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News sentiment in the cryptocurrency market: An empirical comparison with Forex☆

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ABSTRACT

We use high frequency intra-day data to investigate the influence of unscheduled currency and Bitcoin news on the returns, volume and volatility of the cryptocurrency Bitcoin and traditional currencies over the period from January 2012 to November 2018. Results show that Bitcoin behaves differently to traditional currencies. Traditional currencies typically experience a decrease in returns after negative news arrivals and an increase in returns following positive news whereas Bitcoin reacts positively to both positive and negative news. This suggests investor enthusiasm for Bitcoin irrespective of the sentiment of the news. This phenomenon is exacerbated during bubble periods. Conversely, cryptocurrency cyber-attack news and fraud news dampen this effect, decreasing Bitcoin returns and volatility. Our results contribute to the discussion on the nature of Bitcoin as a currency or an asset. They further inform practitioners about the characteristics of cryptocurrencies as a financial asset and inform regulators about the influence of news on Bitcoin volatility, particularly during bubble periods.

1. Introduction

In recent years, Bitcoin has attracted much attention from policymakers, investors, academics and regulators due to its rapid price appreciation. The price of Bitcoin increased markedly over the 12 months from $788 on December 17, 2016 to $19,650 one year later, experiencing an increase of 2394 %. The current debate on the nature of Bitcoin tries to determine whether the digital currency should be considered a financial asset or a medium of exchange, bringing out the need to classify cryptocurrencies as financial instruments and to study the shared characteristics they may have with other well-known financial products. This paper contributes to the literature investigating the intradaily relationship between Bitcoin and the major traditional currencies to assess whether there exists a similar reaction to news sentiment and to provide further evidence on cryptocurrency characteristics to help the debate. Particularly, we investigate how high-frequency unscheduled news releases related to Forex and Bitcoin affect returns, volume and volatility of Forex and whether Bitcoin exhibits similar responses. We provide a comprehensive study for Bitcoin including a sample period of almost seven years of 15-minute data from January 1, 2012 to November 1, 2018. We consider six major currencies against the U.S. Dollar (USD) (counter), namely the Australian Dollar (AUD), the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY) alongside Bitcoin (BTC). Using *Ravenpack News Analytics 4.0*, we construct a sentiment index for each currency and Bitcoin and we examine how currency returns, volume and volatility are affected by the news sentiment using exogenous vector autoregressive model (VAR-X).

Our key results suggest that while Forex comoves and reacts homogeneously to news, Bitcoin behaves differently. There is evidence of a contemporaneous statistically significant relationship between foreign exchange and news sentiment such that positive (negative) news on the base appreciate (depreciate) the exchange rate, while positive (negative) news on the counter decrease (increase) the exchange rate returns. Overall, news on the base increase Forex volume. These findings do not hold for Bitcoin, where an overall low level of significance is found while testing for the contemporaneous news sentiment impact, such that only positive Bitcoin news are informative for Bitcoin returns. We then consider the impact that news sentiment have on Bitcoin one period after due to the existence of potential delays and

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technological advancements issues in the Bitcoin market, and find that both positive and negative news increase Bitcoin returns. This finding is exacerbated during the Bitcoin bubble periods suggesting the strong investors' enthusiasm toward the digital currency. We then focus on intra-day cryptocurrency cyber-attacks and fraud news sentiments and find that such news dampen enthusiasm, reducing volatility in conjunction with negative Bitcoin returns upon arrival of negative cyber-attack news. Results are robust to tests for commonality and multicollinearity.

Our results are particularly relevant for practitioners and regulators. On one side, practitioners are generally concerned about risks and other characteristics of a potential investment into cryptocurrencies. On the other side, regulators aim to better understand possible systemic risks of cryptocurrencies as well as other issues, such as cyber-criminality and fraud. Our results provide insight for both groups of stakeholders to better understand the characteristics of cryptocurrencies.

The remainder of this paper is organized as follows: Section 2 provides a short background on Bitcoin and the related literature on the topic. Section 3 describes the data collection. Section 4 presents the sentiment index construction and the empirical model, while Section 5 presents a discussion of the main results. Section 6 focuses with a numbers of robustness tests. Finally, Section 7 concludes the study summarizing the findings and proposing further analyses.

2. Background and related literature

Introduced in 2008, Bitcoin is a digital currency, namely an electronic cash system without a physical counter value and is infinitely divisible. There is no unique market or a central authority, rather cryptocurrencies such as Bitcoin are decentralized and characterized by a peer-to-peer network fragmented over more than fifteen thousand exchanges. Each transaction must be approved by other users, or nodes, to be validated and recorded on the public ledger, namely the blockchain. Bitcoin is the leading digital currency relative to Litecoin, Ripple, Bitcoin Cash, Ethereum and other cryptocurrencies with a market capitalization of around $217 billion and covering 63.4% of the entire cryptocurrency market[1].

Regarding the debate on the nature of Bitcoin, Bitcoin is originally considered to be money according to its developer, Satoshi Nakamoto. Money should generally serve as a medium of exchange, as a store of value, and as a unit of account. Proponents of the financial asset perspective challenge this view since not all of these properties seem to hold for Bitcoin, for example due to its high volatility. However, neither does Bitcoin adhere to characteristics of traditional financial assets, as it does not mature or pay any dividend for instance. With our study, we aim to identify Bitcoin characteristics which can help the understanding of this new financial product. Current evidence on the debate includes Baur, Hong, and Lee (2018) who claim that Bitcoin is mainly used as speculative investment but that its behavior is unrelated to that of stocks, bonds and commodities. Dyhrberg (2016) further highlights the risk management advantages of using Bitcoin as a medium of exchange. She concludes that the digital currency can be classified as something in between a traditional currency, such as the U.S. Dollar, and a store of value, such as gold.

The examination of Bitcoin and other cryptocurrencies in comparison to foreign exchange has largely focused on their prospective hedging properties. Urquhart and Zhang (2019) base their study on the Baur and Lucey (2010) hedge, diversifier and safe-haven definitions and find that Bitcoin acts as a hedge for the Swiss Franc, the Euro and the British Pound and as a diversifier for the Australian Dollar and the Canadian Dollar and the Japanese Yen at the intra-day level with an hourly frequency. Baumöhl (2019) explores the interconnectedness between six cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens, and NEM) and six traditional currencies (Euro, Japanese Yen, British Pound, Swiss Franc, Canadian Dollar, and Chinese Renminbi), finding that investors benefit from diversifying across the two groups. Other research explores the volatility connectedness between Bitcoin and precious metal markets (Mensi, Sensoy, Aslan, & Kang, 2019) and the dynamic relationship between cryptocurrencies and other financial assets (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018c) further establishing the potential diversification possibilities associated with cryptocurrencies. This paper seeks to compare Bitcoin and traditional currencies but with respect to the reaction to non-scheduled, non-fundamental news sentiment.

There is emerging evidence documenting the influence of news on cryptocurrencies. Corbet, Larkin, Lucey, Meegan, and Yarovaya (2020) document the impact of US monetary policy announcements on Bitcoin and the spillover effects from Bitcoin to other cryptocurrencies around such announcements while other studies establish the connection between cryptocurrencies and news more broadly through macroeconomics news announcements. For instance, Corbet, Larkin, Lucey, Meegan, and Yarovaya (2018a) create a sentiment index for four macroeconomics variables, namely Gross Domestic Product, Consumer Price Index, unemployment and durable goods and find that only stories related to the last two macroeconomic variables appear to be relevant for Bitcoin returns. In contrast to this study, we use unscheduled news for different currencies and compare the effects on Bitcoin to other traditional currencies. Abraham, Higdon, and Nelson (2018) collect information from Twitter Data and Google Trend Data to forecast the price direction of Bitcoin and Ethereum, finding that only tweet volume and not the sentiment is significant for the forecast. Furthermore, Urquhart (2018) uses Google Trends data and finds that volatility and volume are important drivers of next day attention of Bitcoin.

Similarly, there is a long-standing literature on foreign exchange providing evidence that macroeconomic news influences both returns and volatility. However, macroeconomic news cannot completely explain the majority of foreign exchange-rate movements due to the low frequency of the announcements and because the information they convey is not as surprising or unexpected as that of non-scheduled news (Andersen, Bollerslev, Diebold, & Vega, 2003). Evans and Lyons (2005) conclude that exchange rates do not instantaneously react to macro news, while Evans and Lyons (2008) show that only the 30% of the daily price variation of FX is due to macro announcements. Further, Love and Payne (2007) find that not all the information included in scheduled news announcements is impounded in the Forex price. With respect to exchange rate volatility, Omrane and Savaşer (2017) show that the response to different types of macroeconomic news is time varying and differs with some news have a larger effect impact during economic booms and other news having greater impact during the financial crisis period. Dominguez and Panthaki (2006) study the importance that scheduled macroeconomic surprises, non-scheduled fundamental news and non-scheduled non-fundamental news have on foreign exchange. They find that non-scheduled non-fundamental news influence the USD/GBP and the USD/EUR intra-day returns, volatility and transaction intensity. Ederington and Lee (2001) also examine non-scheduled news announcements and find evidence that high volatility persists more after non-scheduled shocks than after scheduled news due to the surprise component. Additionally, research examining the presence of jumps and co-jumps in foreign exchange markets demonstrates that many events are due to or consistent with news releases, see *inter alia* Lahaye (2016), Chatrath, Miao, Ramchander, and Villupuram (2014), and Lahaye, Laurent, and Neely (2011).

Our study extends this literature providing further evidence on the impact of high-frequency non-scheduled news sentiment related to traditional currencies and Bitcoin on returns, volatility and trading volume.

[1] Coinmarketcap.com on July 8, 2019 at 22:42 GMT +0100.

3. Data

3.1. Bitcoin data

We collect data[2] for Bitcoin for the sample period January 1, 2012–November 1, 2018 from *bitcoincharts.com*, a website providing transaction data for most of the Bitcoin exchanges around the world (see, for example, Corbet, Lucey, Urquhart, & Yarovaya, 2019). We consider single trade prices and volume data from Bitstamp[3], one of the oldest and most active Bitcoin exchanges (Brandvold, Molnár, Vagstad, & Andreas Valstad, 2015) providing reliable data[4]. We focus on Bitcoin over U.S. Dollar due to its high liquidity. Data are aggregated into 15-minute intervals to construct log-returns. The original sample consists of 239,616 observations, but we filter the Bitcoin sample to match the Forex opening time[5] reducing the sample to 171,605 observations. For any 15-minute interval with no transaction record, we assume the last recorded price generating a zero return. Volume is measured in logarithms and volatility is the conditional variance from a GARCH(1,1) model.

Table 1 presents the summary statistics for Bitcoin to U.S. Dollar data over the sample period. Historically, Bitcoin returns have been positive and close to zero with a high intra-day volatility of about 58.4%. Bitcoin returns are positively skewed, and kurtosis far exceeds the Gaussian distribution kurtosis, suggesting that they are not normal. The null hypothesis of non-stationarity is clearly rejected according to the Phillips-Perron test results conducted with trend and drift. Bitcoin log-volume mean is about 3.425, showing the historical presence of high-frequency transaction and confirming the intra-day liquidity of Bitstamp. Furthermore, average volatility has been high, around 37.6%.

Fig. 1, panel a plots the sample period Bitcoin price evolution and it shows the rapid price appreciation which peaks on December 17, 2017 at 12:15:00 when the price of one Bitcoin reached 19,650 U.S. Dollars. Subsequently, Bitcoin suffered a rapid drop, probably due to the burst of the bubble (Corbet, Lucey, & Yarovaya, 2018b). Trading volume is plotted in Fig. 1, panel b and reveals insight on the liquidity of Bitstamp at the intra-day level. The highest volume is registered during the burst of the first Bitcoin bubble (July 2013–December 2013, Gerlach, Demos, & Sornette, 2019), particularly on February 10, 2014 at 11:00 AM, when 11,167 Bitcoins were traded within 15 min. Among the other volume peaks, 10,000 Bitcoins were exchanged on January 14, 2015 at 07:15 AM in conjunction with the high turmoil for the Swiss Franc exchange rate. There is also evidence of high transaction activity during the second bubble (January 2016–December 2017, Gerlach et al., 2019) which peaks on March 10, 2017 at 09:00 PM with 9066 Bitcoins traded.

[2] All data are in Universal Time Coordinated (UTC).

[3] Bitstamp is a cryptocurrency marketplace based in Luxembourg since 2011 with more than 3 million of users which allows to trade Bitcoin, Ethereum, Litecoin, Bitcoin Cash and Ripple along with U.S. Dollar and Euro. It utilizes advanced security technologies to guarantee secure and transparent transactions by storing offline the 98% of the digital funds. It is subject to annual audit by one of the Big Four accountancy firms (EY, Deloitte, KPMG, PwC).

[4] One main issue with cryptocurrency data relates to fake reported volumes. Many digital currency exchanges modify and increase their reported volume to influence rankings to appear more attractive to investors. The data provider company Bitwise examined exchanges for fake volumes by monitoring real time trading data from the top 80 cryptocurrency exchanges. Bitwise found that the 95% of reported volume is fake. Only Binance, Bitfinex, Coinbase, Kraken, Bitstamp, bitFlyer, Gemini, itBit, Bittrex, and Poloniex exchanges report reliable volume data. Among these exchanges, we select Bitstamp due to its relative maturity (it is the oldest exchange together with Kraken) and because Bitstamp ranks in the top five exchanges in terms of monthly volume throughout the entire sample. Further information can be found at "Meeting with Bitwise Asset Management, Inc., NYSE Arca, Inc., and Vedder Price P.C", U.S. Securities and Exchange Commission held in March 19, 2019, and at data.bitcoinity.org.

[5] FXCM opens on Sunday 10 PM UTC and closes on Friday 10 PM UTC. It is also closed on Christmas Day, December 25, and New Year 's Day, January 1.

3.2. News sentiment data

News sentiment data for the currencies and Bitcoin are drawn from *RavenPack*, a company that provides real-time news analysis services to institutional investors and financial professionals. *RavenPack News Analytics* is a leading global news database affiliated with *Dow Jones News*, which analyzes relevant information from *Dow Jones Newswires*, regional editions of the *Wall Street Journal*, *Barron's* and *MarketWatch* and has been used in a number of prior studies (e.g. Kolasinski, Reed, & Ringgengerb, 2013; Shroff, Verdi, & Yu, 2014; Dai, Parwada, & Zhang, 2015). *RavenPack* continuously collects and automatically processes hundreds of thousands of articles a day delivering news timestamped to the millisecond from leading publishers and web aggregators, including national and local news, blog sites, industry and business publishers, government and regulatory updates and trustworthy financial websites (see RavenPack News Analytics – 2015 User Guide v.4.0.). *RavenPack News Analytics* is comprised of two main editions: the *Dow Jones* edition and the *Web* edition. In this paper, we use both of these editions to exploit all the information provided by this dataset, similarly to Sabherwal, Sarkar, and Zhang (2011) and more recently Bushman, Williams, and Wittenberg-Moerman (2017), Ho, Liu, and Yu (2018), and Chinco, Clark-Joseph, and Ye (2019).

RPNA4 (*RavenPack News Analytics 4.0*) provides news items which are tagged for each currency as well as timestamp, and most importantly, includes separate scores for relevance, novelty and sentiment[6]. While other studies, such as Birz and Lott (2011), Lott and Hassett (2014), Caporale, Spagnolo, and Spagnolo (2017) and Corbet, Larkin, et al. (2018a), focus on newspaper coverage of scheduled macroeconomic announcements and classify news sentiment by their headlines, RPNA4 also analyzes the news body and provides a sentiment measure on a granular scale. In particular, RPNA4 provides 32 fields for each record, such as timestamp, reference identifiers, scores for relevance, novelty and sentiment, and a unique identifier for each news story analyzed. The principal fields of interest are (RPNA4 code in brackets):

- *Timestamp* (TIMESTAMP_UTC): the date and time (YYYY-MM-DD hh:mm:ss.sss) at which *RavenPack* receives the news item with millisecond precision;
- *Identifier* (RP_ENTITY_ID): a permanent and unique 6 alphanumeric character assigned by *RavenPack* to each entity[7];
- *Relevance*: a score between 0 and 100 that indicates how strongly the news story is related to the entity, higher values mean greater relevance. It follows a brief score interpretation:
  - 100: highly relevant score and context-aware. Entities which receive this relevance score are prominent in the news story and play a key role. RavenPack's relevance analysis goes further the only interpretation of key words or mentions. In fact, its automated classifiers can detect the roles entities play in events like legal disputes and acquisitions or during announcing corporate actions and other categories, understanding the meaning (context awareness). Thus, a score of 100 is given if and only if the news is highly relevant and context-aware.
  - 0–99: score context-unaware, the score is assigned by a proprietary text positioning algorithm based on where the entity is first mentioned, the number of references in the text and the overall number of entities mentioned in the story. However, a score between 90 and 99 is considered significantly relevant. In this case, the entity is mentioned directly in the main title or in the

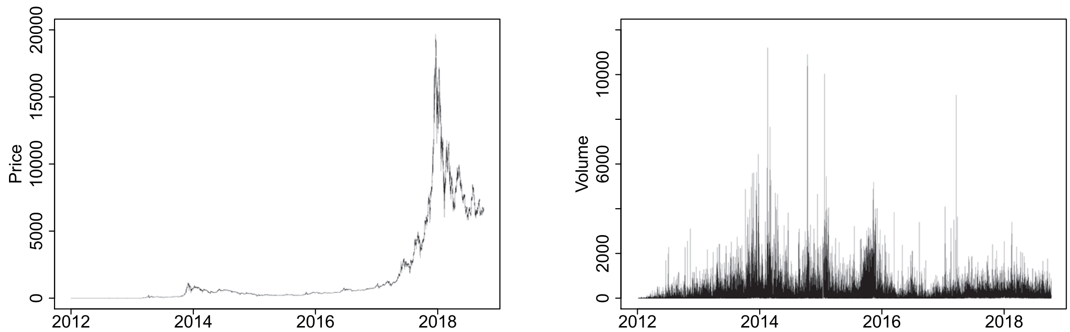
[6] Other studies that use similar Reuters data include Groß-Klußmann and Hautsch (2011) and Riordan, Storkenmaier, Wagener, and Zhang (2013).

[7] RPNA4 Identifiers for AUD, CAD, CHF, EUR, GBP, JPY, USD and BTC are 5A72C2, D74D70, 74086E, 3E823F, DF632D, A753BA, FE1757 and A25816 respectively.

Table 1
Summary statistics Bitcoin data.

	Mean	SD	Skew	Kurtosis	PACF at lag 1	2	3	4	PP test
Log-returns (%)	0.003	0.584	6.798	1101.497	0.043	−0.054	−0.032	−0.016	−398.890*
Log-volume	3.425	1.848	−0.449	2.472	0.720	0.320	0.219	0.168	−287.350*
Volatility	0.376	0.430	10.663	264.822	0.991	−0.115	−0.034	−0.051	−33.366*

Note: Mean, standard deviation (SD), skewness (Skew), Kurtosis, partial autocorrelation (PACF) and Phillips-Perron stationarity test with drift and trend (PP test) for 15-minute percentage log-returns, log-volume and GARCH(1, 1) volatility for Bitcoin to U.S. Dollar for the period Jan 2012 –Nov 2018.
* indicates p-value < 0.01.



(a) Price **(b)** Volume

Fig. 1. Bitcoin price and volume. Note: 15-minute Bitcoin to U.S. Dollar (BTCUSD) price (a) and trading volume (b) for Bitstamp over the sample period Jan 2012–Nov 2018.

headline. A score ranging from 75 to 89 still represents a relevant score, the entity reference is further in the story body. Scores below 75 are not relevant scores.

– *Sentiment*: a score between 0 and 100 representing the sentiment and financial perception of facts. Financial experts categorize stories according to the short-term positive or negative financial impact and rate entity-specific events conveying whether the sentiment was positive or negative and to what extent. The financial expert consensus is combined with traditional language analysis and sophisticated proprietary algorithms dynamically assign an Event Sentiment Score (ESS) based on score ranges assigned by the experts and considering an emotional factor[8], a weather and a climate factor[9], an analyst rating factor[10], a credit rating factor, a fundamental comparison factor[11] and a causalities factor[12]. Positive (or negative) sentiments are associated with scores above (or below) 50 and neutral sentiments are linked to sentiment scores of 50.
– *Novelty*: an integer number between 0 and 100 representing how novel a story is within a 24-hour time window across all news stories. The first story reporting a categorized event is the most novel and important and receives a score of 100. The Event Novelty Score (ENS) represents the order in which entity records are published per news story by attaching scores following a decay function (100 75 56 42 32 24 18 13 10 8 6 4 3 2 2 1 1 1 1 0 …) to each repeated news within 24 h. Hence, the second story of the day matching the first with the same entity and referring to the same event receives a score of 75, the third similar story receives an ENS of 56, and so on. We interpret the second similar story to be only 75% novel, the third one 56% novel, up to the twentieth that has no more novelty power, 0%.

Hafez (2009) provides evidence that only 20% of news stories are relevant and including the remainder mostly adds noise. Following Groß-Klußmann and Hautsch (2011) and Smales (2014b) who find that market prices are affected only by highly relevant news, we sample only news with a relevance score above 90 which in fact results in a sample where all news have maximum relevance score of 100. The sample is further filtered according to one-day novelty to eliminate redundancy among the data. Within the day news are weighted by novelty in order to keep information from related news but place greater emphasis on new stories.

Table 2 presents the descriptive statistics for the 15-minute sample news sentiment data. On average, Bitcoin news items have a neutral average sentiment (mean 0), with the lowest standard deviation of 4.7% compared to the other currencies. Negative average sentiment is linked to the currencies CAD, CHF and JPY. JPY has on average the lowest sentiment of about −0.004. The two leading currencies in terms of number of news are the U.S. Dollar and the Euro with 84,694 and 51,140 news items respectively. The lowest number of news items is that of Bitcoin. The sample data set includes only 3108 positive and negative stories for the digital currency. Phillips-Perron unit-root test statistics with drift and trend always reject the null.

3.3. Foreign exchange data

The lack of a central foreign exchange market presents a major challenge to obtain an aggregate and valid measure of trading volume. While some foreign exchange brokers provide data on historical intraday exchange rates, they only present a portion of the total FX volume. Some practitioners have systematically overcome this limitation by using tick-volume, namely the number of price updates over a certain

[8] There are 5 sales containing groups of words and phrases with different emotional magnitude: *Low Magnitude*, *Moderate Magnitude*, *Substantial Magnitude*, *Severe Magnitude* and *Critical Magnitude*.
[9] Measure extreme weather according to official measure like Richter scale or the Volcanic Eruption Index.
[10] Over 150 different broker and analysts scales for stocks, strong buy, buy, hold, sell, strong sell.
[11] Compares actual versus estimated figures about earning, revenues or dividend and gives a score.
[12] Used as sentiment strength factor for natural disasters and industrial accidents based on the number of fatalities.

Table 2
Summary statistics news sentiment data.

	Mean	SD	Skew	Kurtosis	PP test	No. Obs.
News AUD	0.000	0.117	−0.090	22.374	−392.060*	29,956
News CAD	−0.003	0.117	−0.223	21.785	−389.510*	28,496
News CHF	−0.003	0.085	−0.759	43.187	−396.690*	20,530
News EUR	0.002	0.143	−0.059	14.696	−393.910*	51,140
News GBP	0.001	0.125	−0.020	19.687	−395.500*	36,664
News JPY	−0.004	0.140	−0.195	16.170	−394.870*	37,702
News USD	0.000	0.202	−0.084	7.235	−402.140*	84,694
News BTC	0.000	0.047	1.446	147.476	−382.230*	3108

Note: Mean, standard deviation (SD), skewness (Skew), Kurtosis, Phillips-Perron stationarity test with drift and trend (PP test) and number of observation (No. Obs.) for 15-minute news sentiment data for the Australian Dollar (AUD), the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY), the U.S. Dollar (USD) and Bitcoin (BTC) for the period Jan 2012-Nov 2018.

* indicates p-value < 0.01.

time interval, as proxy for currency trading volume. Marney (2010, 2011) provides evidence that price updates have a high positive correlation with the actual traded volume in FX at the hourly level, which is also the basis for the Marney Volume Indicator (MVI). 15-minute UTC exchange rates[13] and tick-volumes for the pairs AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD and JPY/USD are collected from Forex Capital Markets[14] (FXCM) for the period 1 January 2012–1 November 2018. Fig. 2 shows the exchange rates evolution over the sample period for each pair. Despite the different scale, FX 15-minute exchange rates depict a similar development over the sample period.

Table 3 presents the descriptive statistics for foreign exchange data. Panel a shows traditional currencies returns summary statistics. All the currencies have zero percentage return, for three decimal results, and low volatility consistent with the existing Forex microstructure literature (Dominguez & Panthaki, 2006). Panel b shows summary statistics for volume. On average, the 15-minute log-volume ranges from 6.608 for CAD/USD to a maximum of about 6.975 for EUR/USD. Panel c reports the GARCH(1,1) volatility statistics and overall FX volatility is similar with a average intra-day variability ranging between 0.046 and 0.063.

4. Methodology

4.1. Sentiment indices

We construct sentiment indices for AUD, CAD, CHF, EUR, GBP, JPY, USD and BTC news using only relevant news. Each Event Sentiment Score (ESS) is scaled on a range from $[-1, 1]$, with -1 representing negative and 1 representing positive sentiment news: (ESS-50)/50. The score is further multiplied by a novelty weight factor $w_{j,t,s} = ENS_{j,t,s}/100$, where ENS is the individual news novelty score and 100 represents the maximum novelty score assigned to the first news of the day for a specific entity and event. $w_{j,t,s}$ represents the novelty weight for instrument $j = \{AUD, CAD, CHF, EUR, GBP, JPY, USD, BTC\}$ at time interval t for the series of similar news of the day s and it follows a decay function according to the percentage of novelty of the news. $w_{j,t,s} \in [0, 1]$ such that the closer to 1 the more novel the news in a series of similar news is, within one day. The closer to 0 the lower the novelty, meaning that the news has been repeated many times during the current day.

[13] Mid-quote prices.

[14] FXCM is a Forex retail broker since 1999 based in London. It is a leading Forex provider around the world that trades 24 h, five days a week on the major and the commodity pairs. It allows to trade 39 currency pairs covering most of the trading in FX market.

The resulting novelty weighted sentiment score, WESS (Weighted Event Sentiment Score) keeps the ESS sign without alteration, positive or negative sentiment, but it lowers the ESS magnitude if the specific news has a low ENS (poor novelty power). Each WESS index for the eight instruments is aggregated and simple averaged in 15-minute buckets creating the Average Weighted Event Sentiment Score $AWESS = \sum_{k=1}^{N} WESS_k/N$ which takes a value between $[-1, 1]$. Values above (below) 0 are considered positive (negative) sentiment and values equal 0 are treated as neutral. N represents the number of news within a time bucket and it may vary across intervals because non-scheduled news time arrival is stochastic and not equally spaced.

The bar-plot in Fig. 3 (a) shows the percentage of negative (grey bars) and positive (black bars) news of the currencies, with most currencies having a similar proportion of positive and negative news. The pie-chart in Fig. 3 (b) presents the overall number of news per currency in percentage. The U.S. Dollar has the highest number of stories covering the 29% of the entire sample, followed by the Euro which covers the 17.5%, the Japanese Yen (12.9%) and the British Pound (12.5%). Bitcoin news only account for the 1.1% of the sample.

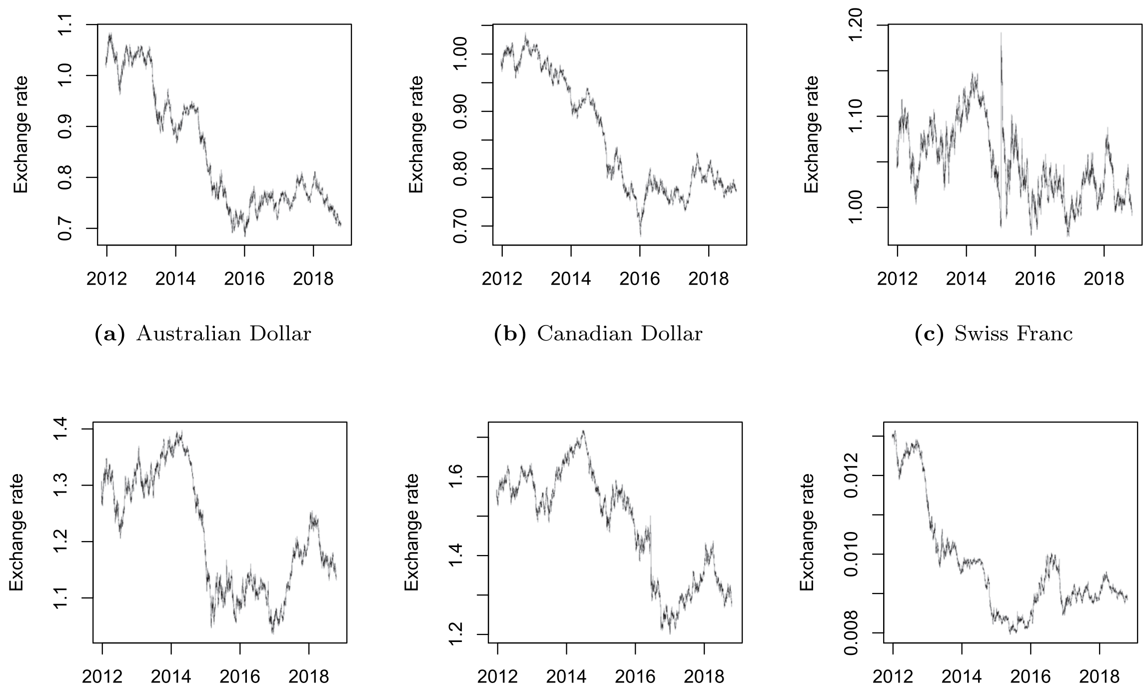
Fig. 4 presents the cumulative number of news for the seven currencies and Bitcoin at the 15-minute level for the period Jan 2012–Nov 2018. The lines' slope determine the rate at which the number of news grows. Forex news grew constantly until mid-2017, as suggested by the absence of changes in the slope in Fig. 4 (a). Subsequently, the lines flatten revealing a lower news intensity. The evolution of Bitcoin news is not discernible from Fig. 4 (a), because of the scale. Fig. 4 (b) replicates Fig. 4 (a) but it uses a different scale allowing a more detailed picture of the Bitcoin news growth rate. There is evidence of an increase in the Bitcoin number of news in 2014 and a sharp increase from 2017, indicating that Bitcoin has received greater investor and media attention during these periods, most likely due to the two biggest Bitcoin bubbles. Starting from 2017, Bitcoin news have grown at a similar rate to that of FX, suggesting the continuous importance of the cryptocurrency.

4.2. The VAR-X model and hypotheses. Impact of sentiment on currencies and Bitcoin

We study the relationship between intra-day Forex and Bitcoin returns, volume and volatility and news sentiment by testing whether the Bitcoin reaction to exogenous high-frequency non-scheduled news sentiment is similar to traditional currencies. We use a vector autoregressive exogenous model VAR-X(p, 0) of the form:

$$\begin{bmatrix} r_{i,t} \\ v_{i,t} \\ \sigma_{i,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a_{rr}^1 & a_{rv}^1 & a_{r\sigma}^1 \\ a_{vr}^1 & a_{vv}^1 & a_{v\sigma}^1 \\ a_{\sigma r}^1 & a_{\sigma v}^1 & a_{\sigma\sigma}^1 \end{bmatrix} \begin{bmatrix} r_{i,t-1} \\ v_{i,t-1} \\ \sigma_{i,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} a_{rr}^p & a_{rv}^p & a_{r\sigma}^p \\ a_{vr}^p & a_{vv}^p & a_{v\sigma}^p \\ a_{\sigma r}^p & a_{\sigma v}^p & a_{\sigma\sigma}^p \end{bmatrix} \begin{bmatrix} r_{i,t-p} \\ v_{i,t-p} \\ \sigma_{i,t-p} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{rAUD}^0 & b_{rCAD}^0 & \cdots & b_{rBTC}^0 \\ b_{vAUD}^0 & b_{vCAD}^0 & \cdots & b_{vBTC}^0 \\ b_{\sigma AUD}^0 & b_{\sigma CAD}^0 & \cdots & b_{\sigma BTC}^0 \end{bmatrix} \begin{bmatrix} AWESS_{AUD,t} \\ AWESS_{CAD,t} \\ \vdots \\ AWESS_{BTC,t} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix}, \tag{1}$$

where $i = \{AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD, JPY/USD, BTC/USD\}$, the dependent variables r_t, v_t and σ_t are log-returns in percentage, log-volume and volatility respectively. $AWESS_i$ are the sentiment indices for each of the currencies which are treated as exogenous variables. In utilizing contemporaneous specifications, we are implicitly assuming that news sentiments are not influenced by contemporaneous returns (Smales, 2014a). We choose the optimal lag-length for our VAR-X(p, s) according to the Akaike Information Criterion (AIC) setting as maximum lags for the dependent variables p equal 4 and for the exogenous s equal 0. One hour of past lags ensures



(a) Australian Dollar (b) Canadian Dollar (c) Swiss Franc

(d) Euro (e) British Pound (f) Japanese Yen

Fig. 2. Foreign exchange evolution. Note: Australian Dollar (a), Canadian Dollar (b), Swiss Franc (c), Euro (d), British Pound (e), Japanese Yen (f) 15-minute exchange rates to US Dollar for the period Jan 2012–Nov 2018.

Table 3
Summary statistics Forex data.

					PACF at lag				
	Mean	SD	Skew	Kurtosis	1	2	3	4	PP test
Panel a: Log-returns (%)									
AUDUSD	0.000	0.066	−0.452	30.237	−0.026	−0.008	−0.001	0.004	−425.600*
CADUSD	0.000	0.050	0.048	39.348	−0.021	−0.004	−0.006	−0.002	−423.430*
CHFUSD	0.000	0.063	26.693	4254.355	−0.033	0.000	0.059	0.012	−427.820*
EURUSD	0.000	0.054	0.316	53.982	−0.021	0.000	0.003	0.006	−422.900*
GBPUSD	0.000	0.055	−3.117	209.595	−0.030	0.001	0.010	0.010	−426.800*
JPYUSD	0.000	0.059	1.533	94.404	−0.010	−0.003	0.000	0.003	−418.640*
Panel b: Log-tick-volume									
AUDUSD	6.821	1.462	−2.872	13.68	0.893	0.185	0.063	0.017	−105.630*
CADUSD	6.608	1.705	−1.789	7.831	0.909	0.218	0.080	0.030	−103.280*
CHFUSD	6.650	1.533	−2.277	10.400	0.890	0.200	0.078	0.021	−108.100*
EURUSD	6.975	1.559	−2.339	11.178	0.905	0.180	0.062	0.012	−100.580*
GBPUSD	6.969	1.635	−2.239	10.193	0.909	0.183	0.074	0.018	−101.150*
JPYUSD	6.973	1.578	−2.343	10.863	0.904	0.186	0.069	0.022	−106.520*
Panel c: Volatility									
AUDUSD	0.063	0.016	1.247	6.379	0.999	−0.059	−0.040	−0.024	−11.201*
CADUSD	0.046	0.026	3.894	38.544	0.923	−0.011	0.002	0.005	−83.122*
CHFUSD	0.052	0.041	33.493	2716.493	0.943	0.002	0.029	−0.153	−69.958*
EURUSD	0.048	0.028	3.856	38.917	0.963	−0.049	−0.012	−0.020	−60.130*
GBPUSD	0.049	0.033	10.791	325.152	0.933	−0.011	0.017	0.018	−77.517*
JPYUSD	0.055	0.026	6.450	115.671	0.959	−0.036	−0.011	0.001	−25.399*

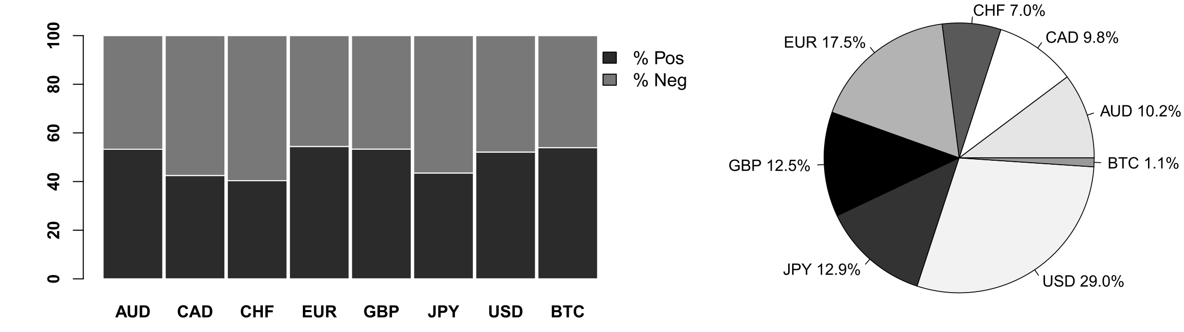
Note: Mean, standard deviation (SD), skewness (Skew), Kurtosis, partial autocorrelation function (PACF) and Phillips-Perron stationarity test with trend and intercept (PP test) for the 15-minute Australian Dollar (AUDUSD), Canadian Dollar (CADUSD), Swiss Franc (CHFUSD), Euro (EURUSD), British Pound (GBPUSD), Japanese Yen (JPYUSD) to U.S. Dollar percentage log-returns (a), log-tick-volume (b) and GARCH(1,1) volatility (c) for the period Jan 2012-Nov 2018.
* indicates p-value < 0.01.

elimination of serial correlation and we are interested in contemporaneous effects of exogenous news. After model comparison simulations, AIC determines as best model the VAR-X(4, 0). We correct for serial correlation and heteroskedasticity in the error term by using Newey West standard errors (Newey & West, 1987).

We separate positive and negative sentiment using dummy variables to test the following main hypotheses:

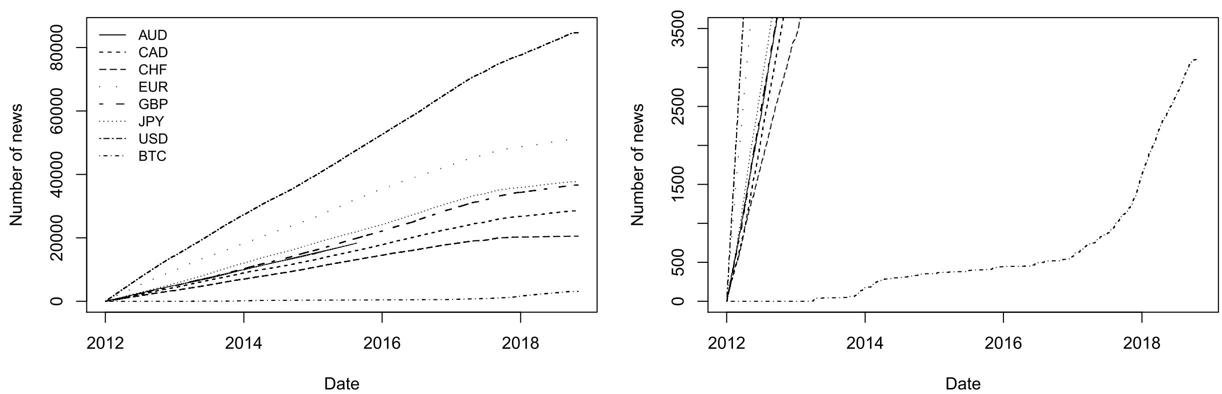
H 1. Positive (negative) news on the base increase (decrease) the exchange rate return, meanwhile positive (negative) news on the counter reduce (increase) the exchange rate return.

H 2. Both negative and positive news on the base and counter increase volume and volatility of the pair.



(a) (b)

Fig. 3. Sample news. Note: (a) presents the relative percentage of 15-minute positive (black) and negative (grey) news for Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) during Jan 2012–Nov 2018. (b) shows the overall sample news proportion for the same period.



(a) (b)

Fig. 4. Cumulative sample news. Note: Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) cumulative sample 15-minute news for the period Jan 2012–Nov 2018. Big scale (a), small scale (b).

H 3. Negative news for the pair (negative news for base, positive news for counter) are expected to be more significant and have a bigger impact on the dependent variables.

where, for instance, we refer to EUR as base and to USD as counter for the exchange rate EUR/USD. H1 is an extension of standard models of exchange rate behavior which state that when positive news arrives for a currency, demand for that currency rises, causing exchange rate appreciation (Dominguez & Panthaki, 2006). H1 claims that negative news for USD, the counter, are considered positive for the pair since the exchange rate denomination is in USD. Therefore, a negative news on USD appreciates the base over USD and *vice-versa*. Positive (negative) news on the counter are negatively (positively) related with exchange rate returns, the reverse idea holds for sentiment on the base. H2 considers that both positive and negative sentiment attached to news contain some information that shocks the Forex and Bitcoin markets increasing the price variability and transaction volume. H3 relates to the asymmetric impact of positive (gains) and negative (losses) environments, first introduced by Kahneman and Tversky (1979) in their prospect theory. We hypothesize that investors dislike bad news more than how much they like good news. Negative news for the pair, namely negative for the base and positive for the counter, have a bigger or equal effect in magnitude on the dependent variables than positive news on the pair implying the existence of an asymmetric instantaneous response for returns, volume and volatility to news according to the news investors' financial perception.

The 15-minute intervals are considered a sufficient time to test for contemporaneous Bitcoin reaction to news, because the average median confirmation time to accepted transactions is 10 min [15]. However, there could be delays in the Bitcoin reaction due to Bitcoin market frictions and technological advancement issues and/or to the low number of high-frequency traders at least during the first part of the sample. To capture these, we also consider VAR-X(4, 1) for Bitcoin.

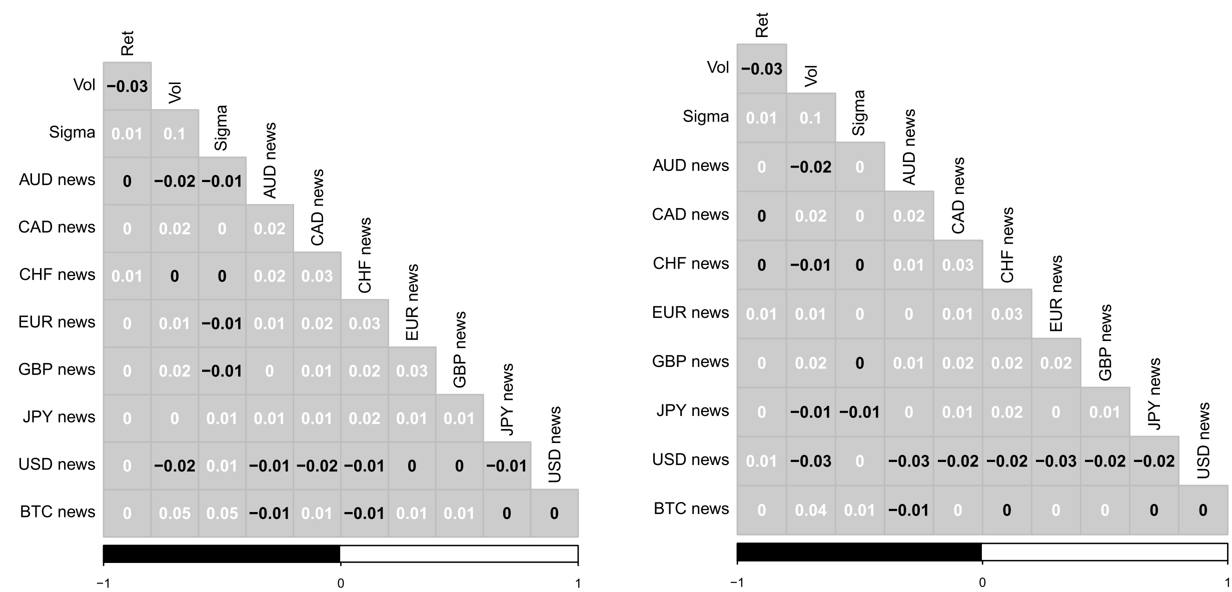
5. Empirical results

To gain an initial understanding of the influence of and potential links between news sentiment related to different currencies, Fig. 5 presents the Pearson correlation coefficients between negative (a) and positive (b) news sentiment for the various currencies in addition to Bitcoin returns, volume and volatility. Correlations between the news sentiments are typically low, never exceeding 0.03. Given this evidence that the news sentiment in each currency is largely uncorrelated with that of other currencies, we proceed with the VAR-X regressions.

5.1. Relationship between news sentiment and Forex

Tables 4–9 report the results for the VAR-X in Eq. (1), separated into positive and negative news for each currency pair. Each table has six columns corresponding to returns, volume and volatility for negative and positive news. Due to our focus on news sentiment and for brevity, lagged values on the dependent variables are not reported.

[15] Time for a transaction to be accepted into a mined block and added to the public ledger (see blockchain.com).



(a) Negative sentiment (b) Positive sentiment

Fig. 5. Pearson correlation. Note: Negative (a) and positive (b) Pearson correlations between Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD), Bitcoin (BTC) sentiments alongside Bitcoin log-returns (%) (Ret), log-trading-volume (Vol) and volatility (Sigma) for the period Jan 2012–Nov 2018.

We find that H1 holds for all the six currency pairs AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD and JPY/USD. These currency pairs have a positive (negative) and highly relevant contemporaneous relationship between positive (negative) news sentiment on the base and the exchange rate returns. This finding is in line with prior literature. Dominguez and Panthaki (2006) find that non-scheduled non-fundamental news influence intra-day foreign exchange returns, although they use an aggregate measure for sentiment indices and do not disentangle negative and positive news.

Columns 1–2 of Table 4 demonstrate that an increase in the measure for negative and positive base AUD news sentiment induces a 1.2% decrease and a 1.2% increase for AUD/USD returns respectively. Table 5 columns 1–2 show a similar reaction for CAD/USD such that an increase in negative news sentiment on CAD induces an instantaneous drop of the 0.7% in returns, while a more positive surrounding generates an immediate appreciation of about 0.8%. The same logic for the

Table 4
Sentiment impact on AUD/USD.

	AUDUSD Return$_t$		AUDUSD Volume$_t$		AUDUSD Volatility$_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD News$_t$	−0.012***	0.012***	−0.055**	−0.007	0.00002	0.00003*
	(0.002)	(0.002)	(0.023)	(0.022)	(0.00002)	(0.00002)
CAD News$_t$	−0.004*	0.007***	0.054***	0.070***	−0.00002	0.00000
	(0.002)	(0.002)	(0.012)	(0.014)	(0.00002)	(0.00002)
CHF News$_t$	0.003	0.002	0.052**	0.050**	0.00003	−0.00001
	(0.003)	(0.003)	(0.022)	(0.024)	(0.00004)	(0.00003)
EUR News$_t$	−0.003**	0.002	0.025*	0.003	−0.00003**	−0.00003*
	(0.002)	(0.002)	(0.015)	(0.014)	(0.00001)	(0.00001)
GBP News$_t$	−0.002	0.007***	0.060***	0.066***	0.00001	−0.00004***
	(0.002)	(0.002)	(0.016)	(0.014)	(0.00002)	(0.00001)
JPY News$_t$	0.001	0.00004	0.042***	0.050***	0.00001	−0.00000
	(0.002)	(0.002)	(0.015)	(0.016)	(0.00002)	(0.00002)
USD News$_t$	0.006***	−0.005***	−0.010	−0.010	−0.00002**	−0.00000
	(0.001)	(0.001)	(0.013)	(0.013)	(0.00001)	(0.00001)
BTC News$_t$	−0.003	−0.008	0.134***	0.087*	−0.00001	−0.00000
	(0.004)	(0.005)	(0.046)	(0.046)	(0.00004)	(0.00004)
Observations	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.001	0.001	0.806	0.806	0.998	0.998
F statistic	11.453***	12.275***	35,705.150***	35,703.490***	4,131,539.000***	4,131,522.000***

Note: VAR-X(4,0) with the Australian Dollar to U.S. Dollar (AUDUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
Sentiment impact on CAD/USD.

	CADUSD Return$_t$		CADUSD Volume$_t$		CADUSD Volatility$_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD News$_t$	−0.005***	0.002*	−0.049**	−0.029	−0.00003	−0.0003
	(0.001)	(0.001)	(0.024)	(0.023)	(0.0003)	(0.0002)
CAD News$_t$	−0.007***	0.008***	0.099***	0.101***	0.00004	0.001**
	(0.002)	(0.002)	(0.014)	(0.016)	(0.0002)	(0.0004)
CHF News$_t$	0.004	0.004	0.051**	0.065**	−0.0001	−0.001**
	(0.002)	(0.002)	(0.022)	(0.027)	(0.0003)	(0.0004)
EUR News$_t$	−0.003**	0.0003	0.024	0.021	−0.001***	−0.0003
	(0.001)	(0.001)	(0.016)	(0.015)	(0.0002)	(0.0002)
GBP News$_t$	−0.002	0.004***	0.071***	0.093***	−0.0004	−0.001**
	(0.001)	(0.001)	(0.018)	(0.017)	(0.0002)	(0.0002)
JPY News$_t$	0.0001	−0.0004	0.042***	0.034*	−0.0001	0.0001
	(0.001)	(0.001)	(0.015)	(0.018)	(0.0002)	(0.0003)
USD News$_t$	0.004***	−0.004***	−0.021	−0.025*	−0.0005***	−0.0004***
	(0.001)	(0.001)	(0.013)	(0.014)	(0.0002)	(0.0001)
BTC News$_t$	−0.003	−0.005	0.154***	0.153***	−0.0003	−0.001
	(0.004)	(0.004)	(0.039)	(0.037)	(0.001)	(0.001)
Observations	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.001	0.001	0.837	0.837	0.860	0.860
F statistic	8.348***	8.360***	43,901.080***	43,902.840***	52,900.350***	52,902.270***

Note: VAR-X(4,0) with the Canadian Dollar to U.S. Dollar (CADUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 6
Sentiment impact on CHF/USD.

	CHFUSD Return$_t$		CHFUSD Volume$_t$		CHFUSD Volatility$_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD News$_t$	−0.004**	0.003**	−0.070***	−0.057**	0.0005	−0.001**
	(0.002)	(0.001)	(0.024)	(0.023)	(0.0004)	(0.0004)
CAD News$_t$	−0.003	0.003	0.097***	0.103***	0.001***	0.001*
	(0.002)	(0.004)	(0.014)	(0.014)	(0.0003)	(0.001)
CHF News$_t$	−0.003	0.006**	0.071***	0.067***	0.001	−0.001
	(0.002)	(0.003)	(0.022)	(0.023)	(0.0005)	(0.001)
EUR News$_t$	−0.006***	0.005***	0.051***	0.039**	0.00003	−0.0002
	(0.001)	(0.001)	(0.016)	(0.015)	(0.0002)	(0.0003)
GBP News$_t$	−0.001	−0.001	0.051***	0.098***	−0.00001	−0.0003
	(0.001)	(0.002)	(0.018)	(0.015)	(0.0003)	(0.0004)
JPY News$_t$	−0.002	0.001	0.014	0.031*	−0.0002	−0.0002
	(0.001)	(0.001)	(0.016)	(0.018)	(0.0002)	(0.0003)
USD News$_t$	0.006***	−0.004***	−0.002	−0.009	−0.001*	0.0002
	(0.001)	(0.001)	(0.014)	(0.013)	(0.0003)	(0.0002)
BTC News$_t$	0.001	−0.005	0.221***	0.094**	−0.001	0.001
	(0.004)	(0.004)	(0.044)	(0.044)	(0.001)	(0.001)
Observations	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.016	0.016	0.803	0.803	0.904	0.904
F statistic	142.754***	141.824***	34,872.450***	34,872.220***	80,977.330***	80,976.600***

Note: VAR-X(4,0) with the Swiss Franc to U.S. Dollar (CHFUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

base sentiment coefficient sign is also verified for the Swiss Franc, the Euro, the British Pound and the Japanese Yen. Tables 7, 8 and 9 columns 1–2 report that EUR/USD, GBP/USD and JPY/USD returns experience statistically significant increases of about 0.6%, 0.7% and 1.2% following a more positive sentiment on the base and conversely, they experience a decrease of about 0.7%, 1% and 1% after an increase in negative news sentiment. CHF/USD supports H1 on the sign but negative news on the base are not significantly affecting returns. All pairs present a negative relationship between returns and news on the counter (USD) supporting H1. There is a reverse-cross-response in Forex for news on the base and counter and this holds for all the currencies adopted in this study.

The traditional currencies used in this study exhibit a common feature which supports H2 as shown in Tables 4–9 columns 3–6.

Table 7
Sentiment impact on EUR/USD.

	EURUSD $Return_t$		EURUSD $Volume_t$		EURUSD $Volatility_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD $News_t$	−0.003*	0.002	−0.062***	−0.051**	−0.00003	−0.0003*
	(0.001)	(0.001)	(0.024)	(0.022)	(0.0002)	(0.0002)
CAD $News_t$	−0.002	−0.002	0.120***	0.098***	0.001***	0.0004**
	(0.002)	(0.002)	(0.015)	(0.014)	(0.0002)	(0.0002)
CHF $News_t$	−0.002	0.006**	0.072***	0.063**	0.0003	0.0001
	(0.002)	(0.002)	(0.022)	(0.025)	(0.0004)	(0.0003)
EUR $News_t$	−0.007***	0.006***	0.038**	0.052***	0.0001	−0.00003
	(0.001)	(0.001)	(0.016)	(0.014)	(0.0002)	(0.0002)
GBP $News_t$	−0.001	0.0005	0.066***	0.094***	−0.0001	0.00001
	(0.001)	(0.002)	(0.017)	(0.013)	(0.0002)	(0.0002)
JPY $News_t$	−0.001	0.00004	0.017	0.041**	−0.0002	−0.0001
	(0.001)	(0.001)	(0.015)	(0.016)	(0.0002)	(0.0002)
USD $News_t$	0.006***	−0.004***	0.001	0.001	−0.0002	0.0001
	(0.001)	(0.001)	(0.013)	(0.013)	(0.0001)	(0.0001)
BTC $News_t$	0.001	−0.008	0.189***	0.145***	−0.0001	0.0001
	(0.004)	(0.006)	(0.046)	(0.040)	(0.0004)	(0.0004)
Observations	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.001	0.001	0.825	0.825	0.930	0.930
F statistic	10.617***	9.489***	40,552.870***	40,551.730***	114,221.600***	114,215.800***

Note: VAR-X(4,0) with the Euro to U.S. Dollar (EURUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
Sentiment impact on GBP/USD.

	GBPUSD $Return_t$		GBPUSD $Volume_t$		GBPUSD $Volatility_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD $News_t$	−0.005***	0.003*	−0.075***	−0.033	−0.001***	0.0005
	(0.001)	(0.002)	(0.024)	(0.023)	(0.0003)	(0.001)
CAD $News_t$	−0.003	0.003	0.107***	0.118***	0.001**	0.001***
	(0.002)	(0.002)	(0.013)	(0.014)	(0.0004)	(0.0004)
CHF $News_t$	−0.0001	0.002	0.078***	0.080***	−0.0001	−0.0004
	(0.002)	(0.002)	(0.023)	(0.025)	(0.0004)	(0.0004)
EUR $News_t$	−0.003***	0.001	0.042***	0.034**	−0.0001	−0.0002
	(0.001)	(0.001)	(0.016)	(0.015)	(0.0002)	(0.0002)
GBP $News_t$	−0.010***	0.007***	0.076***	0.096***	−0.0001	0.0003
	(0.001)	(0.001)	(0.017)	(0.014)	(0.0003)	(0.0003)
JPY $News_t$	−0.001	−0.0002	0.049***	0.049***	−0.001***	−0.0002
	(0.001)	(0.001)	(0.014)	(0.017)	(0.0002)	(0.0002)
USD $News_t$	0.004***	−0.004***	0.011	0.003	−0.0002	−0.0001
	(0.001)	(0.001)	(0.013)	(0.013)	(0.0002)	(0.0002)
BTC $News_t$	0.002	−0.012	0.219***	0.142***	0.002**	−0.00002
	(0.004)	(0.013)	(0.054)	(0.037)	(0.001)	(0.001)
Observations	171,601	171,601	171,601	171,601	171,601	171,601
F statistic	21.887***	20.877***	42,621.400***	42,617.400***	61,336.840***	61,334.460***

Note: VAR-X(4,0) with the British Pound to U.S. Dollar (GBPUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Volume for the Canadian Dollar, the Swiss Franc, the Euro, the British Pound and the Japanese Yen over USD all exhibit a positive and significant reaction to positive and negative news on the base. The arrival of a non-scheduled news in the Forex market determines a surprise and causes a contemporaneous shock which intensifies the currency trading activity at the 15-minute frequency. Independently of the sentiment of the news, volume rises in conjunction with the news arrival. For instance, the Japanese Yen to U.S. Dollar volume rises of about +5.1% for negative and +6.8% for positive sentiment on the base. The British Pound and the Euro transaction volume is positively related to positive news on the base of about 0.096 and 0.052 respectively, and to negative news of about 0.076 and 0.038 respectively. Similar results are found for the Swiss Franc and the Canadian Dollar. These results are consistent with those of Dominguez and Panthaki (2006) such that non-scheduled non-fundamental news lead to an increase in the transaction frequency. Mixed results are found for foreign exchange volatility

Table 9
Sentiment impact on JPY/USD.

	JPYUSD Return$_t$		JPYUSD Volume$_t$		JPYUSD Volatility$_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD News$_t$	−0.0004	0.0001	−0.050**	−0.023	−0.0001	−0.00004
	(0.002)	(0.002)	(0.023)	(0.021)	(0.0001)	(0.00005)
CAD News$_t$	0.001	−0.002	0.050***	0.066***	−0.0001	−0.00004
	(0.002)	(0.002)	(0.014)	(0.015)	(0.0001)	(0.0001)
CHF News$_t$	0.002	0.001	0.055***	0.073***	0.0001	0.00003
	(0.002)	(0.003)	(0.020)	(0.023)	(0.0001)	(0.0001)
EUR News$_t$	−0.002	0.003**	0.038**	0.013	−0.0001**	−0.0001*
	(0.001)	(0.001)	(0.016)	(0.015)	(0.0001)	(0.00004)
GBP News$_t$	−0.0004	−0.003*	0.060***	0.098***	−0.00001	−0.0001**
	(0.002)	(0.002)	(0.017)	(0.015)	(0.0001)	(0.0001)
JPY News$_t$	−0.010***	0.012***	0.051***	0.068***	0.00002	−0.0001
	(0.001)	(0.002)	(0.015)	(0.018)	(0.0001)	(0.0001)
USD News$_t$	0.003***	−0.004***	0.010	−0.004	−0.0001***	−0.00002
	(0.001)	(0.001)	(0.013)	(0.014)	(0.00003)	(0.00004)
BTC News$_t$	−0.003	0.004	0.158***	0.109***	−0.0001	−0.0001
	(0.004)	(0.006)	(0.038)	(0.038)	(0.0001)	(0.0001)
Observations	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.0005	0.001	0.825	0.825	0.990	0.990
F statistic	5.286***	6.211***	40,416.730***	40,420.940***	828,767.400***	828,741.400***

Note: VAR-X(4,0) with the Japanese Yen to U.S. Dollar (JPYUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

response to intra-day news sentiment, and the behavioral bias presented in H3 is not systematically verifiable from the empirical results in Tables 4–9.

Overall, despite the presence of some heterogeneous effects within the Forex results, traditional currencies comove and share homogeneous reactions to news sentiment suggesting the strong inter-linkage of this market. Non-scheduled news create a contemporaneous statistically significant impact on FX returns and volume.

5.2. News sentiment relationship with Bitcoin – comparison with FX

Having documented the behavior of Forex with respect to non-scheduled news sentiment, we study whether Bitcoin behaves in a similar manner. The odd columns in Table 10 present the results of the estimations of the VAR-X(4, 0) for BTC/USD returns (columns 1, 3), volume (columns 5, 7) and volatility (columns 9, 11). In contrast to traditional currencies, news sentiment appears to have little or no significant impact on Bitcoin returns, such that only positive Bitcoin news increase Bitcoin returns of about 7.7%. Contrary to H3, contemporaneous negative Bitcoin news are therefore less important than positive news providing some intuition of Bitcoin users' enthusiasm. In addition, contrary to H1, positive news on the counter USD appreciates BTC/USD of about 2.4%. Negative and positive news on BTC are significant at the one percent level for the contemporaneous trading volume with exogenous coefficients of +0.487 and +0.153 respectively, while sentiment on the counter does not significantly affect volume. Independently from their sentiment score, only news on the base induces a contemporaneous increase in the Bitcoin trading volume. The larger coefficient compared to the FX reaction is explained by the use of two different measures for volume, trading volume for BTC/USD (which considers the size of each trade) and tick-volume for FX. The findings partially support H2 with regard to Bitcoin volume. However, coefficients for volatility are found to be not statistically significant indicating that news sentiment does not seem to affect Bitcoin price variability.

In summary, Bitcoin results deviate from the FX findings during the period January 2012–November 2018, implying that Bitcoin does not share many characteristics with traditional currencies. Particularly, the contemporaneous impact of news sentiment is not as strong and significant as in the foreign exchange market where currencies promptly react to news.

However, the 15-minute time window might not be enough to capture an immediate Bitcoin response to news sentiment due to market frictions, technological advancement issues and a potential low high-frequency traders' activity. The average median confirmation time for Bitcoin transaction is 10 min. Bitcoin sell and buy orders need on average 10 min to be executed and registered in the public ledger. Within the sample period there could be a number of times in which this delay is longer than 10/15 min hence the Bitcoin market might not be able to absorb the effects of contemporaneous news because of this inefficiency. There might be other frictions that do not allow the news sentiment information to be incorporated into Bitcoin prices as fast as it happens in the more efficient Forex market. Therefore, we increase the time window allowing the news sentiment to have sufficient time to generate a potential impact. We control for 1 lag in the exogenous variable increasing our time window to 30 min to check and capture potential effects that unscheduled news arriving at $t-1$ can have on Bitcoin at time t. Table 10 (even columns) reports the coefficient estimates omitting the lag dependent variables and intercept for the VAR-X (4, 1) regressions. The contemporaneous impact is almost unchanged with respect to the VAR-X(4, 0) case. Positive Bitcoin news are positively related to returns with a coefficient of about 0.069, and negative contemporaneous news sentiment again have no power in explaining Bitcoin returns, rejecting H3. Again positive news at time t on the counter increase the returns, rejecting H1. Findings are further consistent with the previous ones for the volume and volatility. Looking at columns 2 and 4, we can observe that negative and positive news on Bitcoin at $t-1$ have an impact on Bitcoin returns at time t suggesting that this market needs more time to digest information because of delays and frictions. Surprisingly, a positive relation between returns and news is found independently of whether the news sentiment is classified as positive or negative. Negative news one period before are positively

Table 10
Sentiment impact on BTC/USD.

	BTCUSD Return$_t$				BTCUSD Volume$_t$				BTCUSD Volatility$_t$			
	|Negative|		Positive		|Negative|		Positive		|Negative|		Positive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AUD News$_t$	−0.003	−0.006	0.012	0.014	−0.050	−0.047	−0.039	−0.037	−0.002	−0.002	0.001	0.002
	(0.016)	(0.016)	(0.016)	(0.015)	(0.034)	(0.034)	(0.034)	(0.034)	(0.001)	(0.001)	(0.002)	(0.002)
CAD News$_t$	0.010	0.012	−0.009	−0.009	−0.011	−0.019	0.043	0.033	−0.003***	−0.003***	−0.001	−0.001
	(0.018)	(0.018)	(0.019)	(0.019)	(0.032)	(0.033)	(0.033)	(0.033)	(0.001)	(0.001)	(0.002)	(0.002)
CHF News$_t$	0.060*	0.058*	−0.005	−0.005	0.023	0.017	−0.010	−0.019	0.0003	0.0002	−0.001	−0.002
	(0.032)	(0.032)	(0.023)	(0.024)	(0.044)	(0.044)	(0.046)	(0.046)	(0.002)	(0.002)	(0.002)	(0.002)
EUR News$_t$	0.024*	0.026**	0.034**	0.032**	0.062**	0.054**	0.083***	0.071**	0.001	0.001	0.001	0.001
	(0.013)	(0.013)	(0.016)	(0.016)	(0.027)	(0.027)	(0.028)	(0.028)	(0.001)	(0.001)	(0.002)	(0.001)
GBP News$_t$	0.023*	0.019	0.030*	0.030*	0.068**	0.056*	0.061**	0.054*	−0.003***	−0.003***	0.001	0.0002
	(0.014)	(0.014)	(0.018)	(0.018)	(0.030)	(0.030)	(0.030)	(0.031)	(0.001)	(0.001)	(0.001)	(0.001)
JPY News$_t$	0.022	0.023	0.009	0.007	−0.009	−0.009	0.003	0.005	0.0003	0.0001	0.0005	0.001
	(0.022)	(0.023)	(0.013)	(0.013)	(0.028)	(0.028)	(0.031)	(0.032)	(0.001)	(0.001)	(0.001)	(0.001)
USD News$_t$	0.008	0.007	0.024*	0.023*	0.008	0.003	−0.019	−0.016	−0.0005	−0.001	−0.002	−0.002*
	(0.011)	(0.010)	(0.013)	(0.013)	(0.020)	(0.020)	(0.021)	(0.021)	(0.001)	(0.001)	(0.001)	(0.001)
BTC News$_t$	0.033	−0.007	0.077**	0.069*	0.487***	0.449***	0.153***	0.122**	0.025	0.025	0.003	0.003
	(0.129)	(0.115)	(0.039)	(0.040)	(0.061)	(0.061)	(0.058)	(0.058)	(0.016)	(0.016)	(0.003)	(0.003)
AUD News$_{t-1}$		0.035**		−0.020		−0.030		−0.033		0.001		−0.003*
		(0.017)		(0.017)		(0.034)		(0.034)		(0.001)		(0.001)
CAD News$_{t-1}$		−0.017		−0.004		0.057*		0.061*		0.001		0.002
		(0.016)		(0.022)		(0.031)		(0.033)		(0.002)		(0.003)
CHF News$_{t-1}$		0.039		−0.003		0.052		0.084		0.002		0.001
		(0.026)		(0.027)		(0.045)		(0.055)		(0.003)		(0.002)
EUR News$_{t-1}$		−0.021		0.016		0.049*		0.080***		−0.001		0.002
		(0.014)		(0.015)		(0.029)		(0.028)		(0.001)		(0.002)
GBP News$_{t-1}$		0.029		−0.008		0.080***		0.034		−0.002*		0.003
		(0.019)		(0.016)		(0.030)		(0.031)		(0.001)		(0.002)
JPY News$_{t-1}$		−0.014		0.013		0.004		−0.014		0.003		−0.002*
		(0.019)		(0.014)		(0.028)		(0.031)		(0.002)		(0.001)
USD News$_{t-1}$		0.011		0.001		0.051**		−0.020		0.001		0.001
		(0.010)		(0.012)		(0.021)		(0.021)		(0.001)		(0.001)
BTC News$_{t-1}$		0.294**		0.074*		0.252***		0.294***		0.0004		−0.0004
		(0.148)		(0.040)		(0.060)		(0.059)		(0.009)		(0.002)
Observations	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.009	0.009	0.009	0.009	0.597	0.597	0.597	0.597	0.983	0.983	0.983	0.983
F statistic	79.936***	58.87***	79.99***	57.36***	12,734.09***	9097.87***	12,731.38***	9096.15***	498,682.00***	356,198.10***	498,586.90***	356,139.10***

Note: VAR-X(4,0) and VAR-X(4,1) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 2, 5, 6, 9, and 10) and positive (3, 4, 7, 8, 11, and 12) sentiments as and exogenous variable.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

related to returns of about 0.294, while positive news generate a smaller impact of about 0.074. This further represents an insight of the investors' enthusiasm toward the digital currency. This behavior is very different from that of Forex, confirming the different nature of Bitcoin to traditional currencies.

5.3. Cross results

Tables 4–10 provide more insights for similarities between Forex and Bitcoin news sentiment. In short, negative and positive news sentiment on BTC are significantly and positively related to all traditional currencies volume. Negative Bitcoin news coefficients are higher than the positive ones, suggesting that they influence more Forex volume. The largest effects highlight that negative financial BTC news are positively related to the CHF/USD, GBP/USD and EUR/USD contemporaneous volume of about 0.221, 0.219 and 0.189 respectively. This cross dependency shows part of the interconnectedness between cryptocurrencies and traditional currencies. The results might imply that foreign exchange investors care about high-frequency news on BTC such that negative perceptions on BTC stories lead investors to very quickly adjust their financial positions in the FX market. On the other hand, apart from some evidence of the influence of the Euro and the British Pound on Bitcoin, such that news on these currencies increase the cryptocurrency contemporaneous returns and volume, Bitcoin is mostly unrelated to Forex news sentiment during the entire sample.

5.4. Isolating the Bitcoin bubble

The impact of good and bad news can depend on the state of the economy in which the news occurs. Andersen et al. (2003) find evidence that bad news in good times have bigger impact than good news in good times because they incorporate more information about the current state of the economy. Positive news are considered to confirm investors beliefs, while negative news surprise them. During the sample period under examination, the nascent Bitcoin market has experienced potential bubbles. We therefore isolate the late 2013 and 2017 bubbles as Gerlach et al. (2019), particularly July 2013–December 2013 and January 2016–December 2017, with a dummy variable in order to investigate whether the reaction of Bitcoin to news during bubble periods differs compared to the whole sample period. Table 11 summarizes the results for the VAR-X(4,0) in the odd columns and VAR-X(4,1) in the even columns. In contrast to Andersen et al. (2003), there is no evidence of a contemporaneous relationship between Bitcoin returns and negative news on Bitcoin (columns 1, 2). While negative news at time t do not surprise the Bitcoin market during the bubble periods, negative news occurring at time $t-1$ have a significant impact. Contrary to standard expectations, rather than causing a decrease in returns, lagged negative news increase returns confirming the irreversible enthusiasm of Bitcoin investors during the bubbles. As additional evidence of this phenomenon, contemporaneous positive sentiment registered during the bubble periods immediately positively affects returns. These results are in line with the Dominguez and Panthaki (2006) findings such that non-scheduled non-fundamental news have a higher impact when many news are hitting the market and during periods of high volatility.

Further comments relate to the significance of contemporaneous positive stories on USD for Bitcoin returns in an opposite direction to H1. Both negative and positive news on the base and the counter during the bubble periods generate an immediate increase in the trading volume for Bitcoin to USD which is also persistent one period after providing evidence for H2. Volatility during this turmoil period is not affected by base news contrary to H2, and only a volatility decrease following negative counter news is found. The behavioral bias presented in H3 is reversed during Bitcoin bubble periods, such that Bitcoin returns are more affected by contemporaneous positive Bitcoin news than negative news. This is in line with the high enthusiasm finding and shows that investors either downplay or reverse negative news during bubbles. Again, BTC/USD seems not to behave in a similar manner to traditional currencies but a higher level of connection with FX news is registered by a higher significance in the BTC/USD volume reaction.

5.5. Relationship of news on cyber-attacks and fraud with Bitcoin

In addition to bubble periods, a further differentiating feature of the nascent Bitcoin market relative to the established Forex market is the concern around criminality. In fact, one key issue related to digital currencies concerns cyber-criminality which forms part of the cryptocurrency trilemma described by Corbet et al. (2019) together with bubbles and regulatory alignments. Further, according to Gandal, Hamrick, Moore, and Oberman (2018), user anonymity characterizes the major problem with technological advances of cryptocurrencies which links them to criminality. While both Forex news and negative news on Bitcoin itself fail to reduce Bitcoin returns as demonstrated in Tables 10 and 11 this may not be the case for news directly related to cyber-criminality. Such news may be anticipated to have a negative relationship with Bitcoin returns, namely able to generate instability among Bitcoin users' and investors' beliefs and potentially mitigate the general enthusiasm toward the digital currency. We test whether news sentiment related to cryptocurrency cyber-attacks and fraud can generate drops in the Bitcoin returns[16]. Results for VAR-X(4,0) and VAR-X(4,1) are reported in Table 12. Contemporaneous news sentiment on cyber-attacks are negatively related with Bitcoin returns of about −0.200, and −0.198(when including 1 lag for the exogenous variable). The arrival of a news about fraud related to Bitcoin is not affecting Bitcoin returns, but it lowers the Bitcoin trading volume one period after. Bitcoin volatility is negatively affected by both news on fraud and cyber-attacks, suggesting that once these news occur, there is a dampening effect on the Bitcoin market. We conjecture that investors have more heterogeneous beliefs on the value of Bitcoin, which deprecates due to the fraud and cyber-attack news.

6. Robustness tests

Although the Pearson correlation coefficients for news sentiments are close to zero motivating our initial analysis, we perform a number of robustness checks to account for the possibility of commonality in news sentiment and potential multicollinearity that may bias the main findings. We also check the robustness of the results at the daily level.

6.1. Commonality in news — R^2

Following Dang, Moshirian, and Zhang (2015), we identify the commonality in news as the R^2 coming from the regression of a news sentiment index on a set of regressors composed by other news sentiment indices. The resulting R^2 measures the level of commonality between the dependent variable news sentiment and the remainder of the news sample. Each sentiment index is regressed on all the other sentiment indices except for itself. For instance, to test how much of the news sentiment for AUD is already explained by all the others news sentiment indices excluding the index for AUD, we regress the AUD sentiment index on the matrix of indices for CAD, CHF, EUR, GBP, JPY, USD and BTC. On the one hand, a very high R^2 would represent a high level of commonality among news and thus imply that AUD sentiment is superfluous for the analysis. On the other hand, a low R^2 would imply that AUD sentiment index is not already explained by the remaining indices and that its inclusion will add value to the study bringing the desired new information on AUD. Table 13 reports the R^2 commonality of each sentiment index with all the other indices (column 1), and with

[16] *Ravenpack* identifies and labels news as fraud or cyber-attacks. We filter this news for relevance to cryptocurrencies and Bitcoin.

Table 11
Sentiment impact on BTC/USD during the bubbles.

	BTCUSD $Return_t$				BTCUSD $Volume_t$				BTCUSD $Volatility_t$			
	|Negative|		Positive		|Negative|		Positive		|Negative|		Positive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AUD $News_t$ × Bubble	0.012	0.006	0.022	0.021	0.030	0.015	0.015	−0.003	−0.002	−0.002	0.001	0.002
	(0.024)	(0.025)	(0.021)	(0.021)	(0.052)	(0.052)	(0.049)	(0.050)	(0.002)	(0.002)	(0.004)	(0.004)
CAD $News_t$ × Bubble	0.039*	0.041*	0.008	0.004	0.092**	0.055	0.152***	0.122***	−0.006***	−0.005***	−0.006***	−0.005***
	(0.023)	(0.022)	(0.021)	(0.021)	(0.046)	(0.047)	(0.046)	(0.047)	(0.001)	(0.001)	(0.002)	(0.001)
CHF $News_t$ × Bubble	0.038	0.043	−0.019	−0.015	0.165***	0.133**	0.205***	0.166***	−0.003**	−0.003	−0.0004	0.0002
	(0.028)	(0.028)	(0.027)	(0.027)	(0.064)	(0.064)	(0.062)	(0.063)	(0.002)	(0.002)	(0.002)	(0.002)
EUR $News_t$ × Bubble	0.023	0.027	0.030	0.030	0.119***	0.083**	0.197***	0.152***	−0.001	−0.001	−0.002	−0.002
	(0.017)	(0.017)	(0.021)	(0.021)	(0.039)	(0.040)	(0.040)	(0.041)	(0.002)	(0.002)	(0.002)	(0.002)
GBP $News_t$ × Bubble	0.034	0.029	0.026	0.026	0.104**	0.071	0.163***	0.126***	−0.005***	−0.004***	−0.002	−0.001
	(0.022)	(0.021)	(0.019)	(0.019)	(0.046)	(0.048)	(0.043)	(0.045)	(0.001)	(0.001)	(0.002)	(0.002)
JPY $News_t$ × Bubble	−0.033	−0.032	0.029	0.030	0.113***	0.093**	0.068	0.039	−0.004***	−0.004***	−0.002	−0.001
	(0.022)	(0.021)	(0.019)	(0.019)	(0.040)	(0.041)	(0.046)	(0.047)	(0.001)	(0.001)	(0.001)	(0.001)
USD $News_t$ × Bubble	−0.002	−0.002	0.028*	0.028*	0.129***	0.101***	0.133***	0.103***	−0.003*	−0.002	−0.004***	−0.003***
	(0.012)	(0.012)	(0.015)	(0.014)	(0.029)	(0.029)	(0.031)	(0.031)	(0.001)	(0.001)	(0.001)	(0.001)
BTC $News_t$ × Bubble	0.072	0.011	0.143***	0.134***	0.543***	0.478***	0.238***	0.185**	0.047	0.050	0.003	0.004
	(0.150)	(0.146)	(0.046)	(0.046)	(0.090)	(0.089)	(0.080)	(0.081)	(0.037)	(0.039)	(0.004)	(0.004)
AUD $News_{t-1}$ × Bubble		0.051**		0.010		−0.014		−0.011		0.001		−0.003
		(0.025)		(0.021)		(0.053)		(0.051)		(0.003)		(0.002)
CAD $News_{t-1}$ × Bubble		−0.037*		0.031		0.163***		0.086*		−0.003**		−0.004***
		(0.022)		(0.020)		(0.045)		(0.047)		(0.001)		(0.001)
CHF $News_{t-1}$ × Bubble		−0.036		−0.039		0.067		0.153**		−0.004***		−0.002
		(0.027)		(0.030)		(0.065)		(0.070)		(0.001)		(0.002)
EUR $News_{t-1}$ × Bubble		−0.030*		−0.003		0.151***		0.198***		−0.003**		0.0001
		(0.017)		(0.019)		(0.041)		(0.039)		(0.001)		(0.002)
GBP $News_{t-1}$ × Bubble		0.041**		−0.003		0.076*		0.085*		−0.002*		−0.003**
		(0.019)		(0.018)		(0.044)		(0.047)		(0.001)		(0.001)
JPY $News_{t-1}$ × Bubble		−0.009		−0.005		0.047		0.071		0.001		−0.002*
		(0.020)		(0.018)		(0.041)		(0.045)		(0.001)		(0.001)
USD $News_{t-1}$ × Bubble		−0.009		0.004		0.117***		0.104***		−0.002***		−0.003***
		(0.012)		(0.014)		(0.030)		(0.034)		(0.001)		(0.001)
BTC $News_{t-1}$ × Bubble		0.415**		0.060		0.272***		0.283***		−0.019		−0.003
		(0.201)		(0.055)		(0.097)		(0.082)		(0.017)		(0.002)
Observations	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601	171,601
Adjusted R^2	0.009	0.009	0.009	0.009	0.597	0.598	0.598	0.598	0.983	0.983	0.983	0.983
F statistic	79.599***	58.120***	79.831***	57.122***	12,736.890***	9101.219***	12,738.010***	9102.244***	498,723.000***	356,239.500***	498,607.900***	356,147.500***

Note: VAR-X(4,0) and VAR-X(4,1) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 2, 5, 6, 9, and 10) and positive (3, 4, 7, 8, 11, and 12) sentiments interaction with bubble periods Jul 2013–Dec 2013 and Jan 2016–Dec 2017 dummy as exogenous variable.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 12
Crime sentiment impact on BTC/USD.

	$Return_t$		$Volume_t$		$Volatility_t$	
	(1)	(2)	(3)	(4)	(5)	(6)
Cyber Attacks $News_t$	−0.200**	−0.198**	0.193	0.164	−0.008*	−0.007*
	(0.096)	(0.095)	(0.194)	(0.193)	(0.004)	(0.004)
Fraud $News_t$	−0.029	−0.045	−0.185	0.538	−0.040***	−0.038***
	(0.116)	(0.187)	(0.455)	(0.735)	(0.007)	(0.007)
Cyber Attacks $News_{t-1}$		−0.019		0.249		−0.006
		(0.119)		(0.197)		(0.005)
Fraud $News_{t-1}$		0.041		−1.859***		−0.005**
		(0.256)		(0.609)		(0.002)
Observations	239,612	239,611	239,612	239,611	239,612	239,611
Adjusted R^2	0.008	0.008	0.601	0.601	0.984	0.984
F statistic	132***	115***	25,787***	22,563***	1,033,223***	904,059***

Note: VAR-X(4,0) and VAR-X(4,1) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Cryptocurrencies cyber-attacks and fraud news sentiments as exogenous variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 13
Commonality in news sentiment.

	With:	
	The others News (1)	USD News (Counter) (2)
AUD News	3.01%***	2.07%***
CAD News	2.05%***	1.80%***
CHF News	2.01%***	1.39%***
EUR News	7.47%***	2.92%***
GBP News	5.68%***	1.88%***
JPY News	6.52%***	2.85%***
USD News	15.21%***	100.00%***
BTC News	0.04%***	0.04%***

Note: R^2 from regressing each sentiment index for the Australian Dollar (AUD), the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY), the U.S. Dollar (USD) and Bitcoin (BTC) on the reminder sentiment indices (1) and on the U.S. Dollar (2).
*** p-value < 0.01.

the USD counter only (column 2). Although there is not a clear threshold to determine whether commonality can be considered low or high, we believe that R^2 results reported in the table are all sufficiently small to overcome commonality. In fact, only 3.01% of the Australian Dollar sentiment is explained by the other sentiment indices and around the 70% of this is explained by its counter USD, as shown in column 2 where the R^2 from the regression of AUD sentiment on USD sentiment is 2.07%. Moreover, only 2.05% of the Canadian Dollar is redundant with a counter commonality of 1.80%. Popular currencies such as the Euro, the Japanese Yen and the U.S. Dollar, which serve as counter for many traditional currencies, share a higher level of commonality in news of about 7.47%, 6.52% and 15.21% respectively. They still bring 92.53%, 93.48% and 84.79% of useful and additional information to the study respectively. Bitcoin reveals a very low R^2 of 0.04% both for its counter and the other news sentiment indices, suggesting an individual informative power of about 99.96% but a potential detachment from the Forex news.

6.2. Multicollinearity in news — residuals sentiment analysis

We further study potential biases stemming from multicollinearity in the news sentiment variables. We use the residuals of the commonality regressions between each sentiment index and the remaining indices presented in the previous paragraph as residual sentiment indices. In this way, the residual individual information from each new sentiment index orthogonal to the other news is used as an exogenous variable and exclude the commonality component. We separate residuals into positive and negative news for each index and absolute values are considered. We repeat the VAR-Xs for each pair using the matrix composed by the residual news sentiment. Results are omitted for brevity. However, findings are consistent since the magnitude, sign and statistical significance of the coefficients remain similar to the previous results. Therefore, our results are robust after taking potential multicollinearity into account.

6.3. Daily analysis

We repeat the analysis at a daily frequency to check whether the main conclusions based on intra-day data hold at a lower frequency. We examine how the average daily sentiment on currencies and Bitcoin affect Bitcoin during the entire sample and during bubbles. Table 14 reports the VAR-X(4,0) results for the daily analysis. In this case, Bitcoin negative news decreases Bitcoin returns providing a more intuitive relation between sentiment and returns, similar to that of Forex. Further, sentiment on the counter also appears to be consistent with H1 at the daily level. However, when we account for the bubble periods, the results confirm our main findings with strong evidence of Bitcoin investors' enthusiasm at the daily level. Both negative and positive news for Bitcoin arriving during bubble periods increase Bitcoin returns, with coefficients of 2.394 and 0.924 respectively. While a daily analysis addresses the technological advancements issue, what low frequency measurement of sentiment on a daily level captures is different from that of its intra-day 15-minute window counterpart. The daily news measures summarize the feeling about the news of the day. Over the full sample, the enthusiasm of Bitcoin investors is not sufficiently strong to counteract the entire-day-negative sentiment, but during bubble periods the extreme positive surrounding around the digital currency dominates any negative news impact confirming our intra-day results. This demonstrates that thee Bitcoin investors' enthusiasm observed at the intra-day level holds at the daily frequency, such that negative sentiments still positively influence returns.

7. Conclusions

In this paper, we investigate whether Bitcoin and foreign exchange returns, volume and volatility share similar characteristics and comove in terms of reaction to high-frequency non-scheduled news sentiment at the 15-minute level for the period January 2012–November 2018. We test three main hypotheses to check for similarities between foreign

Table 14
Sentiment impact on BTC/USD daily level.

	BTCUSD $Return_t$		BTCUSD $Volume_t$		BTCUSD $Volatility_t$	
	|Negative| (1)	Positive (2)	|Negative| (3)	Positive (4)	|Negative| (5)	Positive (6)
AUD $News_t$	−0.063	−0.184*	−681.263***	−420.496*	0.007	0.431
	(0.242)	(0.111)	(189.501)	(246.064)	(0.392)	(0.512)
CAD $News_t$	0.107	−0.079	1988.716***	3250.650***	0.534	1.036*
	(0.154)	(0.170)	(552.832)	(449.754)	(0.459)	(0.606)
CHF $News_t$	0.277	−0.120	−1017.497**	−1985.474***	0.875*	−0.621
	(0.254)	(0.201)	(422.168)	(484.191)	(0.525)	(0.550)
EUR $News_t$	0.002	0.207**	241.653	323.197	−0.191	−0.089
	(0.127)	(0.091)	(184.987)	(227.286)	(0.244)	(0.286)
GBP $News_t$	−0.187	0.100	743.865*	764.472**	−0.330	0.150
	(0.125)	(0.136)	(439.361)	(376.852)	(0.270)	(0.371)
JPY $News_t$	−0.034	0.133	−141.462	90.322	0.698**	−0.242
	(0.131)	(0.103)	(273.014)	(200.298)	(0.328)	(0.274)
USD $News_t$	0.246**	−0.121*	704.007**	22.659	0.287	0.243
	(0.110)	(0.063)	(312.265)	(141.130)	(0.302)	(0.201)
BTC $News_t$	−2.040***	0.232	5240.723***	6264.506***	5.844***	1.007
	(0.472)	(0.398)	(863.004)	(1942.045)	(1.711)	(0.990)
AUD $News_t$ × Bubble	0.303	0.256	−209.063	−462.954	0.175	0.993
	(0.283)	(0.181)	(413.796)	(388.192)	(0.474)	(1.335)
CAD $News_t$ × Bubble	0.125	−0.024	702.367	−873.466	−0.541	−1.976**
	(0.267)	(0.261)	(652.729)	(775.423)	(0.603)	(0.883)
CHF $News_t$ × Bubble	−0.192	−0.269	−412.766	2387.469***	−0.730	−1.959*
	(0.356)	(0.388)	(881.904)	(839.683)	(0.820)	(1.190)
EUR $News_t$ × Bubble	−0.0004	−0.177	793.726*	547.331	−0.470	0.531
	(0.256)	(0.164)	(474.763)	(395.787)	(0.489)	(0.436)
GBP $News_t$ × Bubble	−0.004	−0.088	−754.219	716.844	0.315	0.016
	(0.212)	(0.218)	(570.135)	(611.855)	(0.479)	(0.601)
JPY $News_t$ × Bubble	0.308	−0.299*	444.133	−659.062**	−0.259	0.307
	(0.219)	(0.153)	(402.754)	(309.462)	(0.501)	(0.380)
USD $News_t$ × Bubble	−0.302**	0.304***	124.860	296.275	0.078	−0.191
	(0.136)	(0.096)	(326.007)	(318.290)	(0.327)	(0.281)
BTC $News_t$ × Bubble	2.394***	0.924*	−2069.679	−4370.782*	5.016	−0.258
	(0.898)	(0.503)	(1612.286)	(2286.354)	(3.482)	(1.353)
Observations	2134	2134	2134	2134	2134	2134
Adjusted R^2	0.027	0.016	0.266	0.260	0.528	0.513
F statistic	3.092***	2.216***	28.580***	27.721***	86.121***	81.265***

Note: Daily VAR-X(4,0) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, and 5) and positive (2, 4, and 6) sentiments and sentiments interaction with bubble periods Jul 2013–Dec 2013 and Jan 2016–Dec 2017 dummy as exogenous variable.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

exchange market and Bitcoin. H1 concerns the different impact that negative and positive news have on the pairs returns. H2 focusses on the impact of both negative and positive news on volatility and volume, and H3 relates to the concept of asymmetric impact of negative and positive news. We use VAR-X(4, 0) models to test the assumptions and the results report an almost homogeneous behavior of Forex. We provide evidence that traditional currencies immediately and significantly react to news wire messages coming from the economy. Particularly, negative (positive) news on the pair decrease (increase) the exchange rate returns, and volume rises when both negative and positive news on the base arrive. Conversely, the results for Bitcoin are different from those on Forex, suggesting that Bitcoin does not react similarly to news arrivals compared to traditional currencies.

Using a VAR-X(4, 1), we find evidence of Bitcoin users' enthusiasm such that only positive news on Bitcoin affect Bitcoin returns, while intra-day negative Bitcoin news are ignored by investors. When isolating the Bitcoin bubbles, positive news are found to lead to an immediate increase in Bitcoin returns, reinforcing the Bitcoin investors' enthusiasm effect. Contrary to traditional currencies, negative news sentiment are found to have a delayed positive relationship with Bitcoin returns, against H1. Bitcoin volume increases in conjunction of news arrivals, but Bitcoin volatility seems invariant to news on the base. We provide further insight that particularly cryptocurrency cyber-attack news are negatively related to Bitcoin returns and thus seem to dampen the Bitcoin users' enthusiasm. Together with cryptocurrency fraud news, they also lead to a decrease in volatility of Bitcoin reducing the exuberance in the market.

To further test the robustness of our findings, we take into account potential biases due to multicollinearity in news sentiment indices. We calculate commonality in news as the R^2 from regressing each sentiment index on a matrix composed by all the remaining sentiment indices and we conclude that all the R^2 can be considered sufficiently low to overcome this issue. We calculate the residuals news sentiment by regressing from the commonality regressions and we use them as new sentiment indices for the VAR-X models. Again, results are found to be extremely close to the original ones suggesting that results are robust to multicollinearity tests. In conclusion, we do not find evidence that Bitcoin to U.S. Dollar reacts to non-scheduled news sentiment similarly to traditional currencies.

Our analysis contributes to the general debate on the nature of Bitcoin as to whether it can be considered as an asset or a currency. Our results highlight the differences of Bitcoin to other traditional currencies, since the reaction of Bitcoin to non-scheduled news related to Bitcoin and other currencies differs from other traditional currencies. We further provide insight into differences in the effects during bubble periods.

Our results are further relevant for practitioners and regulators. Investors are concerned about the characteristics of their investment in Bitcoin, such as their risk-return profile. By understanding the reaction of digital currencies to news sentiment in different market conditions, they are better able to assess the volatility and possible risks of their investment. Furthermore, policy-makers have been concerned about systemic risks posed by cryptocurrencies, some issues related to their volatility. We show that Bitcoin volatility is mostly unrelated to currency news, but that news impact increases during bubble periods.

Future research might further test for non-linear reaction of Bitcoin to high frequency news sentiment. Trading strategies could be implemented and standard models of exchange-rate determination could benefit from the inclusion of non-scheduled news sentiment on the base and counter.

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