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Does Bitcoin React to Trump's Tweets?[☆]

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ABSTRACT

This textual analysis with spillover effects examines whether the sentiment expressed in the US President Donald Trump's tweets correlates to price and volume activity in the Bitcoin market. After examining 13,918 tweets from January 2017 to January 2020, we find that negative sentiment is a predictive factor for Bitcoin returns, trading volumes, realized volatility, and jumps. In addition, only negative sentiment has a Granger-causal relation with volatility. We also find that Trump's Twitter sentiment can influence the Bitcoin market in the form of time-varying dependence. This paper also extended the COVID-19 period and found that Trump's sentiment can be a predictive tool to the Bitcoin market during the pandemic. Our results hold robust for alternative cryptocurrencies and offer insights about this market.

1. Introduction

President Donald J. Trump's incessant and sometimes caustic tweeting gathers a worldwide audience. Although Twitter might or might not be an official channel for US policy,[1] Trump's tweets are political news and escalate global uncertainty as suggested by the nearly fourfold increase in the Index of Global Economic Policy Uncertainty from 230.75 at the start of Trump's presidency in 2017 to 907.43 in November 2019.

Financial markets digest Trump's tweets for potential effects, and scholars have documented them. Beckers (2018) found evidence to challenge the Efficient Market Hypotheses after showing that lagged variables for social media news could predict global equity returns the next month. Examining word clusters, Liu (2017) found that Trump tweets featuring 'jobless' and 'worst' preceded equity market declines. Trump tweets also preceded a decline in the S&P500 and an increase in the CBOE Volatility Index during trade disputes with China.

Market values of cryptocurrency now exceed the GDP of 130 countries (Selmi et al., 2018). Cryptocurrency has become a platform for 'Fintech' and 'peer-to-peer' lending. Huynh et al. (2019), Shahzad et al. (2019), and Wang et al. (2019) have indicated cryptocurrencies could be safe-haven investments, implying the property characteristics (Yuneline, 2019). As investors and researchers ask, 'What drives Bitcoin returns?', studies answer with reference to supply and demand (Ciaian et al., 2016), investor attention (Corbet et al., 2014; Urquhart, 2018), speculative bubbles (Cheah and Fry, 2015) or economic policy uncertainty (Demir et al., 2018). Studies also confirm that social media influences cryptocurrency markets. Urquhart (2016, 2018) found that Bitcoin prices could be predicted and joined Beckers (2018) in contributing empirical evidence disputing the Efficient Market Hypothesis. Shen et al. (2019) used a number of hashtags in Twitter platforms and found that the number of tweets written by investors could forecast Bitcoin volatility, volume, or returns.

This study investigates whether Trump's tweets have influenced Bitcoin markets. It differs from earlier studies in that we

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1 https://edition.cnn.com/2017/06/06/politics/trump-tweets-official-statements/index.html

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do not define whether those tweets constitute policy announcements or reflect investor sentiment. We presume, instead, that they obviously constitute a statement from the US Chief Executive, and that – as aforementioned studies proved – they can impose uncertainties on Bitcoin markets. More specifically, we textually assess the sentiment of 13,918 Trump tweets covering January 2017 to January 2020. We cluster text into negative words (indicating downbeat or disapproving attitudes), positive words (indicating optimistic or approving attitudes), and total words (frequency with which Trump tweets). We then measure their spillover effects on prices and volatility in Bitcoin markets.

This study makes five contributions to scholarly literature during 'The Age of Twitter' (Ott, 2017). First, it adds to studies of relations between perspectives in social media and Bitcoin, an innovative payment network and a new kind of money. Second, it combines state-of-the-art textual analysis and sophisticated Vector Autoregression to assess effects on a financial market. Third, it proposes a factor for predicting Bitcoin returns. Our findings are twofold. First, lagged terms denoting Trump's sentiment significantly predict positive Bitcoin returns, negative trading volume, and mixed volatility, but negative sentiment has a Granger-causal relationship only with volatility. Second, spillover effects of Trump's tweeted sentiments on Bitcoin exhibit time-varying dependence, with longer periods showing greater spillovers since 2019. Additionally, the volatility transmission exhibits large fluctuations during shorter periods. Additionally, our study also contributes to the ongoing studies about financial markets and COVID-19 that Trump sentiment, particularly in the disease outbreak, could act as the predictive tool to the Bitcoin markets. To be more precise, there is a relationship between attitudes towards COVID-19 and the Bitcoin returns as well as volume. However, volatility seems to be immune to changes in the President's sentiment. Finally, US President Donald Trump's tweets can possibly act as the predictive power on Bitcoin's jumps by using the framework of Barndorff-Nielsen and Shephard (2006). Differing from Ahn and Kim (2019) regarding the driving factor of Sentiment disagreement, our study considers specific messages containing valuable information from Donald Trump, known as the US President. Therefore, his opinion has been perceived as a political risk (Burggraf et al., 2019). By doing this, our study offers a channel on how social media influencers could impact the Bitcoin market while the current literature examines the role of peer opinions driving this cryptocurrency market (Ahn and Kim, 2019; Shen et al., 2019; Urquhart, 2018).

The paper proceeds as follows. Section 2 generalizes the theoretical framework to investigate how Trump's sentiment might impact cryptocurrency markets. Section 3 discusses our method. Section 4 summarizes how we collect, process, and characterize data. Section 5 presents findings regarding our research question. Section 6 concludes.

2. Theoretical framework

We build upon the theoretical frameworks of Schwert (1981) and Wagner et al. (2018) concerning how prices of financial assets respond to the political news. Since the Trump's tweets could be considered as news (Ajjoub et al., 2020; Burggraf et al., 2019), this study extends an understanding of Bitcoin reactions to the news released from the White House. Simply put, if markets reflect the optimal news from political outcomes, there are changes in differences between expected discounted payoff between two possible states and ex-ante probability that this outcome happens.

P_i is the cryptocurrency price (i) prior to the date Trump posts a tweet. $P_{i,N}$ and $P_{i,P}$ denote the expected prices of cryptocurrency given Trump's expression of negative and positive sentiments. In addition, π_N and $1-\pi_N = \pi_P$ are the probabilities of Trump's sentiments. We make two assumptions. First, discounting over a short period is included. Second, risk aversion is a minor consideration.

$$P_i = \pi_N P_{i,N} + \pi_T P_{i,P} \quad (1)$$

The price change for the Bitcoin given that Trump has tweeted negative words is given by.

$$\Delta P_i = P_{i,N} - P_i = (P_{i,N} - P_{i,P})(1-\pi_N) \quad (2)$$

In sum, prices change once Trump expresses a positive or negative sentiment. That is, investors who might have had no particular impression form one after Trump tweets. We scale the previous equations by the initial price. Thus, returns once a Trump tweet appears are given by.

$$R_i = \frac{P_{i,N} - P_i}{P_i} = \frac{(P_{i,N} - P_{i,P})(1-\pi_N)}{P_i} \quad (3)$$

Each form of cryptocurrency responds to Trump's sentiment differently depending upon the sign and magnitude of the spread between $P_{i,N}$ and $P_{i,P}$. So, we hold the view how investors react and expect on the cryptocurrency prices. If the negative and positive tones of Trump diverged significantly over the period, it would explain why cryptocurrency prices responded strongly. Therefore, in the following part, we would like to mention how we clean up the data and calculate the Trump sentiment for further estimating the expected prices that investors hold in cryptocurrency market.

3. Methodology

3.1. Textual analysis

We first counted how many words appeared in a Trump tweet. Then we consulted the 2016 Loughran and McDonald Master Dictionary to determine how many negative and positive sentiments Trump expressed. Although Ahn and Kim (2019) used a different sentiment dictionary to correlate disagreeable sentiments and Bitcoin prices' fluctuations, we adopted Loughran and McDonald, which is synthesized from Loughran and McDonald (2011), Bodnaruk et al. (2015), and Loughran and McDonald (2016) because it specifies sentiment words that Tetlock (2007) used in their financial context analyses—for example, *loss(es)*, *impairment*, *adverse(ly)*, etc. We created a proxy for negative words as the ratio of negative to total words in each tweet:

$$Negativity = \frac{The\ number\ of\ negative\ words}{The\ total\ words} \times 100 \quad (4)$$

We replicated the procedure to create a proxy for positive words. We also examined the impact of total words in each Trump tweet. The natural logarithm of that total is used for the total of words.

3.2. Spillover effects

We examined whether negative and positive words in Trump's tweets spilt over into Bitcoin trading. We followed Diebold and Yilmaz (2009) in measuring the volatility of any spillover. The method employs forecast error variance decompositions from VAR, but it has two disadvantages: it depends on the order of variables, and it measures only total spillovers. We turned to Baruník et al. (2016) and Diebold and Yilmaz (2012), who capture individual effects by considering invariant-to-variable ordering. Their method is widely applied in financial contexts (Baruník and Kocenda, 2019; Baruník and Křehlík, 2018; Yarovaya et al., 2016). Recently, the study of Foglia and Dai (2021) employed this method to examine how cryptocurrency uncertainty index could impact the cryptocurrency market. Our procedure initially delivered n-dimensional vector RV_t, that has stationary VAR(p) under the following process:

$$RV_t = \sum_{l=1}^{p} \Phi_l RV_{t-l} + \epsilon_t \tag{5}$$

The residual follows the iid vector as $\epsilon_t \sim N(0; \sum_\epsilon)$ whereas Φ_l denotes p matrices having the coefficients. Following that, the invertible VAR process extracts the moving average representation.

$$RV_t = \sum_{l=0}^{\infty} \Psi_l \epsilon_{t-l} \tag{6}$$

We obtained (n × n) matrices from the recursion $\Psi_l = \sum_{j=1}^{p} \Phi_j \Psi_{l-j}$ where $\Psi_l = I_N$ and $\Psi_l = 0$ for $l < 0$. This procedure isolates forecast errors for further computation, which is improved in a previous study by Diebold and Yilmaz (2009). Diebold and Yilmaz (2012) later introduced a method of constructing H-step-ahead point forecasts such that generalized forecast error variance decomposition appears in the matrix:

$$\phi_{ij}^H = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon e_k)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon \Psi_k' e_k)} \qquad j, k = 1, \ldots, N \tag{7}$$

This vector has a moving average coefficient calculated from the forecast at time t. Σ_ϵ denotes the variance matrix for the error vector. k is the kth diagonal element of Σ_ϵ. e_j and e_k are selection vectors, with one as the jth or kth element and zero otherwise. Especially, the normalization process of each row is calculated as $\tilde{\theta}_{jk}^H = \frac{\theta_{jk}^H}{\sum_{k=1}^{N} \theta_{jk}^H}$. Thus, total interconnectedness from volatility shocks in the estimation of total forecast error variance is given by:

$$S^H = 100 \times \frac{1}{N} \sum_{j,k=1:j \neq k}^{N} \tilde{\theta}_{jk}^H \tag{8}$$

Noted that $\sum_{k=1}^{N} \tilde{\theta}_{jk}^H = 1$ and $\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^H = N$. We identified different rolling windows as trading days in one year from $t-199$ to point t because Bitcoin trades continuously. We based VAR lag lengths on Akaike Information Criteria. After calculating total spillover effects, we followed Baruník and Kocenda (2019) to estimate the directional spillover that Trump' sentiments send to Bitcoin and vice versa.

4. Data

We collected 13,920 tweets (365,690 words) from *@realDonaldTrump*, each time-stamped in minutes, from January 2017 to January 2020. Trump was inaugurated on January 20th, 2017, so collection starts with the first moments he used his Twitter account in the White House. The majority of Trump's Tweets express consistently negative attitudes about Mexico (Benton and Philips, 2018), US–China trade relations (Burggraf et al., 2019) and the European Financial markets (Klaus and Koser, 2020).

Fig. 1 shows that negative and positive sentiments moved together from 2017 to 2020. However, the number of negative words slightly exceeds the positive in time-varying connections. There is no significant correlation between proxies for positive and negative sentiments ($\rho = 0.0491$, and OLS regression generating the insignificant coefficient as well, $\beta_{t-stat=0.59} = 0.0214$). Our check implies that Trump's sentiment variables are reliably independent variables.

Bitcoin data are from coinmarketcap.com covering January 2017 to January 2020. We calculated log-returns per Fama and Miller (1972) and the natural logarithm for scaling Bitcoin trading

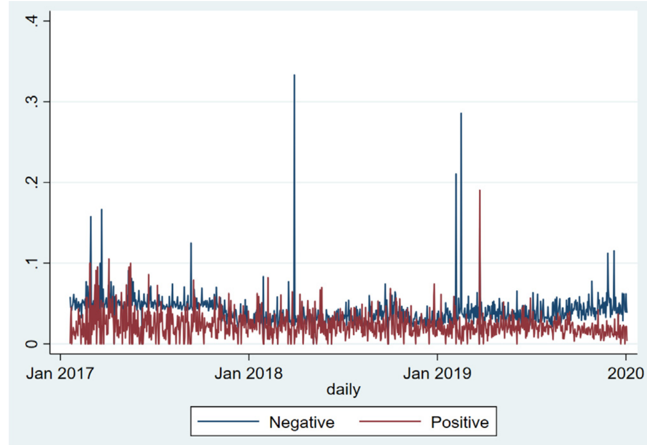


Fig. 1. Time-varying between negative and positive from textual analysis.

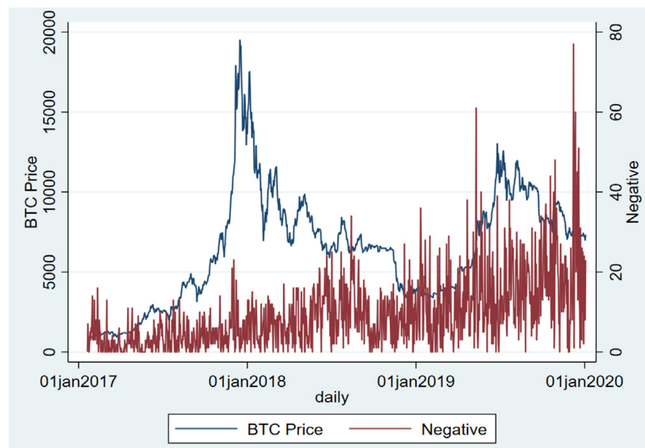


Fig. 2. Time-varying between Bitcoin prices and negative sentiment.

Table 1
Descriptive statistics.

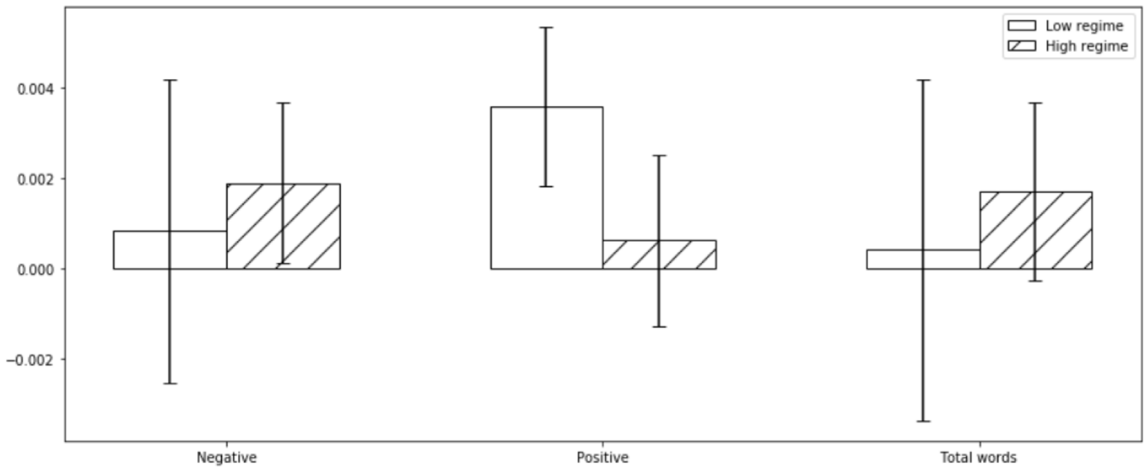
Variable	Mean	Std. Dev.	Skewness	Kurtosis	JB
BTC-Return	0.002	0.042	0.0372	6.5659	567.7***
BTC-Volume	22.261	1.350	−0.9808	3.5838	187***
Negative	0.041	0.019	7.1814	91.989	36000***
Positive	0.023	0.016	2.3721	17.526	1000***
Total	5.514	0.915	−0.6984	3.8341	118.1***

Notes: *** $p < 0.01$, ** $p < 0.05$; * $p < 0.01$. JB denotes Jarque–Bera test for normality.

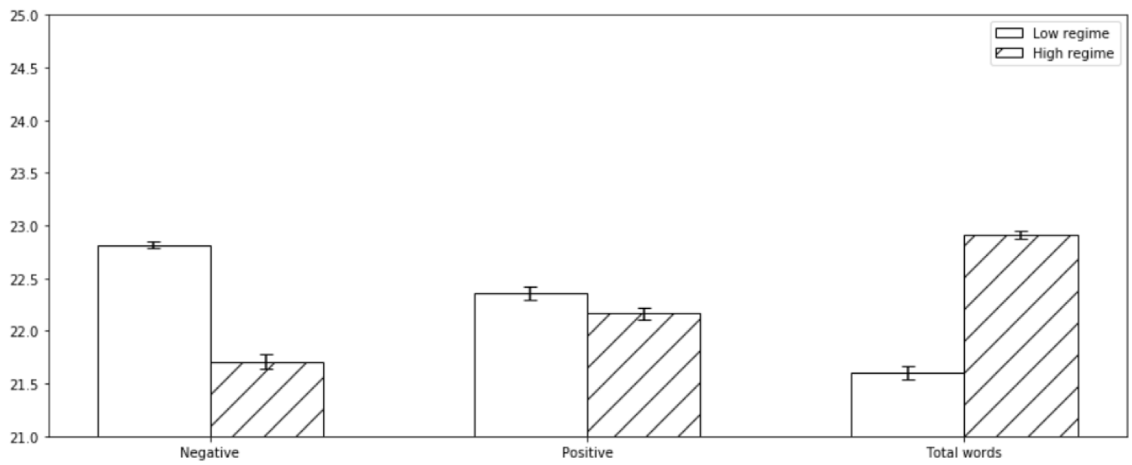
volume. Fig. 2 indicates a positive correlation ($\rho = 0.2483$ with $p < 0.01$) between the number of negative words and Bitcoin prices from January 2017 to January 2020. The correlation between Bitcoin prices and the proxy for negativity varies with time, so we considered time effects to control this phenomenon.

Bitcoin's average returns during the examined period approximate 0.002 (Table 1). Note that negative values from the textual analysis are significantly higher than positive values. Additionally, all variables exhibit non-normal distributions.

We examined Bitcoin's average returns and average trading volume under two regimes (low and high states compared to median values). Fig. 3 shows no significant difference in average Bitcoin returns between low and high regimes. It is statistically insignificant that average Bitcoin returns during high negativity exceed those in the low regime. This effect seems to be opposite for positive states. Negative and positive sentiments in Trump's



(a) Average return



(b) Average trading volume

Fig. 3. Average return and trading volume under two regimes.

tweets and the number of words seem to drive Bitcoin trading volumes, but effects differ significantly during periods of above-average and below-average occurrence of positive and negative words. Our findings endorse Kaminski (2014), who correlates Bitcoin trading volume and sentiments expressed by 57,727 unique Twitter users. The effect of Twitter sentiment on Bitcoin trading volumes is indicated as 'speculative' (Kaminski, 2014; Shen et al., 2019).

Preliminary data analysis provides three conclusions. First, there is no correlation among variables denoting negative, positive, and total words in Trump's tweets. Second, variables are not distributed normally. Third, given time fixed-effects, only trading volume reacts to regimes of above-average positivity and negativity. Fluctuations in Bitcoin returns are statistically insignificant during both regimes.

5. Main findings

5.1. Regression and causal relationship

Table 2 shows the impact of Trump's sentiment on contemporaneous Bitcoin returns. To our surprise, coefficients for contemporaneous sentiment are insignificant. Only negative sentiment correlates significantly and positively with Bitcoin returns at 5%. These findings indicate that increases in Bitcoin prices correlate to Trump's negative sentiments with a one-day lag. A 1% increase in negative sentiment is associated with a next-day increase of 11.0% to 11.7% in Bitcoin prices, depending on the regression considered.

Shen et al. (2019) indicated Twitter does not predict Bitcoin returns, but our negative coefficients are significant at 10%. Differences in method and research question explain the disparity in findings. Previous studies employ the number of times the term 'Bitcoin' is tweeted (@BitinfoCharts) and capture investor sentiment. We consider the sentiment of Trump's tweets.

Among surprising results in Table 3, trading volume declines when Trump's tweets contain more negative words. Moreover, the decline in trading volume contrasts with positive returns under uncertainty regimes. This counterintuitive finding also manifests among conventional asset classes. However, when Bitcoin prices rise, bid–ask spreads widen when Trump tweets more negative words. That finding indicates sellers incorporate greater uncertainty premiums (lower bids, higher ask prices) into immediate trades. This behaviour seems not to apply to traditional financial assets, but Aalborg et al. (2019) and Koutmos (2018) demonstrated it is commonplace for cryptocurrency when Bitcoin trading volume declines during uncertainty. By approaching the microstructure of Bitcoin characteristics, we explain at 1% significance why negative Trump tweets induce positive returns as volumes decline.

Table 2
Impact of Trump's sentiment on contemporaneous Bitcoin returns.

Variables	(1) $BTC_{(t)}$	(2) $BTC_{(t)}$	(3) $BTC_{(t)}$	(4) $BTC_{(t)}$
$Negative_{(t)}$	−0.039			−0.064
	[−0.588]			[−0.986]
$Positive_{(t)}$	−0.031			−0.023
	[−0.435]			[−0.283]
$Total\ words_{(t)}$	−0.000			−0.000
	[−0.053]			[−0.237]
$Negative_{(t-1)}$		0.110**		0.117**
		[1.993]		[2.038]
$Positive_{(t-1)}$		−0.062		−0.061
		[−0.819]		[−0.711]
$Total\ words_{(t-1)}$		0.002		0.002
		[1.026]		[1.086]
$Negative_{(t-2)}$			0.054	0.031
			[0.606]	[0.347]
$Positive_{(t-2)}$			0.026	0.022
			[0.298]	[0.250]
$Total\ words_{(t-2)}$			−0.000	−0.001
			[−0.030]	[−0.353]
Observation	1071	1070	1069	1053
Adjusted R-square	0.004	0.005	0.003	0.007
Time-effect control	Yes	Yes	Yes	Yes

Notes: This table presents OLS regression estimation results. The dependent variable is contemporaneous Bitcoin returns. We use variance inflation factors (VIFs) to check for multicollinearity. Because average mean VIF values for all variables (around 2.45) are well below the threshold of 10, we find no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh et al., 2020).

Table 3
Impact of Trump's sentiment on daily contemporaneous Bitcoin volume.

Variables	(1) $Volume_t$	(2) $Volume_t$	(3) $Volume_t$	(4) $Volume_t$
$Negative_{(t)}$	−8.676***			−6.474***
	[−2.909]			[−2.583]
$Positive_{(t)}$	0.304			−0.315
	[0.185]			[−0.184]
$Total\ words_{(t)}$	−0.020			−0.002
	[−0.564]			[−0.057]
$Negative_{(t-1)}$		−9.195***		−7.396***
		[−3.207]		[−2.998]
$Positive_{(t-1)}$		0.363		0.086
		[0.229]		[0.053]
$Total\ words_{(t-1)}$		−0.037		−0.025
		[−1.035]		[−0.676]
$Negative_{(t-2)}$			−8.867***	−6.934***
			[−3.137]	[−2.993]
$Positive_{(t-2)}$			0.893	1.697
			[0.585]	[1.201]
$Total\ words_{(t-2)}$			−0.059	−0.057
			[−1.608]	[−1.518]
Observation	1071	1070	1069	1053
Adjusted R-square	0.7142	0.7149	0.72	734
Time-effect control	Yes	Yes	Yes	Yes

Notes: This table presents estimations from OLS regression . The dependent variable is contemporaneous Bitcoin volume. We use VIFs to check for multicollinearity. Because average mean VIF values for all variables (1.58) are well below the threshold of 10, we find no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh et al., 2020). Concomitantly, we also control the daily Bitcoin return to predict the Bitcoin volume.

Table 4 depicts the predictive power of Trump's tweets on Bitcoin volatility. Unlike Shen et al. (2019) we find at 5% significance that volatility correlates positively with a two-day lag in the variable denoting Trump's attitudes towards negative tone, and that variable with contemporaneous term correlates negatively with volatility. In our study, we referred to the previous empirical evidence from Huynh et al. (2021b), which estimated the realized monthly volatility by taking the deviation from daily price in one month. Interestingly, this study also found that a high level of global economic policy uncertainty could negatively predict Bitcoin volatility. One of the possible explanations is the bid–ask spread, which implies their risk aversion. Our findings are also consistent with the sound theory by Arrow (1959) and Bernanke (1983). Accordingly, the investors tend to wait and see under a high level of uncertainties. Concomitantly, we also used the approach of GARCH-in-mean (M-GARCH) to capture Bitcoin volatility. We also found that Trump's negative sentiment

Table 4
Impact of Trump's sentiment on monthly contemporaneous Bitcoin volatility.

Variables	(1) $Volatility_t$	(2) $Volatility_t$	(3) $Volatility_t$	(4) $Volatility_t$
$Negative_{(t)}$	−0.818*			−1.083**
	[−1.859]			[−2.093]
$Positive_{(t)}$	−0.366			−0.634
	[−0.383]			[−0.673]
$Total\ words_{(t)}$	−0.010			−0.014
	[−1.479]			[−1.611]
$Negative_{(t-1)}$		−0.506		−0.556
		[−1.204]		[−0.995]
$Positive_{(t-1)}$		0.721		−0.897
		[0.888]		[−1.205]
$Total\ words_{(t-1)}$		−0.005		
		[−0.941]		
$Negative_{(t-2)}$			0.384	1.383**
			[0.996]	[2.314]
$Positive_{(t-2)}$			0.192	−0.105
			[0.326]	[−0.171]
$Total\ words_{(t-2)}$			−0.006	
			[−1.066]	
Observation	37	36	35	35
Adjusted R-square	0.139	0.112	0.137	0.377
Time-effect control	Yes	Yes	Yes	Yes

Notes: This table presents estimations from OLS regression. The dependent variable is contemporaneous Bitcoin volatility. Variance inflation factors (VIFs) confirm that the first and second lagged of total words exhibit multicollinearity with contemporaneous total words (VIF > 10). Therefore, we excluded those variables from the regression (4). Average mean VIF values (2.88) for all variables are well below the threshold of 10, indicating no evidence for multicollinearity. t-tests reject the null hypotheses that Positive = Negative in all regressions. Robust standard deviations are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Lag length of one period is determined by the Schwarz Bayesian information criterion; we examine two days for further insights. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh et al., 2020). Concomitantly, we also control the average Bitcoin return to predict the Bitcoin volume.

Table 5
Vector Autoregressive Granger causality.

Granger causality	χ^2
Negative sentiment does not Granger cause return	1.20
Positive sentiment does not Granger cause return	0.47
Total words does not Granger cause return	0.92
Negative sentiment does not Granger cause volume	2.35
Positive sentiment does not Granger cause volume	2.09
Total words does not Granger cause volume	0.68
Negative sentiment does not Granger cause volatility	8.95***
Positive sentiment does not Granger cause volatility	0.45
Total words does not Granger cause volatility	0.62

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The lag length is determined by the Schwarz Bayesian information criterion as one-level.

Table 6
Trump sentiment and long-term spillovers on volatility.

	Return	Volume	Negative	Positive	Total
Return	25.74	0.17	0.13	0.01	0.03
Volume	7.8	89.75	0.11	0.67	0
Negative	0.35	3.23	32.09	0.25	0.09
Positive	0.19	0.9	0.57	27.91	0.98
Total	1.05	13.07	1.41	0.86	35.14

Notes: This table captures directional spillover from variable j to variable i with rows indicating spillovers on and columns indicating spillovers from. These columns contain net pairwise (i, j)th spillover indices.

(contemporaneous and lagged terms) could negatively predict Bitcoin volatility.[2]

Our findings support Aysan et al. (2019) that changes in historical geopolitical risk data correlate positively with Bitcoin volatility at different quantiles. Therefore, our results also link to the conflicts, political instability, which is through the presidential political announcements, can significantly influence Bitcoin's realized volatility. All in all, Bitcoin's returns, volatility, and trading volumes respond to the sentiment of Trump's tweets, especially, when it is negative.

To test for causal relationships among positive sentiment, negative sentiment, and total words, we employ VAR Granger causality (Granger, 1969). In Table 5 the sentiment of Trump's tweets influences volatility, not returns and volume. Like Shen et al. (2019), we confirm a causal relation between tweeting and Bitcoin volatility, but we find none with respect to returns and volume.

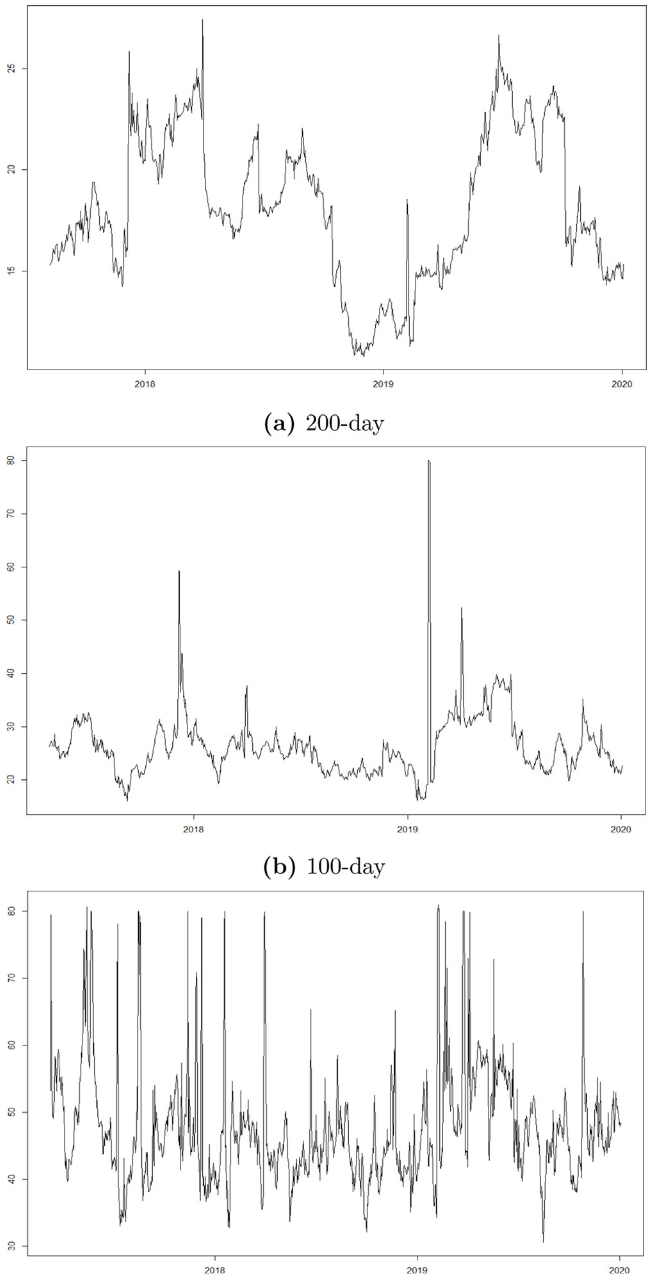
2 The results are available upon request. We thank an anonymous referee for suggesting the insightful analysis, which substantially improves our manuscript.

5.2. Spillover effects of Trump's sentiment on Bitcoin market

Table 6 decomposes indices for the spillover effects of the sentiment in Trump's tweets on Bitcoin. In particular, the negative sentiment contributes more to Bitcoin's returns than positive sentiment. However, OLS estimations reveal no significant coefficients. In addition, a pairwise comparison of spillovers and volatility indicates that positive sentiments in Trump's tweets induce greater daily volatility. The number of words spills over onto returns but not volatility.

Fig. 4 depicts the total volatility of spillover effects across three rolling windows in the time series (three years of daily data). It shows that the effects of Trump's tweets on Bitcoin were particularly high during the 2018 crash and early 2019. Overall, spillover effects are higher during shorter periods. Spillover is dramatic, presenting fluctuations of 30 to 80, during 50 day windows and less dramatic (fluctuations of 15 to 25) for longer periods. These findings indicate that the sentiment of Trump's tweets precipitates wide but fleeting short-term fluctuations on Bitcoin markets.

Ours is the first study to examine the effect of Trump's sentiment on Bitcoin markets using time-varying spillover effects. We find that Bitcoin digital currency is significantly affected by



(a) 200-day

(b) 100-day

(c) 50-day

Fig. 4. Time-varying spillover effects using a different-days rolling window.

the political uncertainty raised by the politician. Although Bitcoin returns rise with the negative sentiment of Trump's tweets, this feature is challenged by the role of non-governmental control as well as safe-haven. Our findings confirm Jiang et al. (2018) that the Bitcoin market is inefficient. The market is clearly not persistent in different rolling windows, which suggests investors should be cautious in presuming any arbitrarily beneficial opportunity or invest with only speculative intent. Our results also suggest Bitcoin's usefulness as a hedge due to heightened returns under Trump's negative sentiment. Fang et al. (2019) demonstrate that Bitcoin and equities correlate positively with economic policy uncertainty.

Fig. 5 shows net spillover effects by component. Positive values indicate net contributors of spillovers and negative values its net recipients. The effects of Trump's tweeted sentiments are weaker before 2019 and stronger after. In contrast, the positive sentiment and the total words are mostly recipient with time-varying values below 0.

Table 7
Impact of Trump's sentiment regarding COVID-19 on Bitcoin market.

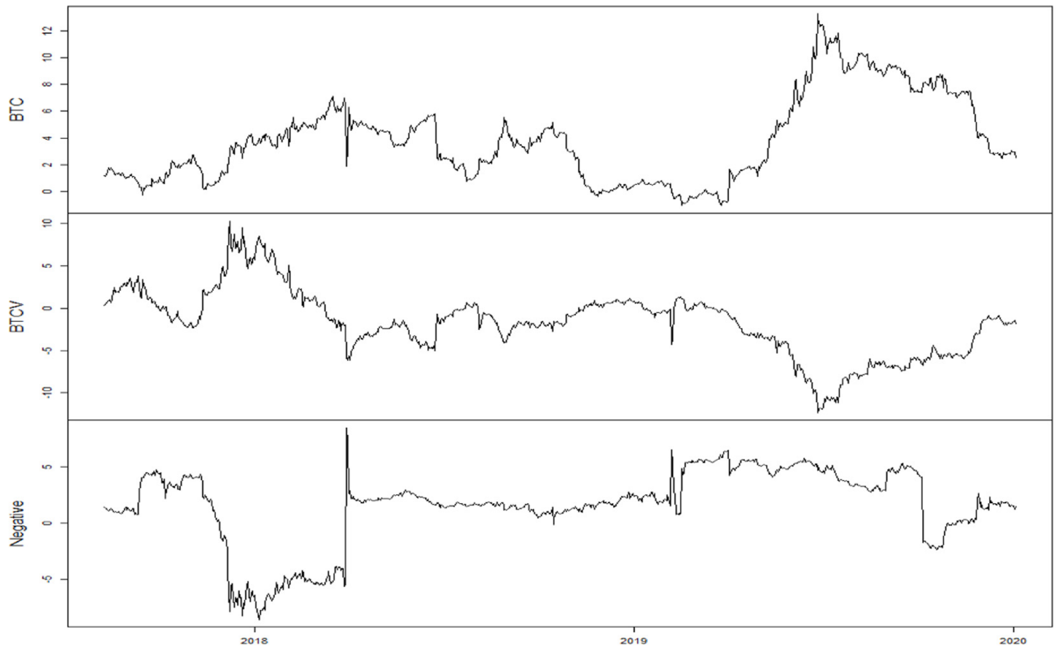
Variables	Return	Volatility	Volume
$COVID\ Negative_{(t)}$	-0.403^{*}	-0.010	0.527
	[-1.871]	[-0.123]	[1.489]
$COVID\ Positive_{(t)}$	0.064^{*}	-0.013	-0.144
	[1.929]	[-0.858]	[-0.500]
$Total\ words_{(t)}$	0.003	0.002	0.044
	[1.000]	[0.501]	[1.318]
$COVID\ Negative_{(t-1)}$	0.010	0.046	-0.021
	[0.424]	[0.706]	[-0.258]
$COVID\ Positive_{(t-1)}$	-0.011	-0.003	0.364^{*}
	[-0.499]	[-0.084]	[1.884]
$Total\ words_{(t-1)}$	-0.002	-0.004	0.035
	[-0.746]	[-0.701]	[1.170]
$COVID\ Negative_{(t-2)}$	0.005	0.000	0.232^{*}
	[1.109]	[0.010]	[1.798]
$COVID\ Positive_{(t-2)}$	0.031	-0.002	0.213
	[1.432]	[-0.053]	[0.885]
$Total\ words_{(t-2)}$	0.000	0.001	0.078^{***}
	[0.087]	[0.354]	[2.640]
Constant	-0.060	-0.011	65.750^{***}
	[-0.221]	[-0.029]	[17.980]
R-squared	0.219	0.02	0.394
Time-effect control	Yes	Yes	Yes

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The lag length is determined by the Schwarz Bayesian information criterion as one-level. This table presents estimations from OLS regression . The dependent variable is contemporaneous Bitcoin volume. We use VIFs to check for multicollinearity. Because average mean VIF values for all variables (less than 2.0) are well below the threshold of 10, we find no evidence for multicollinearity. Robust standard deviations are in parentheses. The daily sample covers the period from December 2018 to October 2020. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh et al., 2020). In addition, we used the Bitcoin return to control the predictive regression model for volume and volatility.

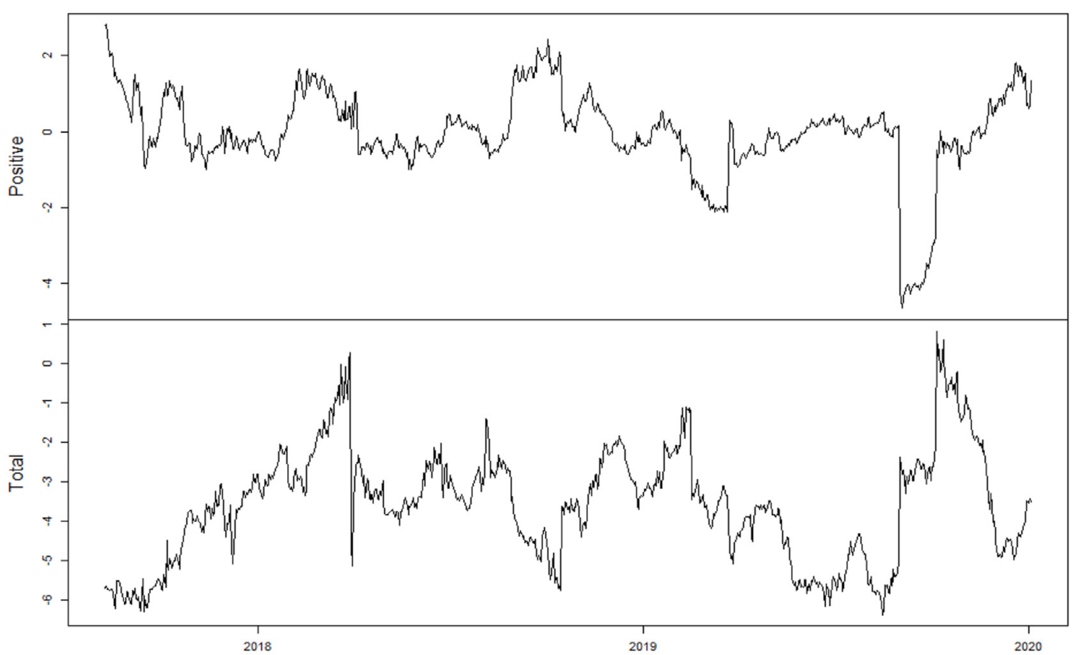
5.3. Trump attitudes towards COVID-19 pandemic and Bitcoin markets

Recently, Rufai and Bunce (2020) confirmed the role of Twitter's G7 leaders in response to the COVID-19 pandemic because it should be considered as the potential source of information on the financial market. Concomitantly, the current literature indicates no linkage between feverish news and stock return changes but volatility (Ambros et al., 2020). However, the role of fake news, as well as investors' sentiment, play an important role (Huynh et al., 2021a). Given the flow of Trump's tweets having responsive policies, this study extends the Trump's sentiment to examine whether this predictive factor holds robust during the pandemic time or not. We constructed the index of negative and positive sentiment by calculating the fraction of a number of negative words in tweets mentioning coronavirus (or COVID-19 pandemic, and so forth) over the total negative words on that day. It holds the same for positive sentiment. Finally, Table 7 represents the impact of Mr. President's attitudes towards the COVID-19 pandemic on the cryptocurrency market.

While the current literature emphasizes the role of media coverage on financial markets during the COVID-19 time (Haroon and Rizvi, 2020), our findings also contribute to the existing literature that the country leader's attitudes could predict the Bitcoin market. Accordingly, the higher the pessimistic (optimistic) sentiment, the lower (higher) Bitcoin's expected return. Differing from the previous findings, we offer an insight that the Bitcoin market reacts immediately (contemporaneous time) instead of a one-day lagged term. However, we also obtain weak evidence



(a) Return, Volume and Negative



(b) Positive and Total words

Fig. 5. Net spillover effects by each component.

that Trump sentiment is associated with the changes in Bitcoin returns at 10% significance level.

Concomitantly, we do not find any evidence that Trump's attitudes towards pandemic could predict the volatility while the Bitcoin volume is likely to respond to Donald Trump's sentiment in COVID-19 from one to two lagged days at 10% significance level. Therefore, our findings confirm the extant literature that sentiment plays a role in improving market liquidity (Burggraf et al., 2020; Liu, 2015). To sum up, the cryptocurrency market reacts like the financial assets when the President's sentiment changed during the pandemic. To be more precise, it requires more (less) risk premium when having negative (positive) feelings from the leader; however, the sentiment is not the source of risk in this period. Our findings also contribute empirical evidence to the ongoing studies about financial markets and COVID-19.

5.4. Do Trump's Tweets trigger the Bitcoin jumps?

In this section, we examine whether Trump's tweets could predict the Bitcoin jumps. We employed the asymptotic distribution theory for a few non-parametric tests of Barndorff-Nielsen

Table 8
The predictive power of Trump's Tweets on the Bitcoin's jumps.

Variables	Positive jumps	Negative jumps
BTC Return	23.433***	−29.895***
	[8.297]	[−8.181]
BTC Volume	−0.227*	−0.527***
	[−1.701]	[−3.412]
$Negative_{(t)}$	−17.282**	−3.436
	[−2.123]	[−0.677]
$Negative_{(t-1)}$	−5.601	−13.515
	[−0.727]	[−1.431]
$Negative_{(t-2)}$	−6.156	−1.492
	[−0.863]	[−0.163]
$Positive_{(t)}$	0.457	−0.645
	[0.080]	[−0.086]
$Positive_{(t-1)}$	−2.018	−3.252
	[−0.333]	[−0.485]
$Positive_{(t-2)}$	6.409	1.669
	[0.926]	[0.282]
$Total\ words_{(t)}$	−0.183	−0.145
	[−1.348]	[−0.894]
$Total\ words_{(t-1)}$	0.253*	−0.047
	[1.709]	[−0.322]
$Total\ words_{(t-2)}$	0.082	−0.058
	[0.594]	[−0.384]
Constant	−19.303*	−56.822***
	[−1.747]	[−4.471]
Time-effect control	Yes	Yes
Pseudo R-squared	0.128	0.175

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. This table presents estimations from the Logit regression. The dependent variable receives binary values (1—jumps detected and 0—otherwise). Robust standard deviations are in parentheses. The daily sample covers the period from January 2017 to January 2020. We used the time-effect to control the dynamics of Bitcoin from the previous literature (Huynh et al., 2020). In addition, we used the Bitcoin return and Bitcoin volume to control the predictive regression model for the Bitcoin jumps.

and Shephard (2006) to construct the binary variables for "Positive jumps" and "Negative jumps" from the hourly return of Bitcoin. Table 8 represents how Trump sentiments correlate with the possibility of having a jump of Bitcoin. Interestingly, only negative sentiments could act as the predictive factor to the Bitcoin positive jumps. Accordingly, when Trump expressed his attitudes towards the negative tone in a contemporaneous period, it was less likely to have positive jumps at the same time. Although we did not find any predictive power of negative sentiment at time (t) on Bitcoin returns, we extended the further empirical evidence that Trump's pessimistic tone negatively correlated with the likelihood of jumps having positive returns. Concomitantly, the higher (lower) return is associated with the higher (lower) possibility of having positive (negative) jumps. However, a decrease in trading volume could increase in the chance of facing new jumps in the largest capitalization cryptocurrency.

5.5. Robustness check

To examine whether the sentiment of Trump's tweets affects other cryptocurrencies, we substituted Bitcoin data with data for Ethereum. Again, we find an association between Ethereum's returns and a one-day lag in sentiment. Negative sentiments relate to lower same-day trading volume and with lags of one and two days. However, we find no Granger causality between Trump's sentiment and Ethereum's returns, trading volume, and volatility. Overall, our findings are still persisted when replacing different cryptocurrency assets.[3] In addition, we employed the predictive regression model to test a relationship between the Trump sentiment and persistent variation in risk. We also found that Trump sentiments positively predict this ratio, representing the aggregate source of risk in the economy (Huang and Kilic, 2019). Hence, the possible channel of Trump's sentiments in predicting the future Bitcoin return could be the market risk (Huynh et al., 2020).[4]

6. Conclusions

This paper has explored relations between Bitcoin's returns, volatility, and trading volumes and the positive or negative sentiments expressed in tweets by the US President Donald J. Trump. We find that the sentiment of Trump's tweets reasonably predicts Bitcoin's returns, volatility, and trading volumes. The more negative Trump's sentiment, the higher returns. However, volatility diminishes when Trump tweets negative sentiments. Trading volume rises with lags of two days and declines contemporaneously. Only volatility and negativity exhibit Granger-causal relationships.

Although Donald Trump is no longer the US President, this study still has some merits. First, this is the first study to offer a relationship between textual analyses in social media account of politician and cryptocurrency markets. Our study also challenges the concept that these coins are independent of the political risk (or any uncertainties arising from the specific government). After controlling the rigorous variables, we found that one Twitter account, particularly the US President, could drive the cryptocurrency markets. This is the typical case of Elon Musk, the richest man in the world (Ante, 2021), who can be an influential and well-known individual on the cryptocurrency market. In doing so, future research could explain how other politicians and billionaires social media accounts could drive the cryptocurrency markets. Second, this paper also discusses the evolution of cryptocurrency markets' behaviours during the pandemic crisis. To be more specific, in normal times, cryptocurrency exhibits its own characteristics in response to the uncertainties. However, in the crisis time, cryptocurrency is likely to respond as the traditional financial assets. Also, future research can consider how cryptocurrencies change during the specific period in their development. Finally, we also found that Trump's tweets with pessimistic feelings could predict the Bitcoin's jumps; therefore, this paper contributes the predictive feature of Trump's tone on how Bitcoin returns jump during the 2017–2020 period. Accordingly, professional traders could keep their eyes on the content on social media to predict when and how Bitcoin exhibits a large movements in its return.

We find evidence of time-varying spillover effects between Trump's sentiments and Bitcoin prices. Longer periods showed lower spillovers in volatility than shorter periods, indicating that the short-term effects of Trump's tweets are greater than their long-term effects. Additionally, the negative effect is most evident during periods of above-average and below-average occurrence of positive and negative words and the total number of words in Trump's tweets. We also find Bitcoin markets seem more sensitive to Trump's negative sentiments after 2018. This study employs daily data. Future studies might garner more insights using intra-day or tick-by-tick data with the existence of cryptocurrency uncertainty indices (Foglia and Dai, 2021) or machine learning approach (Abdullah, 2021).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[3] The results are available upon request.

[4] The predictive regression results are available upon request.

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