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Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin

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ABSTRACT

We study whether news and sentiment about bitcoin regulation, the hacking of bitcoin exchanges and scheduled macroeconomic news announcements affect the volatility of bitcoin, measured as realized variance and its jump component. Our results show that realized variance and its jump component exhibit similar dynamics and react similarly to various types of news. Volatility of bitcoin reacts most strongly to news on bitcoin regulation, positive investor sentiment regarding bitcoin regulation extracted using Google searches, and most notably, hacking attacks on cryptocurrency exchanges. Quantile regression reveals that hacking attacks have particularly strong impact on the upper conditional distribution of bitcoin volatility. We also find that the volatility of bitcoin is not influenced by most scheduled US macroeconomic news announcements, such as government budget deficits, inflation, or even monetary policy announcements. On the other hand, bitcoin responds with increased volatility to announcements of forward-looking indicators, such as the consumer confidence index.

1. Introduction

Value of traditional fiat currencies is influenced by the macroeconomic fundamentals of the issuing country. Bitcoin, on the other hand, is a fully decentralized cryptocurrency. There is no central authority responsible for the value of bitcoin, and bitcoin is not linked to any particular country. This unique feature poses a serious problem for any theorist or practitioner seeking to investigate the behavior of bitcoin prices conditional on a set of hypothesized fundamental determinants. To date, the general consensus has been that bitcoin should be viewed as a form of speculative asset, a highly risky investment (at best), rather than a future currency or long-term investment (e.g., Baur and Dimpfl, 2018a; Baur et al., 2018b; Bouoiyour and

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Selmi, 2015; Bouoiyour et al., 2016; Charfeddine et al., 2019; Cheah and Fry, 2015; Ciaian et al., 2016; Corbet et al., 2019b; Kliber et al., 2019; Kristoufek, 2013; Shahzad et al., 2019; Smales, 2018; Symitsi and Chalvatzis, 2019; Yermack, 2013).

The literature has offered a broad set of conditioning factors potentially affecting bitcoin price formation, including the interaction between supply and demand (Ciaian et al., 2016), market microfundamentals such as the velocity of bitcoin, the exchange trade ratio (e.g., Bouoiyour and Selmi, 2015; 2017; Kristoufek, 2013), the price of gold, (in-)attention paid to bitcoin news (Bouoiyour and Selmi, 2017), market sentiment (Cretarola et al., 2017), the network hash rate as a measure of the computing power used to mine bitcoins (e.g., Bouoiyour and Selmi, 2017; Ciaian et al., 2016; Kristoufek, 2013), news about regulatory actions (Auer and Claessens, 2018), global financial development, oil prices, the EUR/USD exchange rate (van Wijk, 2013), output as an important long-term factor (Kristoufek, 2013), and news related to unemployment and durable goods as associated with bitcoin returns (Corbet et al., 2018a).

In this paper, we study the drivers of bitcoin price volatility and its jump component. The role of a broad set of macroeconomic news announcements has not yet been explored in the existing literature. The existing literature has already considered that monetary policy announcements might play an important role in this respect. For example, Corbet et al. (2017) report a statistically significant response in bitcoin volatility, while Vidal-Tomäs and Ibanez (2017) show otherwise. Bouri et al. (2018) identifies significant sources of bitcoin volatility stemming from other financial markets.

We fill the gap in the literature by studying the role of scheduled macroeconomic news announcements in eight economic categories: consumption, forward-looking indicators, government spending, investments, import-export, monetary policy, prices, and real economic activity. Moreover, we also explore the role of an important class of variables for bitcoin price formation; namely, news related to regulation, sentiment and the hacking of exchange markets.

We find that, systematically, the bitcoin-to-US-dollar exchange rate realized volatility responds only to scheduled news announcements related to forward-looking indicators. Second, news related to potential or implemented regulatory policies increases the observed realized volatility. Specifically, we proxy for the news related to regulation by scanning through articles in the Financial Times newspaper. Next, we find that on the day prior to the publication of news related to the regulation of bitcoin, the volatility of bitcoin increases. Third, we find that bitcoin volatility declines when positive sentiment (derived from Google searches) with regard to bitcoin, cryptocurrencies and regulation increases. Fourth, hacking services related to cryptocurrencies, such as the hacking of cryptocurrency exchanges, leads to increased volatility. These results suggest that hacking is a unique risk factor when pricing bitcoin investments. A particularly large effect is observed for the right tail of the volatility distribution, i.e., the hacking of cryptocurrency exchanges has the potential to lead to extremely volatile periods. Fifth, the jump component has drivers very similar to those of the realized volatility, while news items related to regulation and, particularly, hacking exchange markets have a potentially massive impact on the price formation of the bitcoin.

The remainder of this paper is organized as follows. Section 2, reviews the literature on macroeconomic news announcements and the models that are used in this strand of the research. Section 3 offers a description of the data sources and variables that we use. Section 4 presents the volatility models, namely, the extended heterogeneous autoregressive model (HAR) model and the noncrossing quantile regression model. Section 5 presents our results, and the last section concludes.

2. Literature review

Asset valuation models imply that news about economic conditions (at the macro and asset levels) should affect an asset's price, bitcoin included. The literature on the effect of macro news on different asset types is vast, focusing on stock markets (e.g., Bekaert and Engstrom, 2010; Bernanke and Kuttner, 2005; Flannery and Protopapadakis, 2015; Hirshleifer et al., 2011; Lyócsa et al., 2019; Zolotoy et al., 2017), bond markets (e.g., Balduzzi et al., 2001; Beechey and Wright, 2009; El Ouadghiri et al., 2016; Even-Tov, 2017; Fleming and Remolona, 1997; 1999; Gürkaynak et al., 2005), commodity markets (e.g., Chan and Gray, 2018; Elder et al., 2012; Kilian and Vega, 2011; Smales and Yang, 2015), and foreign exchange markets (e.g., Andersen et al., 2003b; Bauwens et al., 2005; Ben Omrane and Hafner, 2015; Ederington et al., 2019; Evans and Speight, 2010; Ouadghiri and Uctum, 2016; Petralias and Dellaportas, 2015).

In this paper, we take inspiration from this strand of the literature, specifically from the literature examining the price formation of the most traded currency pairs. The relevant literature consistently reports that for currency pairs involving the US dollar, US macroeconomic announcements often have a stronger impact than national surprises (e.g., Andersen et al., 2003b; Jaggi et al., 2016). Hence, without any a priori belief about the correct choice of bitcoin fundamentals, we test for the responsiveness of bitcoin price volatility to US-related macroeconomic news, as is standard in this stream of literature. Our approach thus relates to two strands of literature: one focusing on the fundamentals of cryptocurrency markets and the other on foreign exchange market determinants. A somewhat similar exercise is performed in Corbet et al. (2018a), but it differs in that it uses a limited set of fundamental factors (4) extracted from news headlines and focuses on the effect on returns rather than volatility. Due to the uncertain nature of bitcoin itself (whether it is money, a commodity or a financial asset) and the current lack of a unified theory of bitcoin economics, there are no a priori hypothesized effects of macroeconomic news on bitcoin. The recent empirical evidence confirms that while bitcoin is likely to exhibit speculative bubble behavior suggesting the nonexistence of it having any intrinsic fundamental value (Cheah and Fry, 2015), some role should be played by the fundamentals in the long term when bitcoin might attain the role of a medium of exchange (de la Horra et al., 2019), as theoretically derived by Bolt and van Oordt (2016). Hence, the responsiveness of bitcoin price volatility to specific macroeconomic factors might be considered indirect evidence of bitcoin taking on some of the basic functions of money. Finding the contrary might thus show otherwise. As a consequence, low correlation between bitcoin prices and other types of assets whose price fluctuations are likely to be driven by underlying fundamental macroeconomic forces also suggests that bitcoin represents an asset class of its own, a particular feature that might help to improve overall portfolio performance after its inclusion (as shown in Briere et al., 2015; Platanakis and Urquhart, 2019).

Most studies consistently show that bitcoin-related events play a crucial role in bitcoin price formation (Zhou, 2018). In our approach, we combine various sources of potential disturbances.

First, ongoing discussion on the very nature of bitcoin finds it reflects the regulatory steps taken by responsible bodies. As argued in Bryans (2014), the use of bitcoin for money laundering purposes should instigate appropriate legal action to restrict such unlawful behavior. According to Corbet et al. (2019b), regulation represents one of the key factors affecting the price of cryptocurrencies. Auer and Claessens (2018) show that news on regulatory actions is likely to spur reaction in cryptocurrency markets. Thus, we include a measure of news related to the announcement of regulatory steps taken with respect to bitcoin or other major cryptocurrencies and distinguish among three categories: positive, neutral and negative action.

Second, separate variables are used to capture the introduction of derivative contracts in two major commodity exchanges. According to the Corbet et al. (2018b), the introduction of derivatives increased the volatility on the bitcoin spot market. Similarly, Blau and Whitby (2019) also report an increase in bitcoin's volatility during the post-introduction period; however, other cryptocurrency markets have experienced a greater increase in volatility than the bitcoin market, thereby confirming the presence of spillover effects. As Bouoiyour and Selmi (2019) argue, the positive expectations that drove the bitcoin price immediately after its initial launch were replaced by a subsequent negative trend driven by pessimistic investors (Hale et al., 2018), which might have resulted in initially higher volatility. From a long-term perspective, Kim et al. (2019b) show that realized volatility stabilized at lower-than-pre-introductory levels once the short-term effects faded away.

We also account for abrupt distortions in the cryptocurrency market by incorporating information regarding cryptocurrency cyber attacks. As argued in Kopp et al. (2017), a new form of systemic risk has emerged in recent years related to cybersecurity breaches. As bitcoin was envisaged to operate as an unregulated, unsupervised and virtual asset from the very beginning, it can be highly sensitive to this particular type of risk. In a recent study by Caporale et al. (2019), the presence of cyber attacks decreases the probability of staying in the low-volatility regime.

Finally, it has been shown that bitcoin volatility often surges to unprecedented levels (e.g., Baur and Dimpfl, 2018a), unlike any other type of currently traded asset. To investigate what might be causing this behavior, we study the effect of news on bitcoin price volatility rather than on its returns. The literature often employs GARCH models (e.g., Chu et al., 2017; Ciaian et al., 2018; Klein et al., 2018; Trucíos, 2019; Walther et al., 2019), stochastic volatility models (e.g. Kliber et al., 2019; Phillip et al., 2018), HAR models (e.g., Baur and Dimpfl, 2018a; Catania and Sandholdt, 2019; Yu et al., 2019) or a nonparametric quantile-in-causality approach (Balcilar et al., 2017). We extend this literature by using HAR models combined with a linear noncrossing quantile regression approach because it allows investigation of the effects of conditioning factors across volatility distributions.

3. Data

We study the volatility of bitcoin prices and whether it is driven by (i) macroeconomic news announcements, (ii) news and sentiment related to government policies regarding the cryptocurrency market, and (iii) security breaches of cryptocurrency exchanges. To estimate the bitcoin (BTC/USD) price series volatility and its jump component, we process data on individual trades collected from the Bitstamp exchange. We use data over the entire calendar day and synchronize data according to the UTC time zone. As trading also occurs during weekends, weekends are included, resulting in 2151 observations from January 2013 until December 2018.

3.1. Realized measures

3.1.1. Realized variance

To estimate bitcoin's price variation, we combine four types of volatility estimators. We first consider the standard *realized variance* estimator (in annualized form):

$$RV_t^{(m,s)} = 252 \times \sum_{j=1}^{m} r_{t,j}^2 \tag{1}$$

where P_0 is the first price on a given day, $r_{t,j} = 100 \times \left(P_{t,j} - P_{t,j-1}\right)/P_{t,j-1}$ is the j^{th} intraday return on day *t*, *m* is the number of intraday returns, and *s* denotes the sampling schemes.

Our second class of estimators is adjusted for the possibility that intraday returns exhibit first-order serial dependence. The resulting measure is the *first-order adjusted* realized variance estimator of French et al. (1987), which is also used in Patton and Sheppard (2009) and Liu et al. (2015):

$$RV_{AC,t}^{(m,s)} = 252 \times \left[\sum_{j=1}^{m} r_{t,j}^2 + 2 \times \sum_{j=1}^{m-1} r_{t,j+1} r_{t,j}\right] \tag{2}$$

Our third class of estimators assumes that the overall price variation is a sum of the variation due to the continuous and sudden jump price movements. As we consider discontinuous price movements likely for the highly volatile bitcoin price series, we use two estimators that lead to consistent estimates in the presence of jumps. The *bipower* estimator of Barndorff-Nielsen and Shephard (2004):

$$RV_{BV,t}^{(m,s)} = \frac{252\pi}{2} \times \sum_{j=1}^{m-1} |r_{t,j}||r_{t,j+1}| \tag{3}$$

and the *median realized variance* estimator of Andersen et al. (2012):

$$RV_{MV,t}^{(m,s)} = \frac{252m\pi}{(m-1)(6-4\sqrt{3}+\pi)} \times \sum_{j=2}^{m-1} (med\left(|r_{t,j-1}|, |r_{t,j}|, |r_{t,j+1}|\right))^2. \tag{4}$$

Andersen et al. (2012) shows that the latter has better finite sample properties and, as such, provides an estimate of the variability of the price process due to the continuous component.

3.1.2. Jump component

The jump component is estimated following Andersen et al. (2012) as the difference between the realized variance and the continuous component. However, it is likely that in finite samples, $RV_t^{(m,s)} - RV_{MV,t}^{(m,s)} > 0$ even if there are no jumps or $RV_t^{(m,s)} - RV_{MV,t}^{(m,s)} < 0$. Therefore, we test for the presence of jumps and restrict the jump component to be positive. In particular, following the results of Andersen et al. (2012):

$$JC_t^{(m,s)} = max\left[0, \left(RV_t^{(m,s)} - RV_{MV,t}^{(m,s)}\right) I\left(|JT_t^{(m,s)}| > 1.96\right)\right] \tag{5}$$

where $I(.)$ is a signaling function that returns 1 if the condition applies and $JT_t^{(m,s)}$ is the test statistic for a null of no jump at day t:

$$JT_t^{(m,s)} = \frac{\frac{\sqrt{m}\left(RV_t^{(m,s)} - RV_{MV,t}^{(m,s)}\right)}{RV_t^{(m,s)}}}{\sqrt{0.96max\left(1, \frac{MRQ_t^{(m,s)}}{RV_t^{(m,s)}}\right)}} \tag{6}$$

where $MRQ_t^{(m,s)}$ is the median realized quarticity:

$$MRQ_t^{(m,s)} = 252 \times \left(\frac{3\pi m^2}{(m-2)(9\pi + 72 - 52\sqrt{3})}\right) \sum_{j=2}^{m-1} \left(med\left(|r_{t,j-1}|, |r_{t,j}|, |r_{t,j+1}|\right)\right)^4 \tag{7}$$

3.1.3. Combinations of realized measures

Relying on different assumptions and sampling frequencies, recent advances in financial econometrics have led to the development of many estimators of price variance. We follow the advice of Patton and Sheppard (2009), who suggest creating new estimators by means of simple combinations (averages) across existing individual estimators and sampling frequencies.

In the first stage, we estimate each of the realized measures (variance, jump components) using a *calendar sampling* scheme with last price interpolation and 7 different frequencies (1 sec, 5 sec, 1 min, 10 min, 15 min, 30 min, 1 h). In this sampling scheme, observations are evenly spaced in time. Next, we rely on the *business sampling* scheme, where we use each x^{th} price observation and where the number of prices corresponds to the number of observations using the 7 calendar sampling frequencies defined above (i.e., 86400, 17280, 1440, 144, 96, 48, or 24 observations). In this sampling scheme, observations are evenly spaced over events (price arrivals). If price arrival is correlated with the level of variance, the business sampling scheme should lead to more accurate estimates of the realized variance (Hansen and Lunde, 2006; Oomen, 2006).

However, as the true data generating process is unknown, we follow the approach of Patton and Sheppard (2009) and Liu et al. (2015) and use both the calendar and business time sampling schemes. Therefore, in the second stage, we use the simple average across all sampling frequencies and schemes. Specifically, for the realized variance, we have:

$$RV_t^C = \frac{1}{SM} \sum_{s=1}^{S} \sum_{m=1}^{M} \left(RV_t^{(m,s)} + RV_{AC,t}^{(m,s)} + RV_{BV,t}^{(m,s)} + RV_{MV,t}^{(m,s)}\right), \tag{8}$$

where $S = 2$ corresponds to the two sampling schemes and $M = 7$ to sampling frequencies while C denotes that it is a composite (an average) estimator. For the jump component, the aggregation leads to[1]:

$$JC_t^C = \frac{1}{SM}\sum_{s=1}^{S}\sum_{m=1}^{M} JC_t^{(m,s)} \tag{9}$$

3.1.4. Log transformation in realized measures

Compared to the price series of traditional assets (stocks, commodities, foreign exchange rates, bonds), the variance of the bitcoin price series is known to be extreme, its returns have a high level of kurtosis, and the distribution of the daily levels of variance is extremely skewed to the right. We address this issue by taking the natural logarithm of the variance the jump series. Specifically, the transformed variance, jump, and continuous estimators of interest are:

$$RV_t = ln(RV_t^C) \text{ and } CC_t = ln(CC_t^C) \text{ and } JC_t = ln(JC_t^C + 1), \tag{10}$$

Taking the log of the variance is common in the literature (e.g., Taylor et al, 2017), and we will refer to the transformed measure as *realized volatility*. Andersen et al. (2001), Andersen et al. (2003a), and Andersen et al. (2007) argue that the logarithmic transformation leads to a distribution that is more symmetric and much closer to the normal distribution than are the raw realized volatility series, which is more suitable for standard time-series modeling purposes, e.g. autoregressive volatility models. Furthermore, the logarithmic transformation automatically eliminates the need to impose nonnegativity constraints on the fitted volatilities and, as noted earlier, the need to explicitly address potential outliers. For example, Maheu and McCurdy (2011) explore the predictability of the return distribution and use bivariate systems where the variance equation is based on the logarithm of the realized variance (see their Eq. 3.3 and 3.4). Corsi and Renò (2012) investigate the leverage effect by explaining the logarithm of the variance, continuous and jump component within HAR modeling framework (see their Eq. 2.4, 3.1 and 3.2).

3.2. Macroeconomic announcements

Because the US economy is the largest in the world and the exchange rate for bitcoin is usually quoted against the US dollar, we build our database based on relevant studies focusing on the effect of US macroeconomic news. The existing literature also consistently reports that US macroeconomic announcements often have a stronger impact on the behavior of asset prices than national surprises (e.g., Andersen et al., 2003b; Jaggi et al., 2016).

We use data on scheduled macroeconomic news releases related to the US economy, where the data are collected from Bloomberg, and as before, news announcements are synchronized in the UTC time zone. The news announcements are included to test for the role of the arrival of any new information on the date of a news announcement that is related to the general economic conditions in the US economy. The research question is whether the volatility of the bitcoin price series reacts to economic fundamentals or if its behavior is unrelated to the condition of the US economy.

We follow the work of Andersen et al. (2003b); Cai et al. (2009a); Fatum et al. (2012a); Fatum and Scholnick (2008); Galati and Ho (2003); Jaggi et al. (2016); Laakkonen (2007); Swanson and Williams (2014) and select relevant news from following eight macroeconomic announcement groups: i) real economic activity, ii) household consumption decisions, iii) firm investment decisions, iv) government finances, v) external balances, vi) price evolution, vii) monetary policy decisions, and viii) forward-looking, component-integrating market expectations about future economic development (see Andersen et al., 2003b). An overview of this categorization is presented in Table 1.

The forward-looking indicators group consists of eight individual indices capturing opinions about future real economic prospects as perceived by consumers or nonfinancial corporations. As such, this category partially incorporates indices based on surveys of consumers and managers, which further enriches the analysis by including qualitative sources of information. All of the indicators predominantly focus on real side of an economy, as the most significant announcements from the US are, in general, related to the real economy indicators in contrast to the more important role played by monetary announcements in the euro area (see Laakkonen, 2007).

In the empirical analysis, we do not use the values of the announced macroeconomic variables/indicators or the extent of the surprises; only a dummy variable is recorded for the date of the upcoming scheduled news. Our decision to use dummies is motivated by the fact that surprises will be known only at the announcement on day t, while information about whether the news will be announced is known before, on day $t-1$. In this way, the right-hand side values in our specifications are known the day before the value of the modeled volatility component, which would not be true with surprises included on the right-hand side.

Instead of allowing volatility models to have too many parameters by allowing each macroeconomic news item to have its own variable, we aggregated information about news announcements for each macroeconomic news category (e.g., real economic activity, household consumption decisions); thus, each macroeconomic news category (indexed by i) is represented by only *one* variable, $D_{i,t-1}$, which for each day takes a value from 0 to 1. A value of 0 is returned if, on the next day t, there is no scheduled news announcement report for that category, and a value from 0 to 1 is returned if at least one news

[1] The aggregation for the continuous component leads to $CC_t^C = \frac{1}{SM}\sum_{s=1}^{S}\sum_{m=1}^{M} RV_{MV,t}^{(m,s)}$.

Table 1
An overview of macroeconomic news announcements .

	Galati and Ho (2001)	Anderson et al. (2003)	Laakkonen (2007)	Fatum and Scholnik (2008)	Cai et al. (2009)	Fatum et al. (2010)	Swanson and Williams (2013)	Jaggi et al. (2016)
Real economy								
GDP Annualized QoQ		x	x		x			x
Nonfarm Payroll Employment	x	x	x		x	x	x	x
Retail sales advance MoM	x	x	x		x			
Industrial production MoM	x	x	x	x	x	x		x
Capacity utilization		x	x		x	x	x	
Personal income		x	x		x	x		
Consumer credit		x	x		x	x		
Initial unemployment (jobless claims)		x	x	x	x		x	
Wholesales inventories MoM			x		x			
Employment cost index	x		x					
Wholesale Trade Sales MoM								
Consumption								
Personal consumption expenditures		x	x					
Personal (consumer) spending			x		x	x		
New home sales		x	x		x	x		x
Average hourly earnings all YoY			x					x
Investment								
Durable goods orders	x	x	x		x	x		x
Construction spending MoM		x	x		x			
Factory orders		x	x		x	x		
Business inventories		x	x		x	x		
Government								
Government budget deficit		x			x			
Net export								
Trade balance		x	x	x	x	x		
Current account			x		x			
Prices								
Consumer price index MoM	x	x	x	x	x	x		
Consumer price index YoY			x					
CPI Ex Food and Energy YoY			x					
Monetary policy								
FOMC Rate Decision		x	x		x	x		
Forward-looking								
Conf. Board consumer confidence index		x	x		x	x		x
U. of Mich. Sentiment			x					
Markit US Manufacturing PMI								
NAPM/ISM index - manufacturing	x		x				x	x
NAPM/ISM index - non-manufacturing	x		x					x
Housing starts		x	x		x	x		x
Index of leading indicators		x	x		x	x		
U. of Mich. current business conditions								x

Table 2
Cryptocurrency hacking attacks .

Date	Target	Loss (USD)	Date	Target	Loss (USD)
2018-12-21	Electrum Bitcoin wallets	750 000	2017-07-24	Veritaseum	8 400 000
2018-12-05	Vertcoin 51% attack	10 000	2017-07-17	CoinDash	7 000 000
2018-10-28	MapleChange	6 000 000	2017-06-29	ClassicEtherWallet.com	300 000
2018-10-21	Trade.io cold storage wallets	7 500 000	2017-06-29	Bithumb	8 700
2018-10-15	EOSBet	338 000	2017-04-22	Yapizon	5 000 000
2018-10-06	SpankChain	38 000	2017-02-17	Zcoin	400 000
2018-09-26	Pigeoincoin	15 000	2016-08-02	Bitfinex	65 000 000
2018-09-20	Zaif	60 000 000	2016-07-14	Steemit	85 000
2018-09-09	C-CEX	NA	2016-05-15	Gatecoin	200 000
2018-09-07	Bancor	13 500 000	2016-03-19	naira4dollar.com	15 000
2018-08-04	Livecoin	1 800 000	2016-02-06	Loanbase	8 000
2018-06-20	Bithumb	31 500 000	2016-01-15	Cryptsy	6 000 000
2018-06-11	Coinrail	37 200 000	2015-06-22	Scrypt.cc	NA
2018-06-06	Litecoin Cash 51% attack	NA	2015-03-26	Cryptoine	NA
2018-05-28	Taylor	1 350 000	2015-03-15	AllCrypt	NA
2018-05-22	Verge	1 650 000	2015-02-14	Bter	1 750 000
2018-05-18	Bitcoin Gold 51% attack	18 000 000	2015-01-05	Bitstamp	5 200 000
2018-02-10	BitGrail	170 000 000	2014-05-11	Dogecoin	74 000
2018-01-31	Bee Token	1 000 000	2014-03-19	CoinEx	NA
2018-01-26	Coincheck	524 000 000	2014-03-06	Poloniex	50 000
2017-12-20	EtherDelta	266 789	2014-03-03	Flexcoin	620 000
2017-12-19	Youbit	NA	2014-01-22	Give me coin	230 000
2017-12-06	NiceHash	68 000 000	2013-12-26	Dogecoin wallet	12 000
2017-11-22	Bitcoin Gold	3 300 000	2013-11-17	BiPS	1 000 000
2017-11-22	CoinPouch	655 000	2013-11-11	bitcash.cz	100 000
2017-11-20	Tether	31 000 000	2013-11-07	inputs.io	1 300 000
2017-10-01	OKEx	3 000 000	2013-03-04	bitinstant	12 480
2017-08-21	Enigma	500 000			

item is scheduled to be announced on the next day *t*. For example, in the category of real economic activity, we have 11 scheduled macroeconomic news items. If on the next day, there are 3 scheduled news announcements in the category of real economic activity, the reported value of this variable for that day is 3/11.

3.3. Regulation, sentiment and hacking attacks on crypto-currency exchanges

Recent studies have shown that cryptocurrency markets tend to react to news related to possible regulatory actions (Auer and Claessens, 2018) and cybercrime events related to the hacking of cryptocurrency exchanges. In our model specifications, we control for such actions in three ways: i) we record the dates of important regulatory news using articles from the Financial Times, ii) we estimate market sentiment related to the cryptocurrency markets with a particular focus on regulatory actions, and iii) we record days of hacking attacks on cryptocurrency exchanges.

3.3.1. News articles

To capture the effect of regulations on bitcoin volatility, we manually select the most important news from the Financial Times that is closely related to bitcoin regulation. The Financial Times is an English-language international daily newspaper with an emphasis on business and economic news that is recognized internationally for its authority, integrity and accuracy.

We use the ProQuest newspaper database to filter the articles that contain the keywords 'bitcoin' and 'regulation' (or 'regulatory', 'law', 'rules'). This resulted in 899 articles; these were manually checked, and only articles that were directly related to actual or possible regulation of bitcoin discussed or implemented by the authorities were retained in our database.

This process resulted in 55 news items for the period from January 2013 to December 2018. From each news item, we recorded the date when the regulatory action was discussed by the authorities or journalists, and we used three dummy variables to capture the event. The first dummy returns a value of 1 on the date of the news announcement (FTN_t). It is, however, likely that the news is known at least a day prior to its publication, and therefore, the second dummy returns a value of 1 the day before the news announcement (FTN_{t-1}). The third dummy returns a value of 1 the day after the news announcement (FTN_{t+1}) to control for possible lagged effects or news misspecification.

3.3.2. Google trends on regulatory policy actions

Several recent studies have used volume data from Google searches to explain behavior on the bitcoin exchange market (Aalborg et al., 2019; Cheah and Fry, 2015; Garcia et al., 2014; Kristoufek, 2013; Urquhart, 2018). We estimate the general sentiment by extracting volume of Google searches using two-word phrases in the following form: *'cryptocurrency' + 'key word'*. Our choice of the *key words* is motivated by our intention to capture possible sentiment related to the regulatory action(s). The *'key words'* are subsequently separated into three categories:

- Cryptocurrency supporting sentiment: *approval, currency, asset*.
- Cryptocurrency neutral sentiment: *regulation, law, legal, rule, rules*.
- Cryptocurrency nonsupporting sentiment: *ban, illegal, control*.

Each of these *'key words'* is combined with the following words: *cryptocurrency, bitcoin, ripple, ethereum*, which leads to 44 search phrases.

Google Trends provides anonymous data on the relative search volume of different keywords. Google Trends provides values between zero and 100, where a zero indicates the lowest relative search interest for a given keyword, and 100 represents the opposite within the selected time range. The maximum length of the time period for which Google Trends reports with daily frequency is approximately 90 days. For longer periods, Google Trends provides only weekly and monthly sampling frequencies.

We are interested in daily data for the period from 2013 to the end of 2018. For this period, Google provides relative search volumes only at a monthly frequency. To obtain daily data, we follow the method used by Bijl et al. (2016) and Kim et al. (2019a): we apply a rolling window and calculate the standardized Google Trends (SGT) value. The standardization is achieved by subtracting the average of the past 90 days from the actual Google Trend value that day and dividing this difference by the standard deviation of the previous 90 days.

The calculation of SGT is as follows:

$$SGT_t = \frac{GT_t - \frac{1}{90}\sum_{i=1}^{90} GT_{t-i}}{\sigma_{t-1,t-90}} \tag{11}$$

where GT_t is a raw Google Trend and $\sigma_{t-1,t-90}$ is the standard deviation of the Google Trend for the past 90 days.

Instead of using all Google search volume series in the volatility models, we extract the first principal component for each sentiment group. This was motivated by a desire to decrease the potential noise in the data and the number of parameters needed to estimate the volatility models.

The extracted component is subject to extreme right-tail observations in a manner similar to bitcoin's realized variance. Therefore, we opt to use the logarithmic transformation of the extracted component in the following way:

$$NosT_t = ln\left(100 \times \frac{(RFC_t + |min(RFC_t)|)}{max(RFC_t + |min(RFC_t)|)} + 1\right) \tag{12}$$

where $NosT_t$ is the resulting Google search index estimated for phrases belonging to the negative, not-supportive sentiment group, and RFC_t is the extracted, zero-mean first principal component. The numerator in the equation ensures that $NosT_t \geq 0$, while the denominator ensures that the resulting series is standardized relative to the maximum value in the same way as the raw data on Google search volumes. The same standardization is employed for $SupT_t$ (positive, supportive sentiment) and $NeuT_t$ (neutral sentiment).

3.3.3. *Cryptocurrency cyber attacks*

We create a dataset that contains the main cryptocurrency hacks. The most common victims are cryptocurrency exchanges, online wallet providers, and even the cryptocurrency itself (exploiting bugs in a code, 51% attack, etc.). The reported dates of the attacks were retrieved on 27 June 2018[2]. For the period from 2013 until 2018, we retrieved data on 55 attacks, see Table 2; for 48 of the attacks, we also have the data on estimated direct losses[3] for the owners of accounts on these exchanges, while for the remaining 7 attacks, we adopt a highly conservative approach and assume that the loss is 1 USD[4].

As suggested in Corbet et al. (2019a), suspicious price behavior on cryptocurrency exchanges occurs prior to the announcement of hacking. We therefore create a variable $Hack_t$ that equals the percentage of the estimated loss from the total market capitalization of bitcoins for the day of the official announcement of the hacking and one day prior, 0 otherwise. The dates when attacks have been announced are visualized by vertical bars in Figs. 1, 2, and 3.

3.4. *Derivative contracts on bitcoins*

Finally, we also add two trend variables. The first is the linear time trend, which captures the long-term effect of the changing volatility. The second is a linear time trend, which returns a value of 0 prior to 10 December 2017, thus prior to the introduction of derivatives on the CBOE and CME (18 December 2017), and a time trend value of 1 for 11 December 2017, 2 for 12 December 2017, etc.

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[2] Data are retrieved from https://www.hackmageddon.com/category/security/cyber-attacks-timeline/.

[3] These data are available upon request.

[4] A small positive number is a convenience, as it facilitates our work with the variable in the next steps of our analysis.

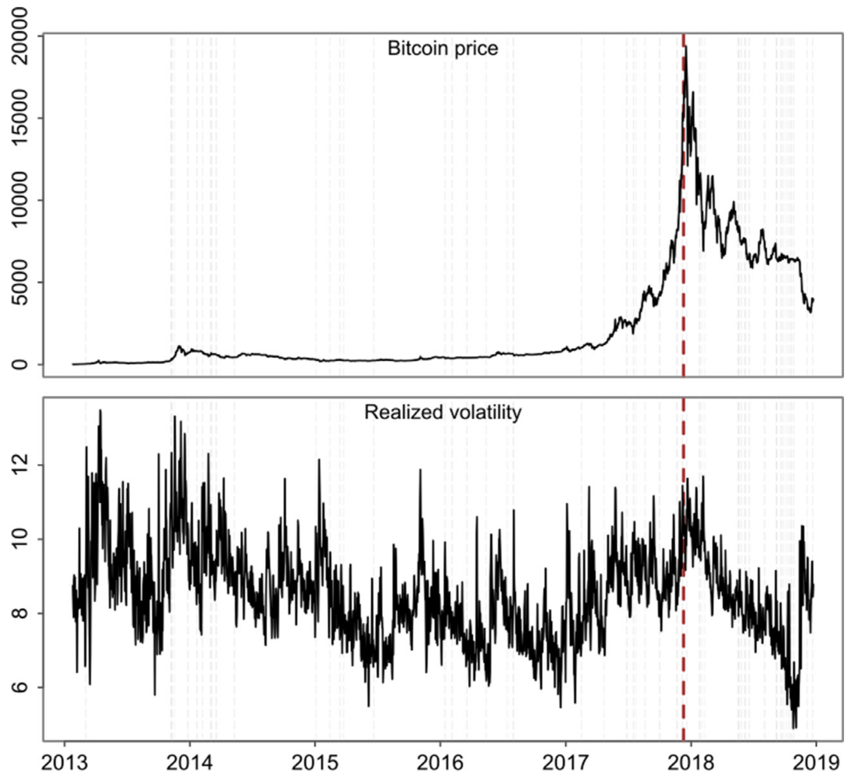

Fig. 1. Bitcoin price and volatility Note: On the y-axis, the values correspond to the price of bitcoin in USD (upper panel) and to the log of the realized variance, i.e., the realized volatility (lower panel).

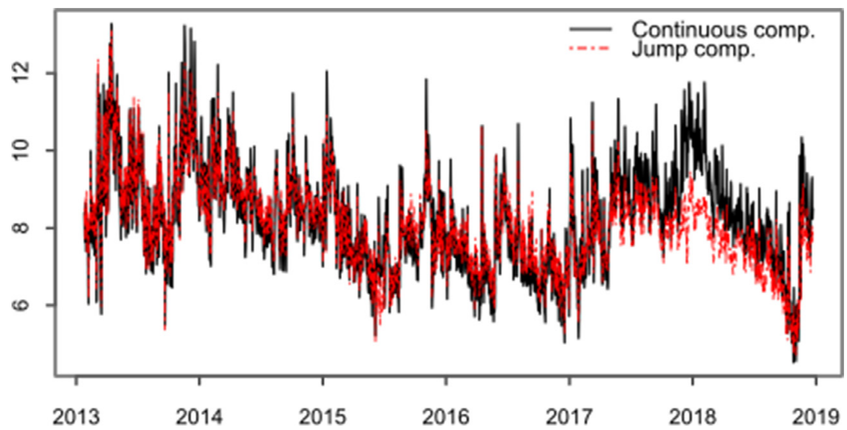

Fig. 2. Bitcoin continuous and jump components Note: On the y-axis, the values correspond to the natural logarithm of CC_t^C and the natural logarithm of $JC_t^C + 1$, where CC_t^C is the average continuous component over different sampling frequencies and schemes and where JC_t^C is the average jump component over different sampling frequencies and schemes (see Section 3.1.4 for details).

4. Volatility model specifications

4.1. Linear HAR model

To estimate the effect of macroeconomic news announcements on the overall level of volatility, we use an augmented model of the standard realized volatility heterogeneous autoregressive model (RV-HAR) of (Corsi, 2009):

$$RV_t = \beta_1 + \beta_2 RV_{t-1}^D + \beta_3 RV_{t-1}^W + \beta_4 RV_{t-1}^M + \epsilon_t \tag{13}$$

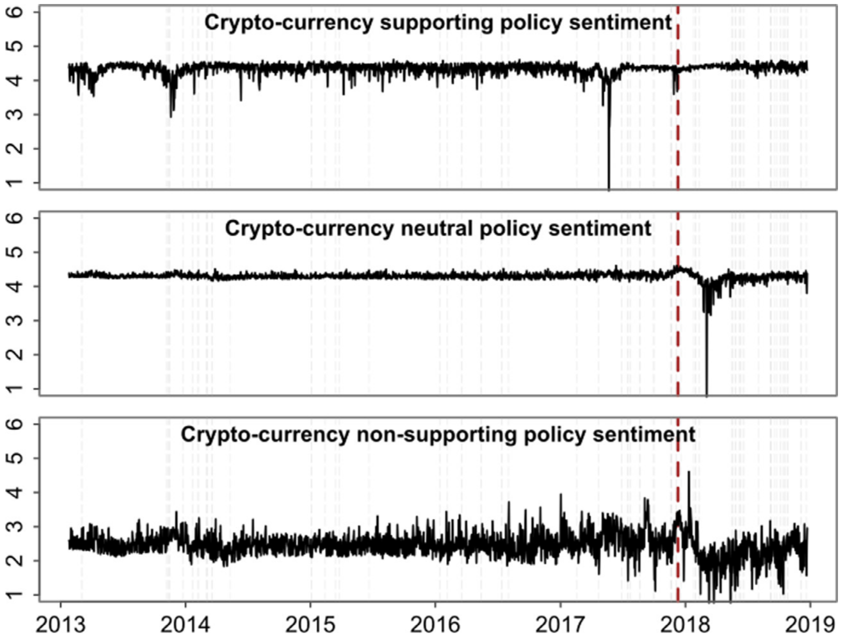

Fig. 3. Google trends.

where RV^D_{t-1} is the lagged daily volatility and RV^W_{t-1}, RV^M_{t-1} are average volatilities over the past day, week (five days), and month (twenty-two days)[5] Although the HAR model is not a long-memory model per se, it is known to capture the long-memory property of the volatility series well. With respect to bitcoin volatility, most of the models in existing studies rely on GARCH class models (e.g., Baur et al., 2018a; Chu et al., 2017; Conrad et al., 2018; Katsiampa, 2017). In a recent study, Trucíos (2019) compare several models to explain bitcoin volatility, including GARCH class models, and show that the HAR model run on the log of realized volatility (HARL model in Trucíos, 2019) performs well in a day-ahead out-of-sample framework. With respect to news announcements, Chan and Gray (2018) and Lyócsa et al. (2019) use HAR class models to model realized and implied volatility as a function of scheduled news announcements. We estimate the following specification, which is an extended version of the standard HAR model:

$$\begin{aligned}RV_t =& \beta_1 + \beta_2 RV^D_{t-1} + \beta_3 RV^W_{t-1} + \beta_4 RV^M_{t-1} + \\ & RV^D_{t-1} \times (\delta_1 FTN_{t-1} + \delta_2 FTN_t + \delta_3 FTN_{t+1}) + \\ & RV^D_{t-1} \times (\delta_4 NosT_{t-1} + \delta_5 NeuT_{t-1} + \delta_6 SupT_{t-1}) + \\ & RV^D_{t-1} \times \delta_7 Hack_t + \delta_8 Trend_t + \delta_9 Trend_t \times I(t > 10\text{th } Dec\ 2017) + \\ & RV^D_{t-1} \times \sum_{i=1}^{8} \gamma_i D_{i,t-1} + \epsilon_t. \end{aligned} \tag{14}$$

The parameters of interest are $\gamma_i, i = 1, 2, \dots, 8$, which correspond to the effect of the macroeconomic news announcement on the volatility of bitcoin. Specifically, the γ_i coefficients indicate how the next day's volatility, at time t, is anticipated to change if a given (i^{th}) macroeconomic news item is announced on the next day – regardless of the outcome of the announced news, which is unknown on day $t-1$. Because of the interaction, the size of this change is expressed with respect to the level of volatility on day $t-1$. Next δ_i, $i = 1, 2, 3$, refers to news articles; δ_i, $i = 4, 5, 6$, refers to google trends; δ_7, corresponds to the hacking of exchange markets; and finally, δ_8 and δ_9, correspond to trends.

Compared to the standard HAR model, our specification uses an interaction of the lagged realized volatility with non-volatility components. We are motivated by our expectation that the effect of the news announcement and/or other non-volatility variables might differ with respect to the current level of market volatility. Therefore, the interaction results in an estimation of changes in the next day's volatility relative to the previous day's level of volatility.

[5] Note that to calculate average weekly/monthly realized volatility, we first calculate realized variance for our sampling frequency and estimator. Next, we average each realized measure across the five/twenty-two days, take the average across estimators, and only then, take the logarithm.

Different model specifications are also considered and are briefly discussed in the specification sensitivity section.

To model the jumps, we follow the same specification, except that the realized volatilities are replaced by jump components:

$$\begin{aligned}JC_t =&\beta_1 + \beta_2 JC^D_{t-1} + \beta_3 JC^W_{t-1} + \beta_4 JC^M_{t-1}+\\ &JC^D_{t-1} \times (\delta_1 FTN_{t-1} + \delta_2 FTN_t + \delta_3 FTN_{t+1})+\\ &JC^D_{t-1} \times (\delta_4 NosT_{t-1} + \delta_5 NeuT_{t-1} + \delta_6 SupT_{t-1})+\\ &JC^D_{t-1} \times \delta_7 Hack_t + \delta_8 Trend_t + \delta_9 Trend_t \times I(t > 10\text{th } Dec\ 2017)+\\ &JC^D_{t-1} \times \sum_{i=1}^{8} \gamma_i D_{i,t-1} + \epsilon_t\end{aligned} \tag{15}$$

Using an autoregressive structure to model the jump components of the volatility process might appear odd, as existing empirical literature suggests that the jump component has small persistence, e.g., Andersen et al. (2007) for US stocks, FX rates and the fixed income security market; see Giot et al. (2010) for US stocks, Ma et al. (2019a,b) for US stocks and crude oil, Slim and Dahmene (2016) for French stocks, Bjursell et al. (2015) for US energy futures, or Chen et al. (2019) for G7 stock markets. However, this is not the case for our estimate of the jump component on the bitcoin price series, where persistence is similar to that of realized volatility, and hence the autoregressive structure of our jump model specification.

We estimate both model parameters via OLS and the standard errors using heteroskedasticity- and autocorrelation-consistent variance-covariance matrices with the quadratic spectral weighting scheme and automatic bandwidth selection procedure as in Newey and West (1994).

4.2. Non-crossing quantile regression HAR model

Given the unprecedented level of bitcoin price volatility, we also explore the role of economic fundamentals in the behavior of realized volatility, RV_t (jump component, JC_t), across quantiles of the distribution. The absolute and relative importance of volatility drivers might differ across quantiles of bitcoin volatility (jump component) distribution. For example, in a recent study, Baur and Dimpfl (2018b) find (in a sample of stock market indices) a tendency toward higher persistence for high-level volatility compared to low-level of volatility.

We therefore estimate our model specifications within a quantile regression framework while modeling the realized volatility (jump component) as linear function of a set of p variables, $\boldsymbol{x}_t = (x_{1,t}, \ldots, x_{1,p})'$, $\boldsymbol{z}_t = (1, \boldsymbol{x}')$. The τ^{th} conditional quantile of the dependent variables is $\boldsymbol{z}_t'\boldsymbol{\beta}(\tau)$, $P(RV_t \leq \boldsymbol{z}_t'\boldsymbol{\beta}(\tau)|\boldsymbol{x}_t) = \tau$, where $\boldsymbol{\beta}$ is a vector of coefficients. Given the check function $\rho(\tau, u) = u[\tau - I(u < 0)]$, the usual single-equation estimator of coefficients is:

$$\hat{\boldsymbol{\beta}}(\tau) = arg\ min_{\boldsymbol{\beta}} \sum_{t=1}^{T} \rho\left(\tau, RV_t - \boldsymbol{z}_t'\boldsymbol{\beta}(\tau)\right). \tag{16}$$

In our empirical application, we consider $\tau = 0.05, 0.25, 0.50, 0.75, 0.95$. In the finite sample, estimating individual quantile regressions for each of the quantiles might lead to the *quantile crossing* problem. An example of a simple case of quantile crossing arises if the intercept is not a monotone function of τ. Moreover, as noted by Bondell et al. (2010), quantile crossing is more likely for extreme quantiles. Bondell et al. (2010) proposes the following estimation procedure, which addresses the quantile crossing problem but is asymptotically equivalent to the standard (single-equation) quantile regression estimator:

$$\begin{aligned}\hat{\boldsymbol{\beta}}(\tau) = arg\ min_{\boldsymbol{\beta}} \sum_{i=1}^{q} w(\tau_i) \sum_{t=1}^{T} \rho\left(\tau, RV_t - \boldsymbol{z}_t'\boldsymbol{\beta}(\tau)\right)\\ \boldsymbol{z}'\boldsymbol{\beta}(\tau_i) \leq \boldsymbol{z}'\boldsymbol{\beta}(\tau_{i-1}), i = 1, \ldots, q\end{aligned} \tag{17}$$

where $w(\tau_i)$ is a weight function that satisfies $w(\tau_i) > 0$. However, as in Bondell et al. (2010), we assume that $w(\tau_i) = 1$ for all i. The restrictions in Eq. 17 address the noncrossing problem. For example, the noncrossing coefficient estimation tries to ensure that if a hacking attack has a smaller effect on the lower quantile of realized volatility than on the median level of realized volatility, the same hacking attack should have at least as large an effect on the larger level of realized volatility as on the median level of realized volatility (i.e., $\beta_{\tau=0.05} \leq \beta_{\tau=0.5} \leq \beta_{\tau=0.95}$). This might also lead to an effect whereby we do not observe large changes in the coefficients across quantiles.

The significance of each of the regressors is calculated using a stationary bootstrap with block lengths drawn from the geometric distribution, where the optimal block length is estimated as in Politis and White (2004) and Patton et al. (2009). The number of bootstrap samples is set to 1000. The bootstrap p-values are calculated using the bootstrap distribution of each of the coefficients.

Table 3
Descriptive statistics of volatility, article news and sentiment variables .

	Mean	S.D.	Skew.	Kurt.	5th	25th	50th	75th	95th	$\rho(1)$	$\rho(5)$	$\rho(22)$	$\rho(100)$
Panel A: Volatility components													
RV_t	8.529	1.268	0.398	3.388	6.665	7.650	8.478	9.293	10.696	0.826	0.645	0.463	0.167
CC_t	8.247	1.340	0.416	3.250	6.248	7.291	8.173	9.061	10.628	0.826	0.645	0.461	0.175
JC_t	8.078	1.155	0.418	3.807	6.306	7.329	8.022	8.744	10.090	0.842	0.687	0.527	0.218
Panel B: Article news - regulation													
FTN_t	0.026	0.158	6.011	37.135	0.000	0.000	0.000	0.000	0.000	0.104	0.049	0.030	0.049
$Hack_t$	0.132	0.654	6.342	42.269	0.000	0.001	0.003	0.027	0.279	0.480	−0.039	0.150	–
Panel C: Sentiment - cryptocurrency (dis)approval													
$NosT_t$	2.463	0.361	−0.303	6.991	1.912	2.260	2.451	2.653	3.063	0.345	0.287	0.146	0.046
$NeuT_t$	4.297	0.139	−15.092	436.897	4.180	4.255	4.302	4.352	4.438	0.295	0.287	0.207	-0.018
$SupT_t$	4.346	0.189	−7.541	141.805	4.061	4.293	4.381	4.452	4.518	0.357	0.246	0.160	-0.035

Notes: S.D. denotes the standard deviation, Skew. and Kurt. skewness and kurtosis, 5th, ..., 95th are percentiles and $\rho(.)$ is the autocorrelation coefficient of a given order.

5. Results

5.1. Sample characteristics

5.1.1. Bitcoin price and volatility series

Before we proceed with the examination of models that link scheduled macroeconomic news announcements to realized volatility and the jump component of the bitcoin price series, it is useful to discuss the specifics of our data. In Fig. 1, we observe the unprecedented rise in the price of the bitcoin and the subsequent fall from the end of 2017 until the end of our series in 2018. Moreover, bitcoin volatility peaked in earlier in 2013, when relative price changes were larger.

Table 3 reports the average value of the realized volatility for the bitcoin price series as 8.529, which corresponds to an annualized standard deviation of 71.12%. This is much higher than reported values for other asset classes. For example, in a recent study, Bollerslev et al. (2018) reports levels of annualized standard deviation for commodities at 25.40%, equities at 20.60%, fixed income at 3.10% and foreign exchange at 10.30%, which are all much smaller than the annualized standard deviation of the bitcoin price series calculated for our sample. Similar values and differences can also be found in other studies over different sample periods, e.g., averages for 105 individual stocks at 21.45% and for the S&P ETF at 10.84% in Patton and Sheppard (2015) and for natural gas and oil ETFs at 29.79% and 21.98%, respectively, in Lyócsa and Molnár (2018), which shows that although the sample periods differ from that of our study, these differences are clearly nontrivial, and as such, bitcoin can be regarded as a highly risky asset class.

Importantly, the volatility series exhibits long-memory properties even at the 100th lag, and the autocorrelation is 0.167. This means that our decision to model volatility using a HAR class of models has merit. The continuous component has very similar characteristics, and as can be observed from Table 4, the two series are also highly correlated[6].

We make an interesting observation with respect to the jumps. In the general finance literature, jumps are considered to be *rare* and *unpredictable*. Table 3 shows that our estimation approach led to pervasive and highly persistent jumps. We identified two potential sources of persistence in JC_t. *First*, the individual jump components $JC_t^{(m)}$ (not the composite) have different persistence across sampling frequencies, with higher persistence if $JC_t^{(m)}$ is estimated from data with a higher frequency and lower persistence if estimated from data with a lower frequency[7] The average persistence of individual jump components $JC_t^{(m)}$ is 0.24, while the persistence after averaging, i.e., of JC_t^C is 0.60. Therefore, part of the persistence comes from the averaging approach of Patton and Sheppard (2009). *Second*, after the log-transformation $JC_t = \ln(JC_t^C + 1)$, the persistence further increased to 0.84. This means that averaging and the logarithmic transformation more than tripled the persistence of our estimate of the jumps[8].

We also considered a third possibility related to the averaging. If a statistically significant jump is detected for at least one sampling scheme and frequency, the resulting average will be a positive number, i.e., we will record a jump event[9] This could also be responsible for the persistence of jumps. For example, if jumps are rare but found regularly (by chance)

[6] As the two series are very similar, and the subsequent volatility models show very similar results, we decided not to directly report the results of our volatility models for the continuous component. These results are available upon request

[7] A more detailed research on the properties of jumps estimated at different frequencies is left for future research.

[8] A similar effect is also observed for the realized variance, albeit to a lesser extent. The average persistence of $RV_t^{(m)}$ is 0.49, the persistence of RV_t^C (after averaging) is 0.58, and after the log-transformation, the persistence of RV_t increased to 0.83. We formally test for the significance in the difference between the persistence of the JC_t and CC_t and find that the differences (for persistence at lag 1, 5, 22 and 100) are not statistically significant at the conventional 5.0% level (two sided p-values are 0.092, 0.073, 0.092, 0.246 for 1, 5, 22 and 100 lag). However, given the existing literature for other asset classes, the fact that JC_t has a persistence comparable to that of CC_t is surprising and is likely specific to our estimation approach based on averaging multiple estimates of jumps and continuous components across sampling frequencies and schemes. The significance test is based on the stationary bootstrap with random block length drawn from a geometric distribution with the expected value by Politis and White (2004), Patton et al. (2009)

[9] Although it will be a small jump event if only one of the jump estimators is significant.

Table 4
Correlation matrix of volatility, article and sentiment variables .

		B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
RV_t	A	0.995	0.934	0.102	0.126	0.091	0.174	0.090	−0.184	0.064	0.006	0.015	0.019	0.001	0.012	0.008	0.035	0.044
CC_t	B		0.899	0.110	0.133	0.099	0.172	0.089	−0.182	0.064	0.009	0.018	0.020	0.005	0.013	0.010	0.036	0.048
JC_t	C			0.061	0.083	0.051	0.161	0.089	−0.184	0.065	−0.012	0.003	0.015	−0.012	0.007	0.004	0.035	0.019
FTN_t	D				0.104	0.104	−0.001	−0.029	0.023	−0.007	−0.002	−0.001	0.036	0.006	−0.034	−0.024	0.001	0.044
FTN_{t-1}	E					−0.008	0.049	-0.026	0.004	−0.004	0.004	−0.024	0.003	−0.008	−0.005	−0.024	0.033	-0.00
FTN_{t+1}	F						0.027	0.012	0.018	−0.007	−0.009	0.030	0.003	−0.008	0.009	−0.024	-0.031	-0.01
$NosT_{t-1}$	G							0.273	−0.205	−0.001	0.033	0.045	−0.001	0.015	0.012	0.008	0.034	0.057
$NeuT_{t-1}$	H								−0.132	−0.001	0.016	0.040	0.013	0.020	0.001	0.010	0.028	0.052
$SupT_{t-1}$	I									0.016	−0.018	−0.004	−0.012	−0.001	0.012	−0.005	−0.030	−0.03
$Hack_t$	J										0.035	−0.015	−0.007	−0.012	−0.008	−0.006	−0.009	0.041
Con_t	K											0.227	−0.058	0.098	0.041	0.005	−0.086	0.474
$ForL_t$	L												−0.062	0.258	0.010	−0.010	0.088	0.119
$GovS_t$	M													−0.029	−0.039	−0.010	0.104	−0.01
Inv_t	N														0.116	0.007	0.040	0.170
$ImpE_t$	O															0.076	0.037	0.120
Mon_t	P																0.075	−0.02
Pri_t	Q																	0.082
$ReaO_t$	R																	

Table 5
Statistical description of scheduled macroeconomic news announcements .

	Characteristics across the whole sample		Characteristics only during events		
	Mean	S.D.	# of Events	Mean	S.D.
Con_t	0.030	0.087	267	0.245	0.094
$ForL_t$	0.042	0.082	513	0.175	0.071
$GovS_t$	0.033	0.179	71	1.000	0.000
Inv_t	0.037	0.100	281	0.283	0.085
$ImpE_t$	0.022	0.102	93	0.500	0.000
Mon_t	0.022	0.148	48	1.000	0.000
Pri_t	0.024	0.092	141	0.359	0.090
$ReaO_t$	0.042	0.072	679	0.132	0.065

Notes: The S.D. denotes the standard deviation.

in a few of the 14 estimators, we would record smaller subsequent numbers of jumps, which would lead to increased persistence. However, we argue that this is not true in our case. First, note in Fig. 2 that the jump component shows considerable dynamics comparable to those of realized volatility or the continuous component. In fact, the jump component is highly correlated with both realized volatility and the continuous component (see Table 4). Second, a simple first-order quantile autoregressive model shows that jumps are first-order persistent across the whole range of quantiles (from $\tau = 0.05$ up until $\tau = 0.95$)[10], i.e., the persistence found in Table 3 is not merely a phenomenon of small (large) consecutive jumps.[11]

5.1.2. Article news about regulation and hacking attacks

The data related to news about regulation and hacking attacks are summarized in Panel B of Table 3. Newspaper articles were rare and do not appear to cluster substantially because the first-order autocorrelation coefficient is small and positive.

The intensity of attacks on cryptocurrencies is highlighted in Figs. 1, and 3 using vertical gray dashed lines. It appears that the attacks are clustered in certain periods of higher vulnerability for crypto markets and correlated with volatility. It also appears that attacks were more likely after a period of bitcoin price increases. In Table 3, we report summary statistics of the estimated percentage losses from total market capitalization. Estimated losses vary considerably and are skewed to the right, with a mean at 0.132% but a median at only 0.004%. Although the largest attack in absolute terms is the January 2018 attack on Coincheck (524*mil. USD*), with an estimated loss equal to 0.278% of total market capitalization, the largest relative to market capitalization was by far that at Mt. Gox (460*mil. USD*), with an estimated loss of 4.47%.

5.1.3. Sentiment - cryptocurrency (dis)approval

The statistics of the sentiment variables in Table 3 suggest that there are periods of higher interest in bitcoin and cryptocurrencies (see Fig. 3). For example, all three sentiment variables exhibit notable persistence and have distributions skewed to the right (particularly nonsupporting, negative news) with fat tails. These results suggest clustering of sentiment, which is also visible in Fig. 3. As expected, the three sentiment variables are positively correlated with each other and are mildly correlated with (the next day's) volatility but much less so with the (the next day's) jump component.

5.1.4. Scheduled macroeconomic news

Finally, Table 5 reports the frequency of news announcements. The highest value is found for real output and forward-looking indicators, which have the highest number of reported news items. Investments and government spending follow. The higher correlations (Table 4) between the macroeconomic news announcements might suggest that the two groups of announcements tend to be scheduled (news reporting) on the same date. This might decrease our ability to identify the effect of a given macroeconomic news item on volatility and the jumps. The highest correlation is the 0.474 between real output and consumption, but otherwise, the correlations are fairly low.

5.2. Volatility models

5.2.1. Modeling the realized volatility

The following Table 6 reports results for both the OLS model and the system of noncrossing quantile regressions. The persistence of volatility does not seem to change substantially across quantiles, as the coefficients on lagged daily and weekly volatility are approximately the same across quantiles (0.509 and 0.156), while for monthly lagged average volatility, the persistence is approximately 22% larger for smaller (5th) quantiles than for larger ones (95th). This result is somewhat surprising, as we expected that volatility persistence would be a high-volatility event, i.e., it would be higher during periods of high volatility (e.g., Baur and Dimpfl, 2018b).

[10] These results are available upon request.
[11] Persistent jumps in bitcoin volatility have been found before, e.g., by Yu et al. (2019).

Table 6
Drivers of Bitcoin volatility .

		OLS	Quantile regression				
		CF	5th	25th	50th	75th	95th
Constant		**0.772[d]**	−0.535	0.246	**0.582[d]**	**0.967[d]**	**1.898[d]**
Panel A: Lagged volatility							
Daily lagged volatility	RV^D_{t-1}	**0.489[d]**	**0.519[d]**	**0.512[d]**	**0.509[d]**	**0.509[d]**	**0.509[d]**
Weekly average volatility	RV^W_{t-1}	**0.144[c]**	**0.156[d]**	**0.156[d]**	**0.156[d]**	**0.156[d]**	**0.156[d]**
Monthly average volatility	RV^M_{t-1}	**0.200[d]**	**0.214[d]**	**0.200[d]**	**0.197[d]**	**0.179[d]**	**0.175[d]**
Panel B: Linear time-trends							
Linear trend $\times\ 10^4$	$Trend_t$	−0.095	**2.613[b]**	**1.413[b]**	0.212	**−0.461[a]**	**−4.476[c]**
Linear trend since 10 Dec. 2017 $\times\ 10^4$	$Trend_t \times I(.)$	−0.869	−9.099	−6.555	−2.435	−0.852	**12.420[b]**
Panel C: Article news - regulation							
Fin. Times News at t	$FTN_t \times RV_{t-1}$	-0.005	−0.004	−0.004	−0.002	−0.002	−0.003
Fin. Times News at t-1	$FTN_{t-1} \times RV_{t-1}$	**0.019[b]**	**0.028[a]**	**0.015[a]**	**0.015[a]**	**0.015[b]**	**0.015[b]**
Fin. Times News at t+1	$FTN_{t+1} \times RV_{t-1}$	−0.004	−0.012	0.001	0.001	0.000	0.000
Panel D: Sentiment - (dis)approval							
Nonsupporting trends t-1	$NosT_{t-1} \times RV_{t-1}$	0.004	0.000	0.000	0.003	0.003	0.011
Neutral trends t-1	$NeuT_{t-1} \times RV_{t-1}$	**0.009[a]**	0.004	0.004	0.004	**0.012[a]**	**0.015[b]**
Supporting trends t-1	$SupT_{t-1} \times RV_{t-1}$	**0.009[b]**	0.005	**0.006[b]**	**0.010[b]**	**0.010[b]**	**0.010[b]**
Hacking attacks t	$Hack_t \times RV_{t-1}$	**0.025[d]**	**0.010[c]**	**0.010[c]**	**0.041[c]**	**0.041[c]**	**0.206[d]**
Panel E: Scheduled macroeconomic news							
Consumption	$Con_t \times RV_{t-1}$	0.004	0.015	0.015	0.015	0.015	0.015
Forward looking	$ForL_t \times RV_{t-1}$	**0.066[c]**	**0.051[c]**	**0.051[d]**	**0.051[d]**	**0.051[b]**	**0.068[b]**
Government spending	$GovS_t \times RV_{t-1}$	0.009	0.006	0.006	0.009	0.009	**0.018[a]**
Investments	$Inv_t \times RV_{t-1}$	−0.004	−0.009	−0.009	−0.009	−0.009	0.001
Import - Export	$ImpE_t \times RV_{t-1}$	0.016	−0.002	**−0.021[a]**	−0.005	0.024	**0.080[a]**
Monetary	$Mon_t \times RV_{t-1}$	0.009	0.004	0.004	0.011	0.011	0.011
Prices	$Pri_t \times RV_{t-1}$	0.012	0.006	0.006	0.006	0.012	0.012
Real output	$ReaO_t \times RV_{t-1}$	0.030	0.017	0.017	0.017	0.017	**0.182[a]**
Model fit							
R^2		72.29%					
adj. R^2		72.03%					

Notes: a, b, c, d denote significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

The linear time trend (see Panel B) indicates that, on average, the overall level of volatility has not changed over time. However, the quantile regressions reveal that the lower quantiles of volatility have increased over time (2.613 and 1.413 at the 5th and 25th percentiles, respectively), while higher quantiles of volatility distribution have decreased over time (−0.461 and −4.476 at the 75th and 95th percentiles, respectively). Moreover, according to our model, the introduction of derivatives has only led to an increase in the extreme quantiles of volatility distribution.

Financial Times articles have a systematic effect on the next day's realized volatility of the bitcoin price series. The estimated coefficient of 0.019 (FTN_{t-1} variable) can be interpreted as a 1.9% increase in realized volatility compared to the previous day's level of volatility.[12] The quantile regression results show that the news articles have almost two times stronger impact on lower quantiles of volatility.

Hacks of cryptocurrency exchanges have a potentially explosive effect driving high levels of volatility (Panel D). The estimated coefficient from the OLS model is 0.025, and that for the conditional 5th percentile model is 0.01, while it is 0.206 for the 95th percentile of the realized volatility. The differences in these estimated coefficients suggest that cryptocurrency hacking events have the potential to lead to periods of extremely high volatility, as the corresponding coefficient is more than 20 times larger for the conditional 95th quantile of volatility than for the 5th quantile. The coefficient 0.206 corresponds to a 2.72% increase in realized volatility when the average value of the $Hack_t$ variable is considered and 0.06% when the median value is used.

Controlling for sentiment also appears to have merit (Panel D). Neutral sentiment, which can be interpreted as a general attention, increases the overall level of realized volatility as well as the supporting (positive) sentiment. The results across quantiles show that the effects tend to increase for extreme quantiles. For example, positive sentiment increases the expected right-tail volatilities more than it increase left-tail volatilities. These results show that a positive attention toward cryptocurrencies actually tends to increase the level of volatility.

The role of macroeconomic news announcements is explored in Panel E, where news announcements are interacted with lagged realized volatility. We find that only releases of forward-looking components tend to systematically lead to realized volatility on the market. This finding does not come as a surprise, as most of the empirical studies consistently highlight the rather speculative nature of bitcoin, which is more sensitive to exogenous market disturbances (crashes, regulations)

[12] Note that because we are working with the log of realized variance and the average realized volatility is 8.529, this effect is quite substantial. For example, comparing the average realized volatility of 8.529 with a 1.9% increase 8.529×1.019 while applying the naive (exponential) transformation to realized variance leads to $exp(8.529) = 5059$ and $exp(8.529 \times 1.019) = 5949$, i.e., a sharp increase in the realized variance.

Table 7
Drivers of jump component of Bitcoin volatility .

		OLS	Quantile regression				
		CF	5th	25th	50th	75th	95th
Constant		**0.791**^{d}	**−0.529**^{a}	0.086	**0.557**^{d}	**1.115**^{d}	**2.528**^{d}
Panel A: Lagged jump							
Daily lagged jump	JC^D_{t-1}	**0.500**^{d}	**0.563**^{d}	**0.551**^{d}	**0.534**^{d}	**0.515**^{d}	**0.515**^{d}
Weekly average jump	JC^W_{t-1}	**0.162**^{d}	**0.164**^{d}	**0.164**^{d}	**0.164**^{d}	**0.164**^{d}	**0.164**^{d}
Monthly average jump	JC^M_{t-1}	**0.186**^{d}	**0.181**^{d}	**0.181**^{d}	**0.181**^{d}	**0.181**^{d}	**0.141**^{c}
Panel B: Linear time-trends							
Linear trend $\times\ 10^4$	$Trend_t$	−0.422	**2.468**^{b}	**1.293**^{a}	0.162	**−1.056**^{c}	**−5.474**^{d}
Linear trend since 10 Dec. 2017 $\times\ 10^4$	$Trend_t \times I(.)$	−1.093	**−7.120**^{a}	**−7.120**^{a}	−2.915	0.296	**12.241**^{b}
Panel C: Article news - regulation							
Fin. Times News at t	$FTN_t \times JC_{t-1}$	−0.005	−0.005	−0.005	−0.002	−0.002	−0.002
Fin. Times News at t-1	$FTN_{t-1} \times JC_{t-1}$	**0.023**^{c}	**0.024**^{c}	**0.024**^{c}	**0.024**^{c}	**0.024**^{c}	**0.024**^{c}
Fin. Times News at t+1	$FTN_{t+1} \times JC_{t-1}$	−0.003	−0.018	0.007	0.007	0.007	0.007
Panel D: Sentiment - (dis)approval							
Nonsupporting trends t-1	$NosT_{t-1} \times JC_{t-1}$	0.002	−0.004	−0.004	−0.001	−0.001	−0.001
Neutral trends t-1	$NeuT_{t-1} \times JC_{t-1}$	0.003	0.001	0.001	0.001	0.003	0.005
Supporting trends t-1	$SupT_{t-1} \times JC_{t-1}$	**0.011**^{c}	**0.007**^{a}	**0.010**^{b}	**0.011**^{c}	**0.011**^{b}	**0.011**^{b}
Hacking attacks t	$Hack_t \times JC_{t-1}$	**0.027**^{d}	**0.012**^{d}	**0.012**^{d}	**0.041**^{d}	**0.041**^{d}	**0.152**^{d}
Panel E: Scheduled macroeconomic news							
Consumption	$Con_t \times JC_{t-1}$	0.002	0.008	0.006	0.006	−0.001	0.036
Forward looking	$ForL_t \times JC_{t-1}$	**0.061**^{c}	**0.071**^{b}	**0.048**^{c}	**0.048**^{c}	**0.048**^{c}	**0.048**^{b}
Government spending	$GovS_t \times JC_{t-1}$	0.008	0.004	0.004	**0.010**^{b}	**0.012**^{b}	**0.029**^{b}
Investments	$Inv_t \times JC_{t-1}$	−0.005	−0.002	−0.004	−0.004	−0.004	0.012
Import - Export	$ImpE_t \times JC_{t-1}$	0.015	−0.001	**−0.020**^{a}	0.001	0.009	0.045
Monetary	$Mon_t \times JC_{t-1}$	0.007	0.005	0.005	0.005	0.008	0.008
Prices	$Pri_t \times JC_{t-1}$	0.016	0.015	0.016	0.016	0.016	0.016
Real output	$ReaO_t \times JC_{t-1}$	0.006	0.006	0.006	0.006	0.004	0.015
Model fit							
R^2		74.08%					
adj. R^2		73.88%					

Notes: a, b, c, d denote significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

or factors influencing its use as medium of exchange in black market transactions and tax avoidance. The effect seems to be larger for extreme quantiles. The coefficient at 0.068 (for the 95th percentile) corresponds to a 6.8% increase in realized volatility only when hypothetically all forward-looking indicators would be reported on the same day. However, when forward-looking indicators are reported, for such days, the average value of the variable is 0.174, i.e., we can expect an average increase in the volatility of $100[\%] \times (0.068 \times 0.174) = 1.18[\%]$. Thus, the effect of the one macroeconomic variable that is actually significant in our model is, even in extreme cases, lower than the effect of news articles, which is estimated to be 1.9% (OLS) and 1.5% (95th percentile). These results show that bitcoin volatility does not appear to react to macroeconomic news announcements in an *economically* substantial way.

However, the statistically significant link between bitcoin volatility and specific class as of macroeconomic announcements, the forward-looking component, might tentatively suggest that there exists some, albeit still subdued, potential for a more fundamental role of bitcoin rather than it being a purely speculative asset. Thus, as in the case of other currency pairs (Swiss frank or EUR in Jäggi et al. (2019); Japanese yen in Fatum et al. (2012b); or a set of emerging economy currencies in Cai et al. (2009b)), the US macroeconomic news related to perceived future economic prospects also affects the volatility of this particular exchange rate (BTC/USD).

Alternatively, as bitcoin currently does not yet fully fulfill the role of a medium of exchange in the real economy (de la Horra et al., 2019), its future utility for transaction purposes will derive from its exchange rate with a widely accepted medium of exchange, the US dollar. Hence, investors wishing to exchange bitcoin for this international currency will ultimately need to incorporate the arrival of new, forward-looking information into their decision-making process.

This particular role of the forward-looking element is corroborated by the theoretical model in Bolt and van Oordt (2016). In that model, the equilibrium value of a virtual currency is formed by three elements: i) the actual use of virtual currency to execute real payments, ii) the decision of forward-looking investors to buy virtual currency, and iii) the elements that jointly drive future consumer adoption and merchant acceptance of virtual currency. From this perspective, forward-looking investors might decide to invest in units of virtual currency given the (perceived) future prospects of its price behavior against the US dollar serving as the standard trading counterpart. These investors might include pure speculators as well as merchants and consumers in possession of virtual currency that is demanded to execute payment transactions.

5.2.2. Modeling the jump component

Table 7 reports results from the model that explains the jump component of the volatility process. In Panel A, we identify a similar level of persistence, which shows the highest dependence on the previous day's volatility, followed by the monthly and weekly levels of volatility. As before, the persistence of jumps changes only slightly across quantiles. Similar to what we observe for realized volatility, we also find that over time, smaller jumps have increased while higher jumps have decreased, leading to an overall 'lack of trend' for the expected jump volatility component. However, the extreme jumps are larger after the introduction of derivatives for bitcoins in the US.

One of the most interesting results thus far is the effect of news related to the regulation of cryptocurrencies and to the hacking of cryptocurrency markets on volatility. A similar effect is observed for the jump component. Indeed, we would expect a larger effect for the jump volatility component, which should correspond to price variation due to the sudden price changes – such changes are likely to happen as a result of unexpected news, i.e., *hacking cryptocurrency exchanges*. From Table 7, we observe that FTN_{t-1} increases the jump volatility component. One day ahead of a report of regulatory news (FTN_{t-1} variable), the jump increases by 2.3%, an effect that is only slightly larger than that exhibited by realized volatility. Surprisingly, the effect of news articles related to regulation is the same across quantiles, i.e., it does not increase the expected extreme levels of the jump volatility component.

The estimated effect of the news related to hacking cryptocurrency exchanges is comparable with our previous results on bitcoin volatility. However, the impact of jumps is slightly lower in the highest quantile but still substantial. The coefficient of bitcoin volatility achieves the value of 0.206 for the 95th percentile, while in case of jumps it is only 0.152. In the case of a hacking event with an average level of the $Hack_t$ variable (0.132) and a coefficient of 0.152 (95th percentile), the expected extreme (95th percentile) jump component of volatility increases by 2% (0.132 × 0.152). These results clearly show that the risk of cryptocurrency exchanges might be one of the main drivers of the jump component and thus should not be omitted when evaluating the risks associated with investments in cryptocurrencies in general.

As before, only positive sentiments seem to be leading jump components, which are slightly higher across the whole distribution. A possible explanation is that when supportive news dominates the market, sudden price movements are more likely; thus, the size of the jump component of volatility is bigger.

With respect to macroeconomic news announcements (Panel E), our results are broadly in line with those found for overall volatility. As before, we confirm that forward-looking indicators tend to increase the size of the next day's jumps. A new result is that a statistically significant and positive effect is also found for the level of the 50th, 75th, and 95th percentiles affected by announcements of government spending. As before, the size of the coefficients suggests that the overall effect is somewhat smaller. We therefore conclude that macroeconomic news has a limited effect on the volatility process of bitcoin.

5.3. Robustness check

Our main results reported above are based on specifications that make use of interaction terms. We also considered two other specifications for modeling both overall volatility and the jump component of volatility. The first alternative specification is estimated without interaction terms, i.e., for overall volatility:

$$\begin{aligned} RV_t =& \beta_1 + \beta_2 RV^D_{t-1} + \beta_3 RV^W_{t-1} + \beta_4 RV^M_{t-1} + \\ & \delta_1 FTN_{t-1} + \delta_2 FTN_t + \delta_3 FTN_{t+1} + \\ & \delta_4 NosT_{t-1} + \delta_5 NeuT_{t-1} + \delta_6 SupT_{t-1} + \\ & \delta_7 Hack_t + \delta_8 Trend_t + \delta_9 Trend_t \times I(t > \text{10th } Dec \text{ 2017}) + \\ & \sum_{i=1}^{8} \gamma_i D_{i,t} + \epsilon_t \end{aligned} \tag{18}$$

and for the jump component:

$$\begin{aligned} JC_t =& \beta_1 + \beta_2 JC^D_{t-1} + \beta_3 JC^W_{t-1} + \beta_4 JC^M_{t-1} + \\ & \delta_1 FTN_{t-1} + \delta_2 FTN_t + \delta_3 FTN_{t+1} + \\ & \delta_4 NosT_{t-1} + \delta_5 NeuT_{t-1} + \delta_6 SupT_{t-1} + \\ & \delta_7 Hack_t + \delta_8 Trend_t + \delta_9 Trend_t \times I(t > \text{10th } Dec \text{ 2017}) + \\ & \sum_{i=1}^{8} \gamma_i D_{i,t} + \epsilon_t \end{aligned} \tag{19}$$

Table 8 reports OLS results and results from the noncrossing quantile regressions estimated for both volatility and the jump component of volatility. Removing the interaction terms leads to qualitatively very similar results for the models explaining volatility and the jump component. As before, we find a positive effect from the daily, weekly and monthly realized volatilities, the variable related to news articles about regulating cryptocurrencies, and supportive (positive) sentiment toward cryptocurrencies. News about hacked cryptocurrency exchanges considerably increases the next day's volatility, and a positive effect is also found for the forward-looking indicators. The trend variables also show that the expected conditional bitcoin volatility has not changed over time while the extremes have decreased over time, but the introduction of the derivatives market seems to reverse this trend.

Table 8
Estimated coefficients from alternative volatility and jump models .

		Modelling RV_t							**Modelling JC_t**					
		OLS	Quantile regression						OLS	Quantile regression				
		CF	5th	25th	50th	75th	95th		CF	5th	25th	50th	75th	95th
Constant		0.137	-0.734	-0.062	0.153	**0.313^{a}**	**1.025^{b}**		**0.393^{a}**	-0.548	-0.054	**0.231^{a}**	**0.661^{d}**	**1.668^{c}**
Panel A: Lagged volatility (jump)														
Daily lagged volatility (jump)	RV^{D}_{t-1}	**0.562^{d}**	**0.569^{d}**	**0.569^{d}**	**0.569^{d}**	**0.569^{d}**	**0.607^{d}**	JC^{D}_{t-1}	**0.552^{d}**	**0.576^{d}**	**0.576^{d}**	**0.574^{d}**	**0.562^{d}**	**0.562^{d}**
Weekly average volatility (jump)	RV^{W}_{t-1}	**0.145^{c}**	**0.157^{c}**	**0.157^{d}**	**0.157^{d}**	**0.157^{d}**	**0.157^{d}**	JC^{W}_{t-1}	**0.163^{d}**	**0.168^{c}**	**0.168^{d}**	**0.168^{d}**	**0.168^{d}**	**0.168^{d}**
Monthly average volatility (jump)	RV^{M}_{t-1}	**0.200^{d}**	**0.204^{d}**	**0.187^{d}**	**0.187^{d}**	**0.187^{d}**	**0.183^{d}**	JC^{M}_{t-1}	**0.186^{d}**	**0.177^{d}**	**0.177^{d}**	**0.177^{d}**	**0.177^{d}**	**0.172^{c}**
Panel B: Linear time-trends														
Linear trend $\times 10^4$	$Trend_t$	−0.076	**2.721^{b}**	**1.361^{b}**	0.360	**−0.384^{a}**	**−4.429^{c}**	$Trend_t$	−0.415	**2.495^{b}**	**1.311^{b}**	0.197	**-1.061^{d}**	**-5.446^{d}**
Linear trend since 10 Dec. 2017 $\times 10^4$	$Trend_t \times I(.)$	−0.908	−8.486	−6.476	−2.170	−0.896	**12.300^{a}**	$Trend_t \times I(.)$	−1.083	**-8.115^{a}**	**-7.847^{a}**	-3.099	1.085	**14.128^{b}**
Panel C: Article news - regulation														
Fin. Times News at t	FTN_t	−0.049	−0.068	−0.068	−0.021	−0.008	−0.008	FTN_t	−0.043	-0.038	-0.038	-0.014	-0.014	-0.014
Fin. Times News at t-1	FTN_{t-1}	**0.188^{b}**	**0.239^{b}**	**0.125^{b}**	**0.125^{a}**	**0.127^{b}**	**0.127^{b}**	FTN_{t-1}	**0.193^{c}**	**0.182^{c}**	**0.182^{c}**	**0.182^{c}**	**0.182^{b}**	**0.182^{b}**
Fin. Times News at t+1	FTN_{t+1}	−0.030	−0.180	0.028	0.028	0.028	0.028	FTN_{t+1}	−0.012	-0.144	0.064	0.064	0.064	0.064
Panel D: Sentiment - (dis)approval														
Nonsupporting trends t-1	$NosT_{t-1}$	0.033	−0.028	−0.028	0.023	0.043	0.106	$NosT_{t-1}$	0.010	-0.042	-0.042	-0.001	-0.001	-0.001
Neutral trends t-1	$NeuT_{t-1}$	**0.074^{a}**	0.022	0.022	0.022	**0.102^{b}**	**0.102^{b}**	$NeuT_{t-1}$	0.022	0.003	0.003	0.003	0.043	0.087
Supporting trends t-1	$SupT_{t-1}$	**0.077^{b}**	0.020	**0.060^{b}**	**0.089^{b}**	**0.089^{b}**	**0.089^{a}**	$SupT_{t-1}$	**0.083^{c}**	0.031	**0.071^{c}**	**0.086^{c}**	**0.086^{b}**	**0.086^{a}**
Hacking attacks t	$Hack_t$	**0.299^{d}**	**0.099^{c}**	**0.099^{c}**	**0.416^{c}**	**0.416^{c}**	**1.838^{c}**	$Hack_t$	0.**0.287^{d}**	**0.126^{d}**	**0.126^{d}**	**0.375^{d}**	**0.375^{d}**	**1.282^{d}**
Panel E: Scheduled macroeconomic news														
Consumption	Con_t	0.056	0.171	0.171	0.171	0.171	0.171	Con_t	0.026	0.130	0.058	0.026	0.026	0.306
Forward looking	$ForL_t$	**0.576^{c}**	**0.439^{b}**	**0.439^{c}**	**0.439^{c}**	**0.439^{b}**	**0.462^{b}**	$ForL_t$	**0.483^{c}**	**0.451^{b}**	**0.377^{c}**	**0.369^{c}**	**0.369^{c}**	**0.369^{b}**
Government spending	$GovS_t$	0.087	0.072	0.072	0.072	**0.072^{a}**	**0.178^{a}**	$GovS_t$	0.073	0.030	0.030	**0.072^{b}**	**0.088^{b}**	**0.250^{b}**
Investments	Inv_t	−0.047	−0.073	−0.073	−0.073	−0.073	0.027	Inv_t	-0.047	0.049	-0.038	-0.038	-0.038	0.126
Import - Export	$ImpE_t$	0.103	−0.074	**−0.190^{a}**	−0.093	0.251	**0.713^{a}**	$ImpE_t$	0.090	0.031	**-0.202^{a}**	0.009	0.084	0.433
Monetary	Mon_t	0.071	0.034	0.034	0.046	0.068	0.068	Mon_t	0.044	0.037	0.037	0.037	0.061	0.061
Prices	Pri_t	0.127	0.127	0.127	0.127	0.183	0.183	Pri_t	0.146	0.135	0.135	0.135	0.135	0.135
Real output	$ReaO_t$	0.292	0.168	0.168	0.168	0.168	**1.730^{a}**	$ReaO_t$	0.071	0.019	0.019	0.019	0.019	0.239
R^2					72.28%							74.07%		
adj. R^2					72.02%							73.82%		

Notes: a, b, c, d denote significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

6. Conclusion

In this paper, we study the volatility of bitcoin and whether it is influenced by news about the regulation of bitcoin, hacking attacks on bitcoin exchanges, investor sentiment and various types of macroeconomic news. To draw sharp conclusions about volatility, we utilize high-frequency data and estimate realized volatility and its jump component, i.e., price variation due to discontinuous price changes. In accordance with the previous literature, we document that the volatility of bitcoin is much higher than that of other financial assets. Similar to other assets, the realized volatility of bitcoin is also highly persistent. We estimate the jump component of volatility as the logarithm of the average across multiple estimators. Such averaging addresses the uncertainty regarding the true data generating process. We find that both the averaging and the logarithmic transformation contribute to the higher persistence of our estimate of jumps. We utilize the HAR model of Corsi (2009) in our analysis and find that both volatility and its jump component have similar drivers.

The volatility of bitcoin is strongly influenced by news about bitcoin regulation. In particular, the volatility of bitcoin is significantly increased a day before an article about bitcoin regulation is published in a newspaper, the Financial Times. This result is consistent with Auer and Claessens (2018), who suggest that regulation is a significant price factor for cryptocurrencies.

Our second key finding is that the hacking of cryptocurrency markets has a strong impact on bitcoin volatility and its jump component. In the latter case, the effect is particularly strong, especially for the right-tail of the jump volatility component.

We extract investor sentiment from Google searches for bitcoin and other major cryptocurrencies separately for positive, neutral, or negative short phrases and words related to bitcoin use and regulation. We find that nonsupporting (negative) and neutral investor sentiment does not have a significant impact on bitcoin volatility, whereas supporting (positive) investor sentiment seems to have a positive effect and leads to an increase in the volatility and jump levels.

Regarding scheduled macroeconomic news announcements, we find little evidence that bitcoin volatility and the jump component react to economic fundamentals. The only category of macroeconomic news to which bitcoin reacts is represented by forward-looking indicators, such as the consumer confidence index.

Altogether, our results show that volatility and its jump component are driven mostly by bitcoin-specific risk factors: regulation and hacking attacks on cryptocurrency markets. Unlike traditional assets, bitcoin is almost uninfluenced by general macroeconomic news, thus leading us to the conclusion that bitcoin is only weakly connected to the overall economy via the forward-looking component.

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