electronic Cash System.” *Decentralised Business Review* 9: 1–9.

Nasekin, S., and C.-Y.-H. Chen. 2020. “Deep Learning-Based Cryptocurrency Sentiment Construction.” *Digital Finance* 2 (1–2): 39–67. doi:10.1007/s42521-020-00018-y.

Ooi, Y. L. 2020. *Analysis of Cryptocurrency Public Sentiment Shifts [Research Project]*. Dublin, Ireland: National College of Ireland.

Rajput, S. K. O., I. A. Soomro, and N. A. Soomro. 2020. “Bitcoin Sentiment Index, Bitcoin Performance and US Dollar Exchange Rate.” *Journal of Behavioral Finance* 0 (0): 1–16. doi:10.1080/15427560.2020.1864735.

Rognone, L., S. Hyde, and S. S. Zhang. 2020. “News Sentiment in the Cryptocurrency Market: An Empirical Comparison with Forex.” *International Review of Financial Analysis* 69: 101462. doi:10.1016/j.irfa.2020.101462.

Shen, D., A. Urquhart, and P. Wang. 2019. “Does Twitter Predict Bitcoin?” *Economics Letters* 174: 118–122. doi:10.1016/j.econlet.2018.11.007.

Shleifer, A., and L. H. Summers. 1990. “The Noise Trader Approach to Finance.” *Journal of Economic Perspectives* 4 (2): 19–33. doi:10.1257/jep.4.2.19.

Štefan, L., M. Peter,P. Tomáš,M. Maria. 2020. "Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin." *Journal of Economic Dynamics and Control*. doi:10.1016/j.jedc.2020.103980. https://www.sciencedirect.com/science/article/pii/S0165188920301482

Subramaniam, S., and M. Chakraborty. 2020. "Investor Attention and Cryptocurrency Returns: Evidence from Quantile Causality Approach." *Journal of Behavioral Finance* 21 (1): 103–115. doi:10.1080/15427560.2019.1629587.

Tetlock, P. C. 2007. "Giving Content to Investor Sentiment: The Role of Media in the Stock Market." *The Journal of Finance* 62 (3): 1139–1168. doi:10.1111/j.1540-6261.2007.01232.x.

Tversky, A., and D. Kahneman. 1974. "Judgment Under Uncertainty: Heuristics and Biases." *Science* 185 (4157): 1124–1131. doi:10.1126/science.185.4157.1124.

Tversky, A., and D. Kahneman. 1992. "Advances in Prospect Theory: Cumulative Representation of Uncertainty." *Journal of Risk and Uncertainty* 5 (4): 297–323. doi:10.1007/BF00122574.

Urquhart, A. 2017. "Price Clustering in Bitcoin." *Economics Letters* 159: 145–148. doi:10.1016/j.econlet.2017.07.035.

van Wijk, D. 2013. *What Can Be Expected from the Bitcoin?*. Rotterdam, Netherlands: Erasmus University Rotterdam.

Wang, G.-J., C. Xie, D. Wen, and L. Zhao. 2019. "When Bitcoin Meets Economic Policy Uncertainty (EPU): Measuring Risk Spillover Effect from EPU to Bitcoin." *Finance Research Letters* 31. doi:10.1016/j.frl.2018.12.028.

Yelowitz, A., and M. Wilson. 2015. "Characteristics of Bitcoin Users: An Analysis of Google Search Data." *Applied Economics Letters* 22 (13): 1030–1036. doi:10.1080/13504851.2014.995359.

Youssef, M. 2020. "What Drives Herding Behavior in the Cryptocurrency Market?" *Journal of Behavioral Finance* 0 (0): 1–10. doi:10.1080/15427560.2020.1867142.

Yue, W., S. Zhang, and Q. Zhang. 2021. "Asymmetric News Effects on Cryptocurrency Liquidity: An Event Study Perspective." *Finance Research Letters* 41: 101799. doi:10.1016/j.frl.2020.101799.

APPENDIX

Table A1: Sample period

Cryptocurrency	Launch Date	From	To
Crypto_Index	03-05-2018	03-08-2017	10-06-2021
Bitcoin	01-01-2009	28-04-2013	10-06-2021
Ethereum	01-07-2015	07-08-2015	10-06-2021
Ripple	01-06-2012	04-08-2013	10-06-2021
Litecoin	01-10-2011	28-04-2013	10-06-2021
Bitcoin Cash	01-08-2017	23-07-2017	10-06-2021
Monero	18-04-2014	21-05-2014	10-06-2021
EOS	31-01-2018	01-07-2017	10-06-2021
Ethereum Classic	30-07-2015	24-07-2016	10-06-2021
Dash	18-01-2014	14-02-2014	10-06-2021
Zcash	28-10-2016	29-10-2016	10-06-2021

Note: This table presents the sample period of the Cryptocurrency Index returns and the ten cryptocurrencies returns.

Table A2: The Breusch-Pagan-Godfrey Heteroscedasticity Test under OLS estimation

	LM		HE	
	F-statistic	p-value	F-statistic	p-value
PANEL A				
Crypto_Index	2.807**	0.025	3.360***	0.01
PANEL B				
Bitcoin	13.953***	0.00	13.776***	0.00
Ethereum	7.914***	0.00	7.976***	0.00
Ripple	16.636***	0.00	16.556***	0.00
Litecoin	5.990***	0.00	5.723***	0.00
Bitcoin Cash	7.000***	0.00	7.128***	0.00
Monero	4.009***	0.00	4.762***	0.00
EOS	17.519***	0.00	18.860***	0.00
Ethereum Classic	17.582***	0.00	17.439***	0.00
Dash	12.361***	0.00	12.363***	0.00
Zcash	7.949***	0.00	8.867***	0.00

Notes: This table reports the Breusch-Pagan-Godfrey heteroscedasticity test statistics under OLS estimation. The rejection of null hypothesis of homoscedasticity at 1%,5%, and 10% significance level is denoted by ***,**,and *, respectively.

Table A3: The Breusch-Godfrey Lagrange multiplier test

	LM		HE	
	F-statistic	p-value	F-statistic	p-value
PANEL A				
Crypto_Index	0.642	0.951	0.772	0.832
PANEL B				
Bitcoin	0.598	0.973	0.601	0.971
Ethereum	0.725	0.553	0.728	0.500
Ripple	0.721	0.889	0.675	0.929
Litecoin	1.265	0.137	1.291	0.118
Bitcoin Cash	0.863	0.700	0.855	0.714
Monero	0.873	0.715	0.881	0.141
EOS	0.871	0.151	0.818	0.240
Ethereum Classic	1.008	0.458	1.000	0.471
Dash	1.217	0.179	1.210	0.186
Zcash	0.793	0.309	0.782	0.310

Notes: This table reports the Breusch-Godfrey Lagrange multiplier test statistics. The rejection of null hypothesis of no serial correlation at 1%,5%, and 10% significance level is denoted by ***,**,and *, respectively. LM is Loughran and Mcdonald(2011) sentiment score and HE is Henry(2008) sentiment score.

Table A4: Variation Inflation Factor

	VIF_{LM}						VIF_{HE}					
	LM	Crypto Bidask	EPU	GR	SPR	Crypto volume	HE	Crypto Bidask	EPU	GR	SPR	Crypto volume
PANEL A												
Crypto_Index	1.055	-	1.008	1.065	1.109	-	1.001	-	1.005	1.000	1.005	-
PANEL B												
Bitcoin	1.036	1.003	1.003	1.002	1.002	1.035	1.004	1.003	1.003	1.002	1.000	1.006
Ethereum	1.019	1.002	1.004	1.004	1.008	1.016	1.067	1.002	1.004	1.004	1.007	1.066
Ripple	1.013	1.001	1.003	1.004	1.007	1.012	1.068	1.001	1.003	1.004	1.006	1.068
Litecoin	1.006	1.016	1.019	1.005	1.007	1.006	1.060	1.016	1.019	1.005	1.006	1.062
Bitcoin Cash	1.030	1.004	1.004	1.006	1.007	1.028	1.083	1.004	1.004	1.006	1.006	1.081
Monero	1.003	1.000	1.003	1.004	1.009	1.002	1.030	1.000	1.003	1.003	1.007	1.030
EOS	1.007	1.008	1.008	1.006	1.008	1.005	1.038	1.008	1.008	1.005	1.007	1.038
Ethereum Classic	1.025	1.001	1.004	1.006	1.007	1.026	1.070	1.001	1.003	1.005	1.006	1.073
Dash	1.039	1.002	1.003	1.004	1.007	1.037	1.078	1.002	1.003	1.004	1.006	1.078
Zcash	1.008	1.000	1.003	1.004	1.007	1.006	1.040	1.001	1.003	1.004	1.006	1.039

Notes: This table presents the Variation Inflation Factor(VIF) of all the variables as estimated in Eq.(5). VIF measures the level of collinearity among the regressors. LM is Loughran and Mcdonald(2011) sentiment score, Crypto Bidask is the bid-ask spread of the cryptocurrencies, EPU is Economic Policy Uncertainty Index, GR is gold returns, SPR is S&P 500 Index returns, Crypto Volume is the volume of the cryptocurrencies, and HE is Henry(2008) sentiment score.

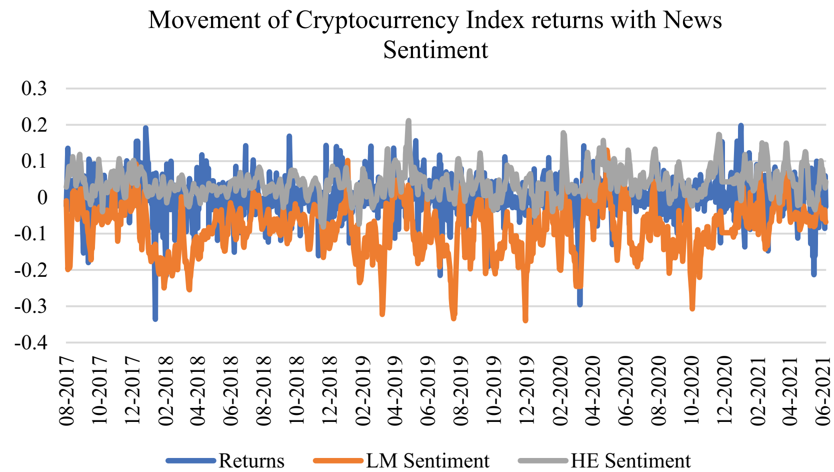

Figure A1. Illustration of movement of News Sentiment (based on LM and HE lexicon) with Cryptocurrency Index Returns