Exploring the Driving Forces of the Bitcoin Exchange Rate Dynamics: An EGARCH Approach

Zhou, Siwen

University of Hamburg

2018

Exploring the Driving Forces of the Bitcoin Exchange Rate Dynamics: An EGARCH Approach

Siwen Zhou*

11 October 2018

Abstract

Bitcoin is a virtual currency scheme that is characterised by a decentralised network and cryptographic transfer verification which has been attracting much public attention due to its technological innovation and its high exchange rate volatility. In this paper, Bitcoin's exchange rate movement from 2011 to 2018 and its relationship with the global financial markets are explored using an EGARCH framework. The results are as follows. First, fundamentals and Bitcoin-related events play a critical role in the exchange rate formation of Bitcoin. Second, the impact of regulation-related events on Bitcoin indicates that market sentiment is responding to market regulation statements. Third, news coverage is an essential factor in driving the volatility of Bitcoin. Fourth, Bitcoin may be a hedge in times of calm financial markets and a safe haven against uncertain economic policy but is likely to expose to flight-to-quality as global financial uncertainty increases. Lastly, the positive effect of the central bank's announcements on Bitcoin is marginal enough to rule out the involvement of global expansionary monetary policy in inflating Bitcoin's exchange rate over the past years, as it may have been the case with traditional asset prices after the great recession.

Keywords: Bitcoin, EGARCH, event analysis, Reuters news, VIX, EPU, financial markets

*University of Hamburg, Department of Economics, Institute for Macroeconomics and Quantitative Economic Policy, Von-Melle-Park 5, 20146 Hamburg, Germany, E-mail: siwen.zhou@wiso.uni-hamburg.de

1 Introduction

Bitcoin is the most successful virtual currency scheme to date. Designed by an anonymous person or a group of people named Satoshi Nakamoto in 2009, the scheme is based on a P2P transaction network (Nakamoto, 2008). Unlike previous closed or unidirectional flow virtual currencies, Bitcoin is created by a transaction verification process and is freely convertible against fiat currencies through several online exchanges. Considered by many as a digital tulip and not backed by any real value or government decree, Bitcoin has gained public interest which eventually led to explosive exchange rate trends, almost matching the value of one ounce of gold at the end of November 2013 and hitting above $19,000 in December 2017 before fluctuating around $6,500 in September 2018.[1] Although the Bitcoin network with sheer computing power reaches more than 300 times the combined power of the top 500 supercomputers (Garcia and Schweitzer, 2015), it can only process seven transactions per second, which is a drop compared to Visa and MasterCard that handle thousands of payments per second. However, Bitcoin's fast transnational transaction speed, low transaction fees and virtually unbreakable cryptography foreshadow an artefact of a future medium of exchange, and its underlying technology is considered as innovative compared to the traditional financial architecture and is being examined by several institutions and companies for potential adoption as a financial infrastructure technology.

The exceptional level of volatility in such a fast-growing market naturally raises the question of which forces determine Bitcoin's exchange rate and whether there is any connection between Bitcoin and the world economy. This paper takes into account a wide range of potential driving forces of the exchange rate level and volatility of Bitcoin in an EGARCH framework, first, to explore to what degree the BTC/USD exchange rate is driven by factors such as fundamentals, information flows, regulatory stance, monetary policy, economic uncertainties, and Bitcoin-specific events, and, second, to determine Bitcoin's hedging and safe haven capabilities.[2]

To the best knowledge, this paper is the first paper dealing with the impact of regulation-related statements on the exchange rate dynamics of Bitcoin. The results are manifold and as follows. First, the results support the findings of the previous literature emphasising the role of fundamentals and Bitcoin-related specific events in explaining Bitcoin's volatile exchange rate dynamics, as suggested by a sharp decline in the volatility persistence, leverage effect and fat tail behaviour after the corresponding variables are incorporated into the model. Moreover, regulation-related events play a significant role in driving the exchange rate of Bitcoin, providing some implications for policymakers

[1] The exchange rate of Bitcoin peaked at USD 1,242 per Bitcoin on 29 November 2013, while gold was trading at USD 1,250 an ounce.

[2] BTC is the abbreviation for Bitcoin. Moreover, according to Baur and Lucey (2010), a hedge is an asset which is uncorrelated or negatively correlated with other assets on average, while a safe haven is an asset which shows these properties only in times of markets distress.

and regulators regarding the sentiment of Bitcoin investors towards market regulation. Expansionary monetary policy worldwide and uncertainty events have a limited, albeit significant positive impact on the exchange rate of Bitcoin. However, since this effect is somewhat marginal, it can be ruled out that an exceptionally loose monetary policy worldwide has contributed to the rise in the Bitcoin exchange rate in recent years, as might have been the case with traditional asset prices. The results also stress the importance of news coverage in driving the volatility of Bitcoin. Concerning Bitcoin's hedging and safe haven capabilities, the results find a non-linear relationship to global uncertainty, as well as a negative relationship to global stock markets. In fact, in times of calm financial markets, Bitcoin can serve as a hedging instrument. However, in times of financial market distress, Bitcoin moves with the markets and therefore does not act as a safe haven against stock market crashes. Bitcoin's safe haven capability is found to be only granted in times of high economic uncertainty. Overall, the empirical findings of this paper contrast with studies that find that the Bitcoin market is completely isolated from the world economy.

This paper is structured as follows. After a brief review of related literature in Section 2, Section 3 highlights the relevance of the chosen variables. The model design, as well as the empirical results, are described in Section 4. The final section of the paper represents a summary of substantial findings, along with a few concluding remarks.

2 Related literature

The increasing popularity of Bitcoin has also attracted the attention of economists, and a considerable amount of exchange rate literature on Bitcoin has emerged. Much attention of earlier literature is being paid to the question of whether Bitcoin is a currency or a speculative asset, and various papers point to the existence of market bubbles in the Bitcoin market caused by public interest (see e.g. Buchholz et al., 2012; Kristoufek, 2013; Yermack, 2013; Glaser et al., 2014; Garcia and Schweitzer, 2015; Bouoiyour and Selmi, 2015b).[3] A fraction of the later literature deals with the characterization of Bitcoin as well, and Cheah and Fry (2015) state the absence of a fundamental value for Bitcoin. Bartos et al. (2015) find Bitcoin follows the hypothesis of efficient markets, which is in sharp contrast with the finding of Cheah et al. (2018). However, the findings regarding a larger body of newer works such as Urquhart (2016), Khuntia and Pattanayak (2018), Wei (2018)

[3]A number of papers which deal with investigating various economic indicators by using search volume index (SVI) from Google Trends have emerged over the past years (Da et al., 2011; Choi and Varian, 2012; Preis et al., 2013; Scott and Varian, 2015). Several works such as Bank et al. (2011), Aouadi et al. (2013), and Ding and Hou (2015) show that the SVI from Google Trends can serve as an adequate proxy for retail investor attention. In this sense, it would be interesting here to consider the impact of the SVI on Bitcoin's exchange rate dynamics. However, when the observation range exceeds 90 days, the SVI is only available on a weekly basis, which means we cannot use its data because our study is based on daily data.

and Bariviera (2017) are more differentiated and conclude that the Bitcoin market is overall inefficient, but there is evidence that Bitcoin may become more efficient over time.

The main part of the later exchange rate literature focuses on the driving forces of Bitcoin's exchange rate dynamics. A number of papers emphasise the role of underlying market forces in driving Bitcoin's exchange rate. MacDonell (2014) and Baek and Elbeck (2015) suggest that Bitcoin's exchange rate dynamics are primarily driven by investors looking outside traditional markets. Koutmos (2018) points to the importance of market microstructure and finds close linkages between Bitcoin returns and transaction activity. Balcilar et al. (2017) highlight the importance of modelling nonlinearity and find that volume can predict returns in relatively tranquil times of the Bitcoin market. Kristoufek (2015) finds some evidence that, despite being a speculative asset, Bitcoin is influenced by standard fundamental factors in the long term.

Several works deal with the interaction between Bitcoin's exchange rate dynamics and macro-financial factors. Van Wijk (2013) finds evidence that macro-financial factors have a significant impact on the value of Bitcoin. In sharp contrast, Ciaian et al. (2016) find that Bitcoin is detached from economic fundamentals. However, newer works such as Bouri et al. (2018a) and Corbet et al. (2018) conclude that the Bitcoin market is not entirely isolated. Similarly, Brière et al. (2015) find that Bitcoin investment delivers high diversification benefits due to low correlations with other financial assets.

The capability of Bitcoin as a hedge and a safe haven has also been explored. Dyhrberg (2016a) shows that Bitcoin is very similar to gold due to volatility persistence and symmetry, thus considering Bitcoin as a potential hedge against market risks. Walther et al. (2018) and Al-Khazali et al. (2018) compare the reactions of gold and Bitcoin to macroeconomic news surprises and concludes that Bitcoin cannot serve as a safe haven. Works such as Bouri et al. (2017b), Bouri et al. (2018b), Bouri et al. (2017a), and Demir et al. (2018) support the idea of Bitcoin being a safe haven or a hedge against economic downturn and uncertainty by testing the relationship between Bitcoin and global uncertainty measures, and Dyhrberg (2016b) shows that Bitcoin can serve as a hedge against the stock market.

Regarding market sentiment, Polasik et al. (2015) discover that Bitcoin's exchange rate is driven by the sentiment expressed in newspaper reports on cryptocurrency, and reports a weak association between Bitcoin returns and global macroeconomic aggregates. Gronwald (2014) shows that extreme movements of Bitcoin are mainly characterised by special events often caused by exceptional news. To capture the overall sentiment in the Bitcoin-dominated cryptocurrency market, Härdle and Trimborn (2015) construct a capitalisation-weighted index as a benchmark for a wide range of cryptocurrencies and finds the corresponding volatility level is generally very high and comparable to that of risky stock markets like the Greece or Russian one.

The impact of political events on Bitcoin has also been researched, and Luther and Olson (2013) take a closer look at the relationship between the Cyprus bailout announcement in 2013 and the subsequent surge in downloads for popular Bitcoin apps. The same phenomenon could also be observed during the Greek crisis, according to Bouoiyour et al. (2015). Glouderman (2014) finds that China has become the market maker and that the closure of the bank accounts of Chinese Bitcoin exchanges due to pressure from the People's Bank of China (PBoC) may cause a shift in Bitcoin trading activities from mainland China to Hong Kong. A number of academic papers also deal with the relationship between Bitcoin and monetary policy. Most of these papers are theoretical and deal with the challenges of Bitcoin on monetary policy. Two empirical papers deal with the impact of monetary policy on Bitcoins exchange rate. Corbet et al. (2017) state that Bitcoins volatility is significantly driven by monetary policy announcements, whereas Vidal-Tomás and Ibañez (2018) find that both the level and volatility of Bitcoin's exchange rate is not affected by monetary policy announcements. Finally, Table 1 gives a summary of the cited exchange rate literature and associated methodology.

In addition to the relevant exchange rate literature, some policy-related literature is also illuminated. Financial authorities such as central banks and International Monetary Fund (IMF) emphasise monetary and financial stability issues in case of broad adoption of Bitcoin. European Central Bank (2012) discusses whether the Bitcoin network is a Ponzi scheme or not. Bank of Canada (2014) expresses its concerns about potential risks to financial stability if Bitcoins were to become mainstream. Ali et al. (2014) question the adoption of Bitcoins in the long run on account of a variety of incentive problems and rule out a potential risk to monetary and financial stability in the UK owing to the Bitcoin's irrelevant status as a payment system. Moreover, the Bank of England (2015) discusses the possibility of issuing central bank-backed virtual currencies and the related consequences. He et al. (2016) point out potential benefits as well as considerable risks from using virtual currencies. While potential benefits of an implementation of the underlying blockchain technology of virtual currencies in established financial structures are particularly highlighted, financial stability would be exposed to potential risks if virtual currencies were to become widely used. To respond to the challenges posed by virtual currencies, an international framework for regulating the use of virtual currencies is to be established.

Regarding the feasibility of the implementation of the underlying blockchain technology of virtual currencies in established financial structures, Mainelli and Milne (2016) from the Society for Worldwide Interbank Financial Telecommunication (SWIFT) institute find that while the use of blockchain for payment clearing and securities settlement can lead to substantial reductions in transaction cost and risk, substantial challenges such as long-term commitment of time and resource and active regulatory support are involved in adapting existing processes and integrating them with the blockchain technology. Last but not least, Bitcoin entered the stage of world-leading academic textbooks, as the eleventh edition of Mishkin (2016) questions the potential role of Bitcoin as the money of the future, albeit highlighting the potential of its underlying technology for fu-

Table 1: Summary of related exchange rate literature

Authors	Methodology	Key results
Market bubbles		
Kristoufek (2013)	VAR/VECM	Yes, Bitcoin's exchange rate is driven by public interests, as measured by search queries on Google Trends and Wikipedia.
Yermack (2013)	Descriptive statistics	Yes, Bitcoin appears to behave more like a speculative investment than a currency.
Glaser et al. (2014)	GARCH	Yes, Bitcoin is rather a speculative asset than as a currency, highlighted by reaction bias of Bitcoin's returns towards positive news.
Garcia and Schweitzer (2015)	VAR	Yes, Bitcoin's excessive returns is driven social media sentiment.
Buchholz et al. (2012)	GARCH	Yes, Bitcoin's volatility has a significant positive effect on its return, which is characteristic for asset bubbles.
Cheah and Fry (2015)	LPPL	Yes, Bitcoin exhibits market bubbles and the fundamental value of Bitcoin is zero.
Market efficiency		
Bartos et al. (2015)	ECM	Yes, Bitcoin follows the efficient market hypothesis (EMH), as it immediately reacts on publicly announce information.
Cheah et al. (2018)	FCVAR	No, the Bitcon market is inefficient as Bitcoin's exchange rate follows a long-memory process.
Urquhart (2016)	Hypothesis tests	Partially yes, the Bitcoin market is overall inefficient but may become more efficient over time.
Khuntia and Pattanayak (2018)	Rolling hypothesis tests	Partially yes, Bitcon's market efficiency evolves with time.
Wei (2018)	Hypothesis tests	Partially yes, the Bitcoin market becomes more efficient as its volatility level is decreasing and its liquidity gets higher.
Bariveria (2017)	Rolling hypothesis tests	Partially yes, Bitcoin's return becomes more efficient since 2014 but its volatility exhibits long memory throughout the sample.
Fundamentals		
MacDonell (2014)	ARMA/LPPL	A primary driving force of Bitcoin's exchange rate is speculation by investors looking outside traditional markets, as suggest by an inverse relationship between Bitcoin and VIX.
Baek and Elbeck (2015)	OLS	Bitcoin's extraordinarily high level of volatility is purely driven by buyers and sellers, since only the bid-ask spread of Bitcoin is significant, which is not the case for macro-financial factors.
Kristoufek (2015)	Wavelet analysis	Bitcoin is a speculative asset but is still influenced by 1. the supply, 2. the price level, 3. and the trading volume in the long term.
Balcilar et al. (2017)	Granger-causality	Trading volume can predict Bitcoin's returns in times of a calm Bitcoin market.
Koutmos (2018)	VAR	Bitcoin's returns are bidirectionally linked to transaction activities, stressing the role of market microstructure in explaining Bitcoin's returns.
Political events		
Luther and Olson (2013)	Descriptive statistics	A surge in downloads for popular Bitcoin apps and a significant increase in the exchange rate of Bitcoin followed the initial announcement of the Cyprus bailout.
Bouoiyour et al. (2015)	Granger-causality	The relationship from the related Google searches and the number of tweets to Bitcoin is significant in the short- and the medium-run.
Glouderman (2014)	Descriptive statistics	The PBoC's efforts to curb Bitcoin's trading activities have led to price fluctuations in the global Bitcoin market, and further pressure from the PBoC may cause a shift in Bitcoin trading activities from mainland China to Hong Kong.
Monetary policy		
Corbet et al. (2017)	GARCH	Yes, Bitcoin's volatility is significantly driven by international monetary policy announcements.
Vidal-Tomás and Ibanez (2018)	GARCH	No, both the level and the volatility of Bitcoin's exchange rate are not affected by international monetary policy announcements.
Market sentiment		
Polasik et al. (2015)	OLS	Bitcoin's returns are driven by 1. the sentiment expressed in newspaper reports on cryptocurrency, 2. Bitcoins popularity, 3. and the total number of transactions.
Gronwald (2014)	ARJI-GARCH	Bitcoin's extreme movements are characterised by one-off events.
Härdle and Trimborn (2015)	Laspeyres/GARCH	1. A capitalisation-weighted index for a wide range of cryptocurrencies is constructed. 2. And the volatility level of the index is comparable to that of Russian or Greek stock markets.
Linkages between Bitcoin and macro-finanical factors		
Van Wijk (2013)	OLS/ECM	Yes, significant impact of macro-finanical factors on Bitcoin's exchange rate.
Bouri et al. (2018a)	VAR-GARCH-M	Yes, the Bitcoin market is completely not isolated and receives more volatility than it transmits to financial markets.
Ciaian et al. (2016)	VAR/ARDL/VECM	No, little support for effects of macro-financial factors on Bitcoin's exchange rate in the long run.
Corbet et al. (2018)	VAR	No, the Bitcoin market is isolated from financial markets and may offer diversification benefits.
Brière et al. (2015)	Descriptive statistics	No, Bitcoin's correlation with other assets is low and may offer diversification benefits.
Bitcoin as a hedge or a safe haven		
Dyhrberg (2016a)	GARCH	Yes, Bitcoin is similar to gold due to volatility persistence and symmetry and thus may serve as a hedge against market risk.
Bouri et al. (2017a)	GARCH	Yes, Bitcoin serves as a safe haven as stock market downturn in the pre-crash period of 2013.
Bouri et al. (2017b)	QQ	Yes, Bitcoin serves as a hedge at both lower and upper quantiles of Bitcoin returns and global uncertainty.
Bouri et al. (2018b)	Copula-based QQ	Yes, Bitcoin can serve as a safe haven against global financial stress at the lower and higher quantiles of the Bitcoin returns.
Demir et al. (2018)	VAR/OLS/QQ	Yes, Bitcoin serves a hedge against economic poliy uncertainty at the lower and higher quantiles of the Bitcoin returns and the EPU.
Dyhrberg (2016b)	GARCH	Yes, Bitccoin can serve as a hedge against the stock market.
Walther et al. (2018)	BEKK-GARCH	No, Bitcoin tends to move with the markets in times of market distress and cannot serve as a safe haven. It is also not a hedge instrument in a portfolio component.
Al-Khazali et al. (2018)	GARCH/EGARCH	No, Bitcoin reacts differently from gold to macroeconomic news surprises and therefore cannot serve as a safe haven.

Notes: VAR stands for vector autoregression, VECM for vector error correction model, GARCH for generalized autoregressive conditional heteroskedasticity, LPPL for log-periodic power law, ECM for error correction model, FCVAR for fractionally cointegrated VAR, ARMA for autoregressive moving average, OLS for ordinary least squares, ARJI-GARCH for autoregressive jump-intensity GARCH, Laspeyres for the Laspeyres index formula, VAR-GARCH-M for VAR-GARCH-in-mean, ARDL for autoregressive distributed lag, QQ for quantile-on-quantile regressions, BEKK for the multivariate GARCH model defined by citetbaba1990multivariate, and EGARCH for exponential GARCH.

ture payment systems.

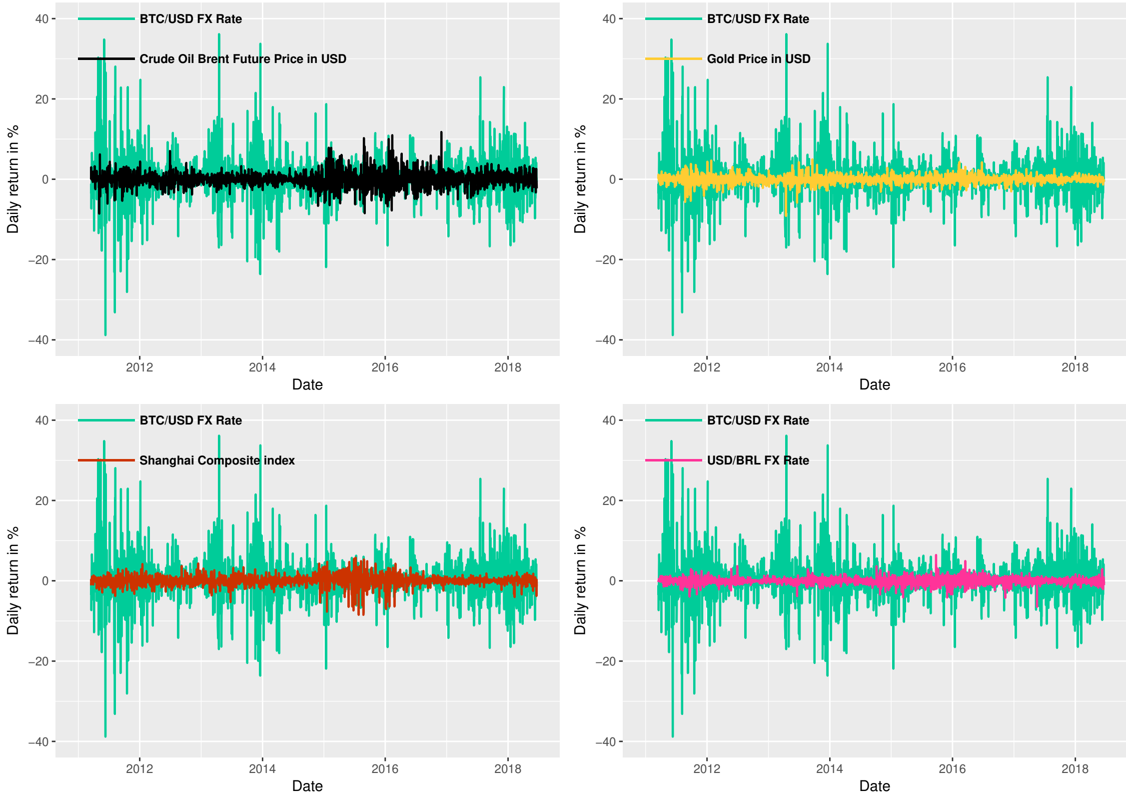
The existing literature has several research gaps. First, as the general opinion is that the exchange rate of Bitcoin is affected mainly by specific events inside and outside the Bitcoin market, it is desirable to quantify the impact of those specific events. Second, to the best knowledge, only Polasik et al. (2015) has focused on the impact of the related press coverage on Bitcoin's exchange rate dynamics. As Bitcoin is widely regarded as a speculative asset, the impact of news would play a significant role in the exchange rate dynamics mechanism. Third, despite its volatile nature, Bitcoin is perceived by many as a hedge and safe haven against global market turmoil. In this context, it should be examined whether Bitcoin's movement is affected by global economic outlook and financial markets movements. Lastly, taking into account the previous points, as the literature cites a wide range of factors influencing the exchange rate of Bitcoin, a significant shortcoming of previous work is that its studies often focus only on certain driving forces of Bitcoin's exchange rate and omits others, resulting in biased inference when performing econometric estimations. Therefore, a broad-based analysis is needed to ensure a correct statistical inference. To some extent, this paper attempts to fill these gaps by quantifying the impact of market forces, specific events, press coverage, macro-financial uncertainties, and global financial markets on Bitcoin's exchange rate dynamics in an estimation framework with a wide range of corresponding explanatory variables.

3 Data

The daily time series of BTC/USD exchange rates used for the investigation is drawn from Coindesk at www.coindesk.com/price. The time series starts on 16 March 2011 and ends on 21 June 2018, based on data availability of subsequent time series. Coindesk's exchange rate represents an average of exchange rates on the leading Bitcoin exchanges and therefore better describes the Bitcoin exchange rate globally than that of a single exchange. It is worth noting that Bitcoin exchanges never close at weekends and holidays.

Looking at the movement behaviour of the BTC/USD exchange rate, it is evident that Bitcoin's exchange rate volatility is vastly higher than that of any commodities, stock indices, and currencies. Four comparisons are given in Figure 1. First, as the world's most-traded commodity, the falling price of crude oil as from end-2014 owing to general oversupply and China's economic slowdown led to drastic fluctuations in the price movement. Yet these fluctuations are just on par with the day-to-day fluctuations of the Bitcoin exchange rate in the corresponding period. Second, as an example for a volatile emerging market stock index, the bursting of the Chinese stock market bubble in the second half of 2015 is accompanied by a sharp rise in volatility of Shanghai Composite index, which is also on a similar level as Bitcoin's volatility. Third, despite many similar-

Figure 1: Bitcoin exchange rate volatility



Sources: Coindesk; Quandl; Reuters Datastream.

Notes: FX Rate is the abbreviation for foreign exchange rate, and BRL is the abbreviation for Brazilian real. The missing data on weekends and holidays are imputed via the Last-Observation-Carried-Forward method.

ities between gold and Bitcoin, such as inelastic supply, costly production process, and lack of government backing, gold maintains its value above USD 1,000 over time as its daily price return fluctuates mostly within 2%, while Bitcoin's exchange rate return fluctuates mostly within 10%. Fourth, when comparing Bitcoin with Brazilian real, as one of the world's most volatile currency, Bitcoin's average fluctuation is roughly seven times larger than that of the latter one.

At the current stage, Bitcoin's exchange rate dynamics cannot be explained by the acceptance beyond its trading purpose, as the vast majority of the activity among Bitcoin users consists of speculation rather than real payments (Goldman Sachs, 2014). According to Bitpay (2017), a leading Bitcoin payment processor, payment transactions only make up about 2.5% of total transactions as of November 2016. As the share of real payments is, mostly, far lower than 1% throughout Bitcoin's transaction timeline, the driving forces behind Bitcoin's growth are to be found outside its underlying economy.

For the following quantitative analysis of the Bitcoin exchange rate, potential influencing factors such as fundamentals, information flows, regulatory stance, monetary policy, economic uncertainties, global financial markets, and Bitcoin-specific events will be described in the next subsections. This serves as a motivation for choosing explanatory variables for the further steps.

Fundamentals

The website www.Blockchain.info provides a wealth of statistics about the Bitcoin market. Many times series are available on a daily basis and provide a comprehensive insight into the activities within the market. The following stationary daily times series extracted from the website will be used in our analysis.[4] (i) The percentage change in the hash rate; (ii) The percentage change in the number of transactions; (iii) The logarithm of miners revenue in BTC; (iv) The logarithm of trading volume in BTC. A hash function is a function that transforms an unencrypted message into a short, fixed-length output. A hash is the output of a hash function and, as it relates to Bitcoin, the hash rate describes the number of found adequate hash values per second in a transaction verification process. A higher hash rate indicates a higher processing power, as it increases the opportunity of receiving the Bitcoin reward. The unit of account of the hash rate is giga hash per second (GH/s). The revenue of miners is composed of the numbers of Bitcoins mined per day and the aggregated transaction fees. Given that the level of transaction fees tends to be negligible mostly over time, the revenue of miners is approximately equal to the number of Bitcoins mined per day, representing the daily money growth of Bitcoin. Lastly, the logarithm of the daily illiquidity measure proposed by Amihud (2002), being the ratio of absolute Bitcoin return and its dollar trading volume, is used to measure the liquidity of Bitcoin. As such, a higher value of the measure indicates lower liquidity. The Amihud (2002) measure is one of the most widely used liquidity proxies in the finance literature due to its simplicity and robustness.

Economic uncertainties and financial markets

Looking back at Bitcoin's exchange rate rally during the crisis in Cyprus in 2013 as well as in Greece in 2015, Bitcoin appears to benefit from political and financial uncertainty. To contribute to the debate on whether Bitcoin can be a hedge against uncertainty or a safe haven in times of market distress, prominent measures for uncertainty are used. The first measure is the price of gold, which is commonly seen as a hedge and a safe haven, as it has historically maintained its real value over time. The relationship between gold and assets such as equities, bonds, and US dollars has been widely studied in the literature relying on homoskedastic regression and GARCH-type models (see, e.g., Baur and Lucey 2010; Baur and McDermott 2010; Capie et al. 2005; Ghosh et al. 2004; Joy 2011). The literature widely agrees that gold serves as a hedge against stocks and US dollar but not bonds. While some publications, such as Baur and Glover (2016), question the safe

[4] To test on stationarity of the times series, we use a unit root test developed by Perron (1997), which considers one endogenously determined structural break in the intercept. The results are available upon request.

haven property of gold, the widely-held view among economists is that when markets become turbulent, some investors tend to convert their assets into gold, which drives up its price up, thus serving as insurance against adverse market events. Moreover, gold is also positively affected by unfavourable (surprising) macroeconomic news (see, e.g., Roache and Rossi 2010; Caporale et al. 2017).

The second measure, the daily Economic Policy Uncertainty (EPU) index constructed by Baker et al. (2015), reflects the frequency of articles containing uncertainty-related words in 1,500 U.S. newspapers. As such, a higher EPU value implies increased uncertainty about future economic policy. Several papers using the EPU index have been published in the last years which deal with the impact of economic policy uncertainty on macroeconomic fundamentals. For example, Karnizova and Li (2014) and Balcilar et al. (2016) emphasise the capability of high-frequency EPU values in forecasting recessionary regimes for the U.S. economy. Considering that Bitcoin is mainly traded outside the U.S., it should be noted that the EPU index is geared to the U.S. economy as most newspapers are likely to report mainly on domestic uncertainty issues. However, it is certain that (i) U.S. newspapers also will report on major uncertainty-related events outside the U.S., and, (ii) that uncertainties arising from the U.S. economy as the largest economy in the world will affect the global economy. In this context, the EPU index can also serve as an indicator providing valuable information on the expected uncertainty about the political and economic climate at a global level.

The third measure, the global VIX (GVIX) index, is constructed in the spirit of Bouri et al. (2017b) and represents the first principal component of volatility indices (VIXs) of 14 developed and developing stock markets. The stock markets of Brazil, Canada, China, France, Germany, India, Japan, Mexico, Russia, South Africa, Sweden, Switzerland, the UK, and the US are taken into account. Additionally, it is scaled to the level of the VIX by using the min-max normalisation with minimum and maximum of the VIX to avoid negative values and to facilitate the interpretation of this global measure. A volatility index is a forward-looking volatility measure which represents expected future market volatility over the next 30 calendar days by averaging the current prices of the respective stock market index options. Often referred to as the "fear index", a high volatility value represents increased financial market uncertainty. In other words, investors buy stock market index put options when they fear a potential decline in the stock market, resulting in a surge in the VIX. The well-known US VIX index based on S&P 500 has become a standard measure for US and global uncertainty in empirical finance and economics literature (Bloom, 2009; Mody, 2009). Against this background, the GVIX index is used to obtain a better measure for global uncertainty than the US VIX index. It is worth noting that VIX and EPU follow different concepts. While the EPU index attempts to capture economic policy uncertainty, a VIX index echoes financial market uncertainty. Two measures are used with the aim of capturing different types of macroeconomic uncertainty.

Lastly, to check the relationship between Bitcoin and global stock markets, the stock market indices S&P Global 1200, MSCI World, and MSCI Emerging Market (EM) included. The S&P Global 1200 index is a stock market index capturing 31 countries and about 70 per cent of global stock market capitalisation. It thus reflects the overall performance of the stock markets worldwide. The MSCI World represents a collection of around 1,600 shares from 23 industrialised countries. As such, it serves as a standard benchmark for measuring stock market performance in industrialised countries. Similarly, the MSCI EM consists of nearly 850 stocks from 23 major emerging economies and is used to measure the stock market performance in developing countries. All variables are drawn from Datastream, except the EPU, which is drawn from the www.policyuncertainty.com.

Events dummies

Three types of events are considered in this paper: regulatory events, monetary policy events, and Bitcoin-specific events. First of all, it should be mentioned that the events in these three sets from September 2011 to December 2017 are taken from the Bitcoin-related set of Vidal-Tomás and Ibañez (2018), who updated the corresponding event set of Feng et al. (2017) with the aim of creating a database of events that could be used by different authors, and also provided an event set describing the main monetary policy announcements worldwide. These events are divided into positive and negative events, whereby the value of an event on a respective day is one and zero otherwise. As such, they enter the study as dummy variables in the form $D_{.}^{+/-}$ = 1 if a positive/negative event occurs, 0 otherwise.

The events relevant to regulation on Bitcoin are taken from the policy-related events from the Bitcoin-related event of Vidal-Tomás and Ibañez (2018) from June 2013 to December 2017. From January 2018 onwards, the news collection software Factiva will be used to find all news of Reuters relevant to Bitcoin regulation using the search term "Bitcoin". Consequently, the event set will be extended until 21 June 2018, which is the cut-off date for this paper. The details are found in Table 6 in the Appendix. There are 20 positive and 37 negative events, as proxied by the dummies $D_{REGT}^{+/-}$. The positive events relate in particular to a more open attitude by the authorities towards Bitcoin, including the renunciation of greater regulation, the approval of licenses for Bitcoin business activities and the recognition of Bitcoin as a payment method. The negative events are mostly related to statements by authorities warning investors of risks in dealing with Bitcoin, indicating the need for stronger regulation, and determining or suggesting the handling of Bitcoin by financial institutions.

The international monetary policy event set used in this paper is based on the monetary policy event set of Vidal-Tomás and Ibañez (2018) and is extended to include all major monetary policy announcements from Federal Reserve (FED), the European Central Bank (ECB), the Bank of Japan (BoJ), and the Bank of England (BoE) between 16 March

2011 and 21 June 2018. Additionally, five bailout- and Brexit-related events are removed from the set to ensure a straight monetary policy event set. Following the approach of Vidal-Tomás and Ibañez (2018), each of the added events is first classified according to whether the event is expansionary or contractionary. That is, expansionary (respectively, contractionary) policies are classified as positive (respectively, negative) events. Then the reaction of the respective stock market, namely S&P 500, EuroStoxx 50, FTSE 100 and Nikkei 225, is reviewed on the given event day to correct the classification if necessary. A positive (respectively, negative) reaction of the respective stock market indicates a surprising loosening (respectively, tightening) of monetary policy. The set is described in Table 8 in the Appendix. Overall, the set contains 57 events, of which 40 are positive and 17 are negative events, as proxied by $D_{MP}^{+/-}$. The majority of the statements is predominantly positive, as the international monetary policy stance has mainly been loose since the outbreak of the financial crisis and monetary policy appears to be slowly returning to normal, as the recovery of the global economy has progressed slowly since then.

Regarding the specific events related to Bitcoin, all the policy events are removed from the Bitcoin-related event set of Vidal-Tomás and Ibañez (2018), which is then extended until 21 June 2018, as described in Table 8 in the Appendix. Overall, of a total of 44 events, 18 are positive and 26 negative. The positive (respectively, negative) events are represented by $D_{SE}^{+/-}$. It is striking that while the negative events often involve hacking events, the positive events are mostly related to the acceptance of Bitcoin as a payment method and the entry of Bitcoin into the financial market.

The presentation of the event dummies ends with a brief reminder of the limitations of using dummy variables in regression analysis. Although dummy coding is a powerful tool for describing various qualitative events, its outcome needs to be carefully interpreted. Severe multicollinearity can occur when all dummy variables enter the estimation simultaneously. Hence, regression estimations are carried out by including dummy variables sequentially. As in all regression analysis, dummy variables can carry some effects from unobserved factors, resulting in omitted variables bias. Lastly, some crucial events can also be missing in a dummy variable, which may also lead to omitted variables bias.

News coverage

It has been widely studied whether investors' trading decisions are influenced to some degree by news coverage related to the corresponding asset. Since Bitcoin has been attracting public attention since 2013, a considerable amount of articles can be found in the mainstream press. To capture the effects of the news coverage, news from Reuters, as the largest news agency worldwide, will be collected. The news collection software Factiva is used to search all Reuters news using the search term "Bitcoin". For measuring the impact of news flows, a news frequency time series is generated, which contains the daily number of collected news. Also, a news dummy time series is generated, in order to capture the effect of mere news presence. If there is any news per day, the dummy will take a value of one, otherwise zero. Unlike the event dummies, both the news dummy and the news frequency variable are not divided into positive and negative categories, as it is difficult to clearly determine the mood of the daily news, given that there are usually several news articles per day which may have different views on Bitcoin-related topics. An attempt in this direction has been made by Polasik et al. (2015), who extract the tone of relevant news using a keyword-based approach and find that the Bitcoin' return increases (respectively, decreases) with positive (respectively, negative) news. In any case, it can be assumed that media attention will cause Bitcoin's exchange rate to move regardless of direction. Therefore, it seems more appropriate to focus on the role of news coverage in driving Bitcoin's exchange rate volatility rather than its exchange rate level.

4 Model design and empirical results

The paper by Engle (1982) was a major inspiration for research focusing on financial time series. Since then, a rich body of literature on the design of heteroscedastic financial time series has been developed. Engle (1982) introduced the Autoregressive Conditional Heteroscedasticity model (ARCH) which is capable of describing the volatility clustering of financial time series in the short and medium run. However, to capture the nature of volatility, ARCH models often require a large number of lags. In order to address this issue, Bollerslev (1986) introduced the generalised Autoregressive Conditional Heteroscedasticity model (GARCH) which adds an autoregressive component to the conditional variance equation of the ARCH model and greatly enhances information implicitly contained in the conditional variance. Especially high-frequency exchange rate dynamics seem to be well captured by GARCH models.

Since the exchange rate seems to have structural breaks, conventional unit root tests are likely to be biased. Hence, we use a unit root test developed by Perron (1997), which considers one endogenously determined structural break in the intercept. For the log value of the exchange rate, the test statistic is -3.42 with a break on 14 January 2013, while the critical value for rejecting the null hypothesis (the series has a unit root and is therefore non-stationary) is -4.82 at 10%. For the daily return of the exchange rate $y_t = \frac{P_t - P_{t-1}}{P_{t-1}}$, the test statistic is -15.47 with a break on 07 June 2011, while the critical value remains the same. A unit root developed by Lumsdaine and Papell (1997) with two structural breaks on 02 November 2013 and 04 December 2013 produces results similar to the previous ones.[5] These results support using first differencing owing to stationarity. An ARCH(1) test proposed by Engle (1982) (227.75, p-value = 0.00) points to the presence

[5]The detailed results are available upon request.

of heteroscedasticity in the return series which justifies the application of GARCH-type models. The framework used for the model selection has the general form

$$
\begin{aligned}
y_t &= \mu + \phi y_{t-1} + \varepsilon_t, \\
\varepsilon_t &= \sigma_t z_t, \quad z_t \sim \text{i.i.d.}(0,1),
\end{aligned} \tag{1}
$$

where y_t is the daily return of Bitcoin's exchange rate, μ is the mean intercept. ϕ is the first-order autoregressive parameter. ε_t is the residual dependent on the standardised residual z_t is a strong white noise process i.i.d.(0,1) and the conditional volatility σ_t, which can be formed by a wide range of GARCH-type models, as described in Table 2.[6] For choosing the optimal GARCH-type model, the approach of Katsiampa (2017) is followed which takes the log-likelihood value, information criteria, and diagnostic tests into account. However, two aspects in the selection process differ from that of Katsiampa (2017). First, Katsiampa (2017) relies exclusively upon GARCH(1,1)-type models in the selection process, leaving an open question mark on whether higher-order GARCH-type models are better suited to capture Bitcoin's volatility. Although GARCH (1,1)-type models are standard candidate models in the relevant literature, as they are often sufficient to capture and forecast the volatility of many financial returns, their use may result in significant underfitting given the exceptionally high volatility of Bitcoin. Against this backdrop, it may be more appropriate to use higher-order GARCH models to capture volatility persistence and fat tail behaviour more satisfactorily. Therefore, the selection of the lag order is of critical importance, and lags up to (5,5) will be tested in the selection process. Second, against strong evidence of the existence of fat tails in the financial return data, Katsiampa (2017) chooses Gaussian error distribution, which can be problematic owing to frequently large exchange rate movements in the Bitcoin market. Regarding the higher moments of the daily return of the Bitcoin exchange rate, the kurtosis is 15.69, and the skewness is 0.70, indicating a leptokurtic and right-skewed distribution of the return. A JB test (18,025, p-value = 0.00) soundly indicates that a normal distribution fails to replicate the fat tails. Overall, these figures suggest that the standardised residuals likely have a fat-tailed distribution. Therefore, the skewed Generalised Error Distribution (GED) is chosen to capture the leptokurtosis and skewness of the standardised residuals.

The information criterion used is the Akaike information criterion (AIC), and the diagnostic tests include ARCH(1), Ljung-Box(15), and Jarque-Bera (JB) tests, which test squared standardised residuals for heteroscedasticity, squared standardised residuals for autocorrelation, and standardised residuals for normality, respectively.[7] The estimation results of the GARCH-type models in Table 3 indicate two potential optimal models.

[6] Details of these GARCH-type models can be found in Ghalanos (2018).

[7] The Bayesian information criterion (BIC) is not considered because it penalizes model complexity more severely than AIC and therefore often refers to GARCH(1,1)-type models, which is unlikely to capture the high volatility level of Bitcoin. Although AIC is known to be at risk of overestimating the number of parameters, overfitting appears to be less problematic than underfitting given Bitcoin's high volatility. The Hannan-Quinn information criterion(HQC) points to the same lag orders as AIC and is therefore not presented as well.

Table 2: Description of the GARCH-type models used for model selection

GARCH	$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$
EGARCH	$\ln \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \left[\lvert z_{t-i} \rvert - E(\lvert z_{t-i} \rvert) \right] + \gamma_i z_{t-i} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2)$
TGARCH	$\sigma_t = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i} (\lvert z_{t-i} \rvert - \gamma_i z_{t-i}) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}, \quad \gamma_i \leq 1$
GJR-GARCH	$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 I_{t-i} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \quad I_{t-i} = \begin{cases} 1, & \varepsilon_{t-i} \leq 0 \\ 0, & \varepsilon_{t-i} > 0 \end{cases}$
NGARCH	$\sigma_t^\lambda = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^\lambda + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\lambda$
NAGARCH	$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 (z_{t-i} - \eta_i)^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$
AVGARCH	$\sigma_t = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i} (\lvert z_{t-i} - \eta_{2i} \rvert - \eta_{1i}(z_{t-i} - \eta_{2i})) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}, \quad \lvert \eta_{1i} \rvert \leq 1$
APARCH	$\sigma_t^\lambda = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^\lambda (\lvert z_{t-i} \rvert - \gamma_i z_{t-i})^\lambda + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\lambda, \quad \gamma_i \leq 1$
CGARCH	$\sigma_t^2 = q_t + \sum_{i=1}^{p} \alpha (\varepsilon_{t-i}^2 - q_{t-i}) + \sum_{j=1}^{q} \beta_j (\sigma_{t-j}^2 - q_{t-j}),$
	$q_t = \omega + \rho q_{t-1} + \theta(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$
FIGARCH	$\sigma_t^2 = \left(\omega - \bar{\varepsilon}_{t-i}^2 \right) + \sum_{i=1}^{p} \alpha_i \left(\varepsilon_{t-i}^2 + \bar{\varepsilon}_{t-i}^2 \right) + \sum_{j=1}^{q} \beta_j \left(\sigma_{t-j}^2 - \varepsilon_{t-j}^2 \right),$
	$\bar{\varepsilon}_{t-j}^2 = \varepsilon_{t-j}^2 + \left(\sum_{k=1}^{\infty} \pi_k L^k \right) \varepsilon_{t-j}^2, \qquad \pi_k = \prod_{1 \leq i \leq k} \frac{i-1-\delta}{i}$

Notes: EGARCH is the abbreviation for the Exponential GARCH model, TGARCH for the Threshold GARCH model, GJR-GARCH for the Glosten-Jagannathan-Runkle GARCH model, NGARCH for the Nonlinear GARCH model, NAGARCH for the Nonlinear Asymmetric GARCH model, AVGARCH for the Absolute Value GARCH model, APARCH for the Asymmetric Power ARCH model, CGARCH for the Component GARCH model, IGARCH for the Integrated GARCH model, and FIGARCH for the Fractionally Integrated GARCH model.

While AIC points to the EGARCH(3,3) model, the JB test statistic in the CGARCH(1,2) model has fallen the most compared to those in other models, suggesting its superior ability in explaining Bitcoin's volatility. However, there are two issues when using the CGARCH(1,2) model in this paper. First, the CGARCH model class divides the conditional variance into a transitory and a permanent component to investigate the short and long-run movements of the volatility, making it difficult to precisely position the explanatory variables, and thus to examine the driving forces of the volatility. Second, the significantly lower value of the JB test of the CGARCH(1,2) model compared to those of other GARCH-type models indicates that the permanent component of the conditional variance, which is a time-varying following AR(1)-type process, already captures the driving forces of the volatility well without the inclusion of explanatory variables. The addition of explanatory variables is therefore likely to produce insignificant results. For these reasons, the EGARCH(3,3) model is eventually chosen. The results of the diagnostic tests show that ARCH effects have been well captured by the EGARCH(3,3) model, suggesting that this EGARCH specification appears to adequately describe the volatility of the daily return of Bitcoin's exchange rate.

In the next step, the explanatory variables enter the EGARCH(3,3) model. The empirical methodology employed is closely related to the study by Funke et al. (2015). The mean and conditional variance equations take the following form for the daily return of Bitcoin's exchange rate y_t and the associated volatility σ_t:

$$
\begin{aligned}
y_t &= \mu + \sum_{j=0}^{\hat{N}} \kappa_j \hat{v}_{t-j} + \phi y_{t-1} + \varepsilon_t, \qquad \varepsilon_t = \sigma_t \cdot z_t \\
\ln \sigma_t^2 &= \omega + \sum_{l=0}^{\tilde{N}} \psi_l \tilde{v}_{t-l} + \sum_{i=1}^{3} \left(\alpha_i (\lvert z_{t-i} \rvert - E(\lvert z_{t-i} \rvert) + \gamma_i z_{t-i} \right) + \sum_{j=1}^{3} \beta_j \ln \sigma_{t-j}^2
\end{aligned} \tag{2}
$$

Table 3: Estimation of the GARCH-type models

	GARCH	EGARCH	TGARCH	GJR-GARCH	NGARCH	NAGARCH	AVGARCH	APARCH	CGARCH	FIGARCH
Preferred (p,q)	(1,1)	(3,3)	(1,2)	(2,1)	(1,2)	(1,2)	(1,2)	(1,2)	(1,2)	(1,1)
					Mean equation					
Constant μ	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(17.37)	(9.95)	(39.23)	(39.38)	(29.43)	(46.13)	(37.68)	(52.59)	(3.45)	(37.63)
AR(1) ϕ_1	-0.012***	-0.010***	-0.019***	-0.017***	-0.016***	-0.017***	-0.017***	-0.017***	-0.013***	-0.017***
	(-11.57)	(-5.55)	(-30.29)	(-27.16)	(-23.94)	(-20.55)	(-23.83)	(-19.74)	(-3.59)	(-13.32)
					Variance equation					
Constant ω	0.001**	-0.048***	0.001***	0.001***	0.001***	0.001**	0.001***	0.001*	0.001***	0.001**
	(2.46)	(-19.17)	(4.68)	(2.64)	(3.71)	(2.37)	(4.63)	(1.71)	(3.03)	(2.48)
ARCH α_1	0.197***	0.474***	0.282***	0.182***	0.302***	0.257***	0.284***	0.301***	0.171***	0.210***
	(8.77)	(10,414.98)	(11.32)	(8.98)	(9.47)	(9.08)	(12.61)	(9.11)	(3.56)	(4.07)
ARCH α_2		0.031***		0.001						
		(547.68)		(0.01)						
ARCH α_3		-0.407***								
		(-11,493.27)								
GARCH β_1	0.802***	0.763***	0.485***	0.833***	0.464***	0.390***	0.461***	0.457***	0.389***	0.718***
	(31.34)	(13,261.93)	(32.36)	(39.54)	(15.03)	(9.18)	(32.32)	(16.36)	(12.20)	(7.39)
GARCH β_2		0.994***	0.296***		0.306***	0.351***	0.318***	0.313***	0.391***	
		(23,061.14)	(17.70)		(10.29)	(8.87)	(23.04)	(12.11)	(11.90)	
GARCH β_3		-0.764***								
		(-31,372.34)								
EGARCH γ_1		-0.030***								
		(-1,214.50)								
EGARCH γ_2		0.002***								
		(3.23)								
EGARCH γ_3		0.056***								
		(1,952.39)								
TGARCH γ			-0.022							
			(-0.51)							
GJR-GARCH γ_1				0.162***						
				(3.48)						
GJR-GARCH γ_2				-0.194***						
				(-4.67)						
NGARCH λ					1.247***					
					(16.22)					
NAGARCH η_1						-0.068				
						(-0.68)				
AVGARCH η_{11}							0.052			
							(1.50)			
AVGARCH η_{21}							-0.101***			
							(-8.08)			
APARCH λ								1.252***		
								(8.92)		
APARCH γ_1								-0.022		
								(-0.43)		
CGARCH ρ									0.999***	
									(60,904.74)	
CGARCH θ									0.088***	
									(8.54)	
FIGARCH δ										0.787***
										(6.46)
					Diagnostic tests					
LogL	5,094.88	5,123.90	5,106.47	5,101.63	5,107.34	5,099.10	5,106.82	5,107.46	5,101.93	5,102.05
AIC	-3.83616	**-3.85072**	-3.84135	-3.83695	-3.84201	-3.83580	-3.84086	-3.84134	-3.83717	-3.83877
ARCH(1)	0.93	0.01	1.26	0.01	0.34	0.11	0.79	0.41	0.01	0.03
	(0.34)	(0.91)	(0.26)	(0.93)	(0.56)	(0.74)	(0.38)	(0.52)	-(0.98)	(0.87)
LB(15)	8.21	3.29	6.43	5.54	5.98	7.00	5.85	6.13	7.11	6.48
	(0.92)	(1.00)	(0.97)	(0.99)	(0.98)	(0.96)	(0.98)	(0.98)	(0.95)	(0.97)
JB	11,026***	12,303***	13,707***	13,202***	13,657***	11,292***	14,207***	13,746***	**7,881*****	9,263***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Sample from 16 March 2011 – 21 June 2018. ***, **, * indicator significance at 1%, 5% and 10% levels respectively. For the parameters t-values robust to heteroscedasticity are given in parentheses. For the residual tests prob-values are given in parentheses. LB(15) is the Ljung-Box Q-statistic for 15 lags. ARCH(1) is the LM-test for 1st order ARCH effects. JB ist the Jarque-Bera test for normality. Diagnostic tests are carried out on the standardised residuals. The models are estimated in R, using the package *rugarch* and the nonlinear solver algorithm *SOLNP*.

On the mean equation side, μ is the mean intercept. ϕ is the AR(1) parameter. ε_t is the residual dependent on the conditional volatility σ_t and the standardised residual z_t following a skewed GED distribution. κ_j are the parameters of the explanatory variables vector $\hat{v} = \{\hat{v}_{t-\hat{N}}, \ldots, \hat{v}_t\}$. In the conditional variance equation, ω is the variance intercept. The ARCH parameter α determines the size effect of the standardised residuals on volatility which captures the general impact of a shock on the volatility. The GARCH parameter β captures the persistence of the volatility. The leverage parameter γ captures the sign effect of the standardised residuals on the volatility, i.e., negative γ implies that negative shocks have a greater impact on the volatility than positive shocks. ψ_l are the parameters of the exogenous variables vector $\tilde{v} = \{\tilde{v}_{t-\tilde{N}}, \ldots, \tilde{v}_t\}$.

The fundamental variables in the mean equation are the percentage change in the hash rate (HR) and the logarithm of Amihud's measure of illiquidity (AMI). Since an increasing hash rate means more aggregated computation power, mining is considered to be an indicator of investment activities in the Bitcoin market and competition among the miners. As such, a higher hash rate points to intensified competition and could create constant downward pressure on the exchange rate, as miners are likely to be forced to sell some Bitcoins in order to invest in more computing power and thus to keep pace with the competition. Therefore, HR is expected to have a negative sign.[8] In a speculative market, when many investors buy an illiquid asset such as Bitcoin, the price can increase rapidly. Consequently, it is expected that lower liquidity translates to higher returns. Therefore, AMI is expected to carry a positive sign.

On the dummy variables side, the positive/negative event dummies for regulatory events $D^{+/-}_{REGT}$, monetary policy events $D^{+/-}_{MP}$, and Bitcoin-specific events $D^{+/-}_{SE}$ enter the mean equation. Regarding the positive events, it is expected that (i) a positive regulatory event encourages market participants to buy Bitcoin in the expectation of a higher probability that Bitcoin will become mainstream in the future and thus its demand and exchange rate will increase, leading to a higher exchange rate today; (ii) a positive monetary policy event signals a prolonged period of low interest rates, leading to an increase in Bitcoin's exchange rate against the background that all asset prices tend to rise when monetary policy is loose; (iii) a positive Bitcoin-specific event boosts the overall market sentiment, leading to higher demand for Bitcoin. Therefore, the dummies D^{+}_{REGT}, D^{+}_{MP}, and D^{+}_{SE} are expected to carry a positive sign. The expectations of the negative events on Bitcoin's exchange rate are vice versa and therefore not further explained. Hence, D^{-}_{REGT}, D^{-}_{MP}, and D^{-}_{SE} are expected to carry a negative sign.

To test Bitcoin's hedge capability against global uncertainty and market risks, the logarithm of GVIX and of EPU, as well as the percentage change of the price of gold and of the stock market indices S&P Global 1200, MSCI World, and MSCI EM are included in the conditional mean equation, denoted as ln(GVIX), ln(EPU), Δ%Gold, Δ%SPG 1200,

[8] Wang and Liu (2015) have shown that the average time lag between getting a Bitcoin from mining and selling it dropped from 19 days in 2011 to around 1.5 days in 2013. Accordingly, it is reasonable to assume that mining and selling now occur within one day and hence, HR is included with no time lag.

$\Delta\%$MSCI World, and $\Delta\%$MSCI EM respectively. As a proxy for global financial market uncertainty, an increase in GVIX is expected to lead to an increase in the exchange rate in the Bitcoin market, assuming Bitcoin can serve as a hedge instrument. It can also be expected that increasing economic policy uncertainty proxied by EPU raises the exchange rate of Bitcoin. The literature suggests that gold serves as a hedge against a falling stock market, so this should logically also apply to Bitcoin as a potential hedge, and the relationship between Bitcoin and gold is expected to be positive. Therefore, ln(GVIX), ln(EPU), and $\Delta\%$Gold are expected to have a positive sign, while $\Delta\%$SPG 1200, $\Delta\%$MSCI World, and $\Delta\%$MSCI EM are expected to carry a negative sign. With regard to safe haven capabilities, a potential non-linear relationship between the Bitcoin market and global uncertainty is examined, i.e., whether Bitcoin's hedge capability holds with increasing uncertainty, since Bitcoin as a volatile asset may be subject to flight-to-quality in times of market turbulence. Consequently, the quadratic terms of ln(GVIX) and ln(EPU) are included in the conditional mean equation, denoted as $(\ln(\text{GVIX}))^2$ and $(\ln(\text{EPU}))^2$. The outcome is uncertain. One possible scenario is that Bitcoin can serve as a safe haven in times of market distress, leading to a positive impact of $(\ln(\text{GVIX}))^2$ and $(\ln(\text{EPU}))^2$. The other option is that Bitcoin moves with the markets when the global uncertainty is high, as indicated by a negative impact of $(\ln(\text{GVIX}))^2$ and $(\ln(\text{EPU}))^2$.

The fundamental variables in the conditional variance equation are the logarithm of trading volume in BTC (TVOL), the percentage change in the number of transactions (NOTX) and the logarithm of the revenue of miners in BTC (MREV). A key feature in the foreign exchange market microstructure literature is the relationship between exchange rate volatility and trading volume. It is a stylized fact that this relationship is positive, and the so-called mixture of distribution hypothesis first proposed by Clark (1973) argues that volatility and trade volume are positively correlated because both are positively linked to information arrival, as suggested by several empirical studies such as Tauchen and Pitts (1983), Karpoff (1987), and Gallant et al. (1992). Hence the trading volume variable TVOL is expected to carry a positive sign. Results from more recent literature, such as Easley and O'hara (1992), Jones et al. (1994), Jones and Seguin (1997), and Ané and Geman (2000) argue that transaction frequency counts more than volume in explaining volatility. Therefore, the variable NOTX is expected to carry a positive sign as well. Revenue of the miners is virtually equal to the Bitcoin supply growth per day. Despite the fixed supply design, the growth fluctuates in practice nearly 11% on average.[9] Since it is expected that miners sell some of the mined Bitcoins, an increase in total revenue positively influences the supply. In a speculative market, the reaction of demand to a higher supply is unpredictable, higher revenue of the miners does not necessarily lead to a decline in exchange rates, but might as well results in a surge. Hence, a positive effect on the volatility is expected, and MREV is added in the conditional variance equation.

Moreover, the conditional variance equation contains the number of Reuters news

[9]Source: `https://blockchain.info`; author's calculation.

per day (NFRQ) as well as the Reuters news presence dummy (D_{NEWS}). Works such as Goodhart et al. (1993) and Andersen et al. (2007) show that the mere presence of an announcement drives the volatility. Therefore, we expect a positive link between NEWS and volatility. Although the mixture of distribution hypothesis emphasises the role of public information arrival in driving trading volume and volatility, papers investigating the relationship between the number of news released by major newswires and volatility in financial markets find little explanatory power of the number of news collected by Reuters (Berry and Howe, 1994) or Dow Jones (Mitchell and Mulherin, 1994) with respect to volatility. In that light, the effect of the variable NEWS on volatility is uncertain.

Lastly, including dummy variables into GARCH models bears severe risks in the estimation. Doornik and Ooms (2008) show that GARCH models with dummy variables in the mean equation may cause multimodal likelihood. Since reaching a global maximum of the log-likelihood function is mandatory, the EGARCH parameter estimations are looped with 100 different random initial parameters to ensure finding the most likely parameters. Also, to avoid further possibilities of multimodality, the solution proposed by Doornik and Ooms (2008) by adding the corresponding dummy variable with one lag in the conditional variance equation is applied as a robustness check.

Coming to the empirical results, the estimations of the EGARCH(3,3) models, including fundamental variables and related event dummies, are presented in Table 4. Further estimations including Bitcoin news coverage, global uncertainty and financial market variables are shown in Table 5. Regarding the diagnostic tests, first, the squared standardised residuals are not autocorrelated owing to the insignificant results of the ARCH test and the Ljung-Box test, suggesting that the volatility clustering behaviour is well captured by the EGARCH(3,3) model. Second, designed for detecting any neglected asymmetry in the conditional variance, the sign bias, the size bias, and the joint effect tests are all insignificant, implying that the asymmetry in volatility is well captured. Third, the non-explanatory coefficients are significant at the 1% level except for the AR(1) parameter ϕ. Taken together, these results support the choice of the EGARCH(3,3) specification.

In Table 4, we first consider Model I which is the EGARCH(3,3) model estimation without explanatory variables. The insignificant mean AR(1) coefficient (ϕ = -0.010) suggest that there is little exchange rate level memory, implying an uneven evolution of the Bitcoin exchange rate over time. The first ARCH coefficient (γ_1 = 0.473) implies that the volatility is highly sensitive to market events in the sample period. The GARCH parameter estimates (β_1 = 0.763, β_2 = 0.995, and β_3 = -0.765) suggests highly persistent conditional volatility over time, as the half-life of a volatility shock $\frac{\ln 0.5}{\ln(\beta_1+\beta_1+\beta_1)}$ is $\frac{\ln 0.5}{\ln(0.763+0.995-0.765)} = 98.67$ days, i.e., it takes the conditional variance about three months to return to half of its initial level. The first leverage coefficient (γ_1 = -0.031) suggests the presence of leverage effect, as for a standardised shock with magnitude one, the ratio between negative and positive standardised shocks is $\frac{\sigma_t^2(z_{t-1}=-1)}{\sigma_t^2(z_{t-1}=1)} = \frac{\exp(-0.031\times-1)}{\exp(-0.031\times1)} = 1.063$, i.e., the impact of a standardised negative shock of size one is about 6% stronger than

Table 4: EGARCH(3,3) model estimates including fundamental and event variables

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
					Mean equation				
μ	0.002***	0.012***	0.011***	0.012***	0.011***	0.002***	0.010***	0.011***	0.010***
	(10.12)	(20.14)	(28.36)	(62.30)	(8.70)	(23.28)	(28.26)	(32.22)	(38.90)
ϕ	-0.010	-0.012	-0.011**	-0.013***	-0.013	0.001	-0.012***	-0.010	-0.00035
	(-0.092)	(-0.49)	(-2.34)	(-7.45)	(-0.64)	(-0.77)	(-4.90)	(-0.23)	(-0.87)
Fundamental variables									
AMI		0.00051***	0.00046***	0.00053***	0.00044***		0.00041***	0.00042***	0.00040***
		(10.25)	(18.72)	(50.74)	(5.71)		(31.78)	(24.20)	(38.81)
HR		0.00002	0.00003***	0.00002***	0.00003	0.00001	0.00002***	0.00002	0.00002***
		(1.28)	(10.20)	(6.33)	(0.96)	(0.53)	(5.78)	(1.44)	(44.58)
Positive event variables									
D^{+}_{REGT}			0.008***						0.008***
			(16.47)						(30.75)
D^{+}_{MP}				0.002***					0.00021***
				(12.32)					(23.75)
D^{+}_{SE}					0.007***				0.005***
					(7.75)				(35.78)
Negative event variables									
D^{-}_{REGT}						-0.033***			-0.033***
						(-72.32)			(-61.89)
D^{-}_{MP}							0.00028***		0.00028***
							(20.59)		(7.82)
D^{-}_{SE}								-0.039***	-0.038***
								(-48.05)	(-52.42)
					Variance equation				
ω	-0.050***	-5.709***	-5.696***	-5.540***	-5.652***	-6.544***	-5.616***	-4.976***	-5.493***
	(-10.74)	(-42.76)	(-16.93)	(-105.24)	(-5.67)	(-9.96)	(-34.30)	(-15.13)	(-61.73)
α_1	0.473***	0.500	0.494***	0.503***	0.495***	0.510***	0.492***	0.484***	0.511***
	(5,515.15)	(1.38)	(7.69)	(20.54)	(2.87)	(8.70)	(10.33)	(10.83)	(13.66)
α_2	0.032***	0.746**	0.750***	0.748***	0.748***	0.761	0.746***	0.732***	0.753***
	(1,626.12)	(2.49)	(6.12)	(33.69)	(2.58)	(1.14)	(8.73)	(11.40)	(13.71)
α_3	-0.406***	0.405***	0.407***	0.403***	0.406***	0.420***	0.405***	0.391***	0.399***
	(-5,270.13)	(4.99)	(5.75)	(21.61)	(2.35)	(7.28)	(7.89)	(9.66)	(12.12)
β_1	0.763***	-0.629	-0.641***	-0.633***	-0.643	-0.610	-0.643***	-0.672***	-0.647***
	(4,215.52)	(-29.66)	(-42.72)	(-90.89)	(-17.36)	(-14.62)	(-57.10)	(-23.56)	(-50.23)
β_2	0.995***	0.598	0.601***	0.603***	0.601	0.573	0.603***	0.627***	0.613***
	(15,323.76)	(68.23)	(33.21)	(88.01)	(15.63)	(14.96)	(48.04)	(33.83)	(47.75)
β_3	-0.765***	0.736	0.746***	0.741***	0.747	0.709	0.749***	0.785***	0.755***
	(-4,574.62)	(20.83)	(33.21)	(92.23)	(26.24)	(16.74)	(79.78)	(31.08)	(59.02)
γ_1	-0.031***	0.500	-0.003	0.003	-0.004	-0.016	-0.005	-0.005	-0.001
	(-868.08)	(0.01)	(-0.01)	(1.44)	(-0.06)	(-0.45)	(-0.20)	(-0.07)	(-0.34)
γ_2	0.002***	0.746	0.012	0.017***	0.012	-0.011	0.011	0.014	0.006
	(2.70)	(0.06)	(0.10)	(3.34)	(0.15)	(-0.24)	(1.04)	(0.28)	(0.27)
γ_3	0.055***	0.405	0.020	0.023***	0.021	0.002	0.022*	0.027	0.015
	(1,032.80)	(0.04)	(0.69)	(3.52)	(0.21)	(0.05)	(1.71)	(1.34)	(0.91)
Fundamental variables									
NOTX		0.278***	0.270***	0.273***	0.269***	0.300***	0.266***	0.228***	0.251***
		(25.62)	(17.36)	(84.77)	(23.71)	(8.70)	(46.20)	(4.70)	(41.62)
TVOL		0.001	0.001	0.001***	0.001	0.002	0.001	0.001	0.001
		(0.06)	(0.61)	(3.65)	(1.34)	(1.14)	(1.44)	(0.68)	(0.97)
MREV		0.110**	0.118***	0.101***	0.113***	0.155***	0.116***	0.110***	0.128***
		(2.03)	(7.58)	(24.78)	(3.00)	(7.28)	(13.64)	(3.16)	(21.84)
					Diagnostic tests				
LogL	5,123.97	5,140.35	5142.17	5140.37	5,41.04	5,139.38	5,140.36	5147.12	5156.38
ARCH(1)	0.01	0.13	0.12	0.11	0.12	0.12	0.11	0.01	0.02
	(0.91)	(0.72)	(0.73)	(0.74)	(0.73)	(0.73)	(0.74)	(0.94)	(0.90)
LB(15)	3.34	6.53	6.55	6.36	6.48	6.84	6.45	7.91	7.39
	(0.99)	(0.97)	(0.97)	(0.97)	(0.97)	(0.96)	(0.97)	(0.92)	(0.95)
JB	12,428***	10,788***	10,529***	11,068***	10,722***	8,083***	10.622***	7,743***	6,919***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Skewness	-0.86	-0.42	-0.40	-0.44	-0.41	-0.20	-0.41	-0.25	-0.15
Kurtosis	13.48	9.83	12.72	9.96	12.81	11.54	12.77	11.35	7.90

Table 4 Cont.: EGARCH(1,1) model estimates including fundamental and event variables

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Negative sign bias test	0.30	0.54	0.43	0.55	0.45	0.23	0.43	0.35	0.05
	(0.77)	(0.59)	(0.67)	(0.59)	(0.65)	(0.82)	(0.66)	(0.72)	(0.96)
Poistive sign bias test	0.92	0.93	0.97	0.90	0.94	1.12	0.95	0.81	1.21
	(0.36)	(0.35)	(0.33)	(0.37)	(0.35)	(0.26)	(0.34)	(0.42)	(0.23)
Joint effect test	0.96	2.09	1.67	2.21	1.70	1.31	1.66	1.36	1.48
	(0.81)	(0.55)	(0.64)	(0.53)	(0.64)	(0.73)	(0.65)	(0.72)	(0.69)

Notes: Sample from 16 March 2011 – 21 June 2018. ***, **, * indicator significance at 1%, 5% and 10% levels respectively. For the parameters t-values robust to heteroscedasticity are given in parentheses. For the residual tests prob-values are given in parentheses. LB(15) is the Ljung-Box Q-statistic for 15 lags. ARCH(1) is the LM-test for 1st order ARCH effects. JB ist the Jarque-Bera test for normality. The sign bias test examines the asymmetric impact of positive and negative shocks upon the conditional variance. The positive and negative size bias tests examine whether the magnitude of positive respectively negative shocks affects the conditional variance. The joint effect test examines the simultaneous presence of sign and size bias. Diagnostic tests are carried out on the standardized residuals. The models are estimated in R, using the package *rugarch* and the nonlinear solver algorithm *SOLNP*.

that of a standardised positive shock of the same size. The leverage effect gets more pronounced with stronger standardised shocks, as the impact of a standardised negative shock of size five is about 36% stronger than its positive counterpart, leading to the conclusion that Bitcoin's exchange rate volatility is affected more effectively by negative shocks, contradicting the findings of symmetric response of Bitcoin's exchange rate volatility to shocks found by Dyhrberg (2016a). In fact, these findings are consistent with those of Bouoiyour and Selmi (2015a), which argues that Bitcoin is likely to be driven by negative rather than positive shocks. Lastly, while the magnitude of skewness (= -0.86) has not declined, the kurtosis (= 13.48) and JB test (= 12,428) of standardised residuals compared to those of daily return of Bitcoin suggest that a fraction of fat tails have been captured by the specification. At the same time, these values also indicate that the fat tails regarding the standardised residuals are still present to a high degree, underlining the need for explanatory variables to capture the driving forces of Bitcoin's exchange rate dynamics.

On the fundamental side, the liquidity and trading volume variables (AMI, TVOL) perform adequately just as expected, confirming the negative impact of liquidity on the exchange rate level as well as the positive link between trading volume and volatility. Notably, a 1% increase in trading volume leads to a 0.28% increase in the conditional variance, supporting the role of market microstructure in explaining Bitcoin's volatility. As the trading volume in the Bitcoin markets is dominated by speculation, the results also suggest that Bitcoin's volatile movement is driven by speculative forces, consistent with the findings of MacDonell (2014). The insignificant coefficient of the variable NOTX, however, does not suggest trading frequency drives the volatility, which seems to contrast the findings of Koutmos (2018), stating that transaction activities are linked with changes in Bitcoin's exchange rate. When excluding TVOL from Model II, NOTX becomes significant, providing some evidence that trading activity is dominated by volume rather than frequency.[10] Consequently, the results may suggest that single large trades are rather responsible for Bitcoin's volatile movements than the sheer number of trading transactions, underlining the lack of transparency of the Bitcoin market where individual

[10]The results are available upon request.

wealthy traders can manipulate Bitcoin's exchange rate at the expense of others.

However, in contraction to the expectation, the coefficient of the competition indicator variable (HR) is slightly positive throughout the models in Table 4, indicating that the hash rate has some positive influence on the exchange rate. One possible explanation is provided by Kristoufek (2015), who argues that increasing competition, as proxied by the hash rate, combined with rising costs for hardware and electricity, will drive more miners out of the market. As an alternative to mining, they can invest directly in Bitcoin, resulting in higher demand and a higher exchange rate. The parameter estimate for the Bitcoin supply variable (MREV) indicates that a 1% increase in Bitcoin's supply leads to a 0.11% increase in the conditional variance, suggesting that a higher supply translates to higher volatility in the Bitcoin market. Lastly, as the half-life of a volatility shock decreases from 98.67 to $\frac{\ln 0.5}{\ln(\beta_1+\beta_1+\beta_1)} = \frac{\ln 0.5}{\ln(-0.629+0.598-0.736)} = 1.98$ days and the leverage coefficients γ_1, γ_2, and γ_3 become insignificant upon the entry of the market fundamental variables, the results suggest that Bitcoin's exchange rate volatile movements are primary driven by fundamentals.

The performance of the related event dummies in Table 4 matches its expectations except for one case. In Model VI, the liquidity variable AMI is dropped due to correlation issue with the dummy D^{-}_{REGT}. Turning to the positive events, the results confirm that positive regulation-related, monetary policy, and Bitcoin-related specific events lead to increasing exchange rate of Bitcoin. While a positive regulation-related event and Bitcoin-related specific event lead to an increase in Bitcoin's exchange rate by 0.8% and 0.7%, the impact of the positive monetary policy events is considerably weaker. Regarding the negative events, the results show that a negative regulation-related event and a Bitcoin-related specific event lead to a decrease in Bitcoin's exchange rate by 3.3% and 3.9%, respectively. The considerable decline in the skewness (= -0.20 respectively -0.25) and the JB test statistics (= 8,083 respectively 7,743) of the standardised residuals in Model VI and VIII compared to previous specifications shows that negative regulation-related and Bitcoin-related specific events are among the main drivers of Bitcoin's volatile movement to date. Surprisingly, negative monetary policy events appear to have a positive impact on the exchange rate, albeit the effect is minimal. One possible explanation could be that tapering announcements contained in the negative monetary policy event set might be responsible for inflating asset prices, thereby potentially offsetting the negative impact of the other negative monetary policy events on Bitcoin's exchange rate.[11] Lastly, Model IX shows that the results are robust when the variables simultaneously enter the regression.

To summarise the results of Table 4, the estimated parameters of the explanatory variables support the findings of previous literature emphasising the role of fundamentals in explaining the volatile dynamics of Bitcoin. Notably, negative regulation-related and Bitcoin-related specific events have a critical impact on the exchange rate level, as do, to a lesser extent, their positive counterparts, while expansionary monetary policy world-

[11] Tapering is the unwinding of the asset purchase volume regarding a quantitative easing program.

wide events have a limited, albeit significant, positive impact on Bitcoin's exchange rate.

In Table 5, the Bitcoin news coverage, global uncertainty and financial market variables enter the models. As financial markets are only open during the workdays, the missing values on weekends and holidays of $\Delta\%$Gold, ln(GVIX), ln(EPU), $\Delta\%$SPG1200, $\Delta\%$MSCI World, and $\Delta\%$MSCI EM are imputed using the approach Multivariate Imputation by Chained Equations (MICE), as developed by Buuren and Groothuis-Oudshoorn (2010). Pioneered by the theory in Rubin (1987), multiple imputation generates imputed values by repeatedly combining drawn values of the parameters from a joint distribution of the observed data. The key advantage of multiple imputation over straight-forward approaches such as deleting missing values or replacing missing values with the mean of the observed data is that it provides more accurate estimates of the parameters and their standard errors (Little and Rubin, 1989; Allison, 2002) while maintaining the overall statistical power. In practice, specifying an appropriate joint distribution for large numbers of variables can be a difficult task. The MICE approach, in turn, draws imputed values from univariate distributions of each variable conditional on other variables using generalised linear models for each conditional distribution to predict missing values. However, MICE lacks the theoretical foundation regarding that the set of specified conditional distributions may not correspond to any joint distribution, which indicates against the employment of univariate distributions. Despite this major drawback, simulation-based research shows that MICE performs well in practice.

Overall, the parameter estimates are significant and mostly in line with their expectations. Model I and II show that a Reuters news (NFRQ) increases the conditional variance by about 3% and the presence of Reuters news (D_{NEWS}) increases the conditional variance averagely by about 9%. The results underline the role of news coverage in driving the volatility of Bitcoin's exchange rate, especially when the number of reports on Bitcoin soars. Global uncertainty variables are sequentially regressed against the daily return of Bitcoin in Model III-V. The variable AMI is dropped from Model IV and V due to correlation issues with ln(GVIX) and ln(EPU). Gold has a positive impact on the conditional mean, which supports Bitcoin's hedging ability. ln(GVIX) meets its expectations and has a positive effect on the conditional mean, providing some support for Bitcoin's hedging capability. However, $(\ln(GVIX))^2$ carries a negative sign, which suggests that the hedging capability diminishes with increasing global financial market uncertainty. With the corresponding parameter estimates, differentiation of the Bitcoin return with respect to ln(GVIX) shows that Bitcoin's positive relationship with GVIX disappears and becomes negative when GVIX takes a higher value than about 18. Since the GVIX has the same order of magnitude as the VIX due to its construction and its median is about 17, this result suggests that Bitcoin can be a hedge in times of calm financial markets, but moves with the markets in times of market distress, arguing against Bitcoin's safe haven capability. A likely explanation is that financial distress tends to trigger flight-to-quality behaviour, causing some investors to turn their Bitcoins into cash or safe assets.

Table 5: EGARCH(3,3) model estimates including fundamental, event, news, uncertainty, and financial market variables

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
					Mean equation					
μ	0.010***	0.010***	0.010***	-0.072***	0.004***	0.010***	0.011***	0.010***	-0.046***	-0.57***
	(20.89)	(35.15)	(36.98)	(-64.32)	(57.91)	(48.49)	(53.34)	(22.18)	(-264.93)	(-244.66)
ϕ	0.005*	0.001***	-0.001**	0.008***	0.006***	0.006***	0.003**	0.002	0.003	0.008***
	(1.69)	(3.33)	(-2.21)	(3.04)	(7.45)	(9.15)	(2.04)	(0.09)	(1.82)	(10.81)
Fundamental variables										
AMI	0.00041***	0.00041***	0.00041***			0.00041***	0.00045***	0.00040***	0.00045***	
	(22.13)	(33.84)	(37.22)			(50.53)	(53.98)	(22.28)	(37.07)	
HR	0.00003***	0.00003***	0.00002***	0.00002**	0.00001	0.00002***	0.00002***	0.00002***	0.00003**	0.00003***
	(4.73)	(11.51)	(21.14)	(2.28)	(0.71)	(31.14)	(28.13)	(2.97)	(2.06)	(18.32)
Positive event variables										
D^{+}_{REGT}	0.008***	0.008***	0.008***	0.011***	0.009***	0.008***	0.008***	0.008***	0.010***	0.010***
	(32.10)	(27.94)	(32.87)	(9.24)	(47.06)	(38.55)	(34.52)	(5.61)	(5.31)	(52.98)
D^{+}_{MP}	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***	0.002	0.002	-0.00042	0.002***
	(18.31)	(5.94)	(8.84)	(2.94)	(28.15)	(52.85)	(1.26)	(0.96)	(-0.64)	(42.67)
D^{+}_{SE}	0.005***	0.005***	0.005***	0.006***	0.006***	0.005***	0.005***	0.005***	0.006***	0.008***
	(37.00)	(3.28)	(30.19)	(26.66)	(34.87)	(40.94)	(40.80)	(1.08)	(42.39)	(86.68)
Negative event variables										
D^{-}_{REGT}	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.034***	-0.034***
	(-47.73)	(-70.11)	(-62.88)	(-18.73)	(-93.96)	(-67.21)	(-88.97)	(-41.17)	(-76.10)	(-46.69)
D^{-}_{MP}	0.00021***	0.00025***	0.00028***	-0.00010	0.00006***	-0.00015***	0.00005	0.00019	-0.00026	-0.001***
	(3.31)	(15.68)	(17.76)	(-1.32)	(9.91)	(-12.11)	(1.06)	(0.009)	(-0.14)	(-24.01)
D^{-}_{SE}	-0.038***	-0.038***	-0.039***	-0.038***	-0.039***	-0.038***	-0.019***	-0.038***	-0.038***	-0.036***
	(-55.20)	(-54.87)	(-6.66)	(-17.63)	(-35.27)	(-64.58)	(-64.81)	(-29.99)	(-60.08)	(-30.14)
Uncertainty and financial markets variables										
Δ%Gold			0.00003***						0.00033***	0.00062***
			(5.72)						(4.80)	(22.30)
ln(GVIX)				0.051***					0.044***	0.042***
				(148.18)					(794.99)	(665.86)
$(\ln(GVIX))^2$				-0.009***					-0.008***	-0.007***
				(-60.26)					(-547.14)	(-303.78)
ln(EPU)					-0.001***				-0.001***	
					(-58.77)				(31.48)	
$(\ln(EPU))^2$					0.00013***				0.00012***	
					(41.05)				(50.58)	
Δ%SPG1200						-0.00027***			0.00001	-0.00009***
						(-23.95)			(0.11)	(7.80)
Δ%MSCI World							-0.00042***		-0.00018***	
							(-27.75)		(-1.65)	
Δ%MSCI EM								-0.00032***	0.00009	
								(-3.04)	(0.82)	
					Variance equation					
ω	-7.698***	-6.128***	-5.464***	-5.962***	-5.778***	-5.504***	-5.869***	-5.781***	-8.416***	-9.104***
	(-26.00)	(-44.62)	(-61.89)	(5.00)	(37.79)	(-63.44)	(-95.12)	(-6.89)	(-23.54)	(-126.46)
α_1	0.517***	0.507***	0.509***	0.511***	0.510***	0.512***	0.511***	0.508***	0.516***	0.520***
	(6.00)	(12.72)	(13.53)	(8.37)	(13.85)	(12.61)	(14.48)	(8.58)	(11.33)	(11.87)
α_2	0.736***	0.735***	0.752***	0.750***	0.749***	0.754***	0.760***	0.743***	0.728***	0.741***
	(5.71)	(14.49)	(14.63)	(8.46)	(16.35)	(12.85)	(16.09)	(7.77)	(14.09)	(17.25)
α_3	0.422***	0.397***	0.399***	0.404***	0.402***	0.400***	0.405***	0.397***	0.431***	0.451***
	(4.92)	(10.01)	(11.40)	(6.95)	(11.89)	(10.88)	(11.11)	(6.53)	(9.71)	(12.87)
β_1	-0.553**	-0.616***	-0.650***	-0.643***	-0.641***	-0.646***	-0.633***	-0.631***	-0.531***	-0.526***
	(-47.77)	(-20.28)	(44.98)	(-7.90)	(-41.52)	(-48.49)	(-61.89)	(-10.21)	(-7.60)	(-60.27)
β_2	0.537***	0.599***	0.613***	0.599***	0.602***	0.612***	0.600***	0.600***	0.516***	0.488***
	(37.51)	(28.45)	(49.73)	(5.25)	(38.97)	(52.13)	(57.71)	(14.88)	(10.91)	(48.75)
β_3	0.657***	0.727***	0.757***	0.743***	0.746***	0.754***	0.735***	0.731***	0.633***	0.622***
	(56.96)	(31.76)	(51.69)	(10.52)	(50.87)	(57.09)	(70.27)	(11.85)	(11.49)	(68.28)
γ_1	-0.003	-0.001	-0.001	-0.015	-0.014	0.001	0.001	0.004	-0.004	-0.014
	(-0.14)	(-0.19)	(-0.09)	(-0.51)	(-0.49)	(0.54)	(0.54)	(0.09)	(-0.13)	(-0.30)
γ_2	0.005	0.005	0.005	-0.012	-0.008	0.006	0.006	0.016	0.006	-0.007
	(0.18)	(0.17)	(0.11)	(-0.30)	(-0.18)	(0.53)	(0.91)	(0.14)	(0.15)	(-0.13)
γ_3	0.011	0.014	0.014	0.003	0.008	0.015	0.011	0.020	0.011	0.001
	(0.30)	(0.47)	(0.59)	(0.11)	(0.24)	(0.72)	(0.48)	(0.17)	(0.35)	(0.01)
Fundamental variables										
NOTX	0.314***	0.261***	0.249***	0.262***	0.258***	0.250***	0.272***	0.269***	0.346***	0.364***
	(28.44)	(16.84)	(35.95)	(15.09)	(33.43)	(41.89)	(43.95)	(6.53)	(14.39)	(60.39)
TVOL	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	
	(0.59)	(0.95)	(1.12)	(1.20)	(1.33)	(1.16)	(1.16)	(0.68)	(0.80)	
MREV	0.248***	0.180***	0.127***	0.154***	0.141***	0.130***	0.132***	0.123***	0.276***	0.307***
	(9.87)	(11.12)	(14.83)	(3.24)	(20.60)	(18.58)	(21.51)	(2.62)	(13.97)	(37.32)

Table 5 Cont.: EGARCH(3,3) model estimates including fundamental, event, news, uncertainty, and financial market variables

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
News variables										
NFRQ	0.029***								0.032***	0.035***
	(2.58)								(4.33)	(6.89)
D_{NEWS}		0.090*							0.019	
		(1.70)							(0.58)	
					Diagnostic tests					
LogL	5162.53	5157.42	5,156.43	5,152.19	5,149.78	5,156.76	5,155.49	5,156.39	5.167.86	5,160.74
ARCH(1)	0.10	0.02	0.01	0.03	0.01	0.01	0.08	0.01	0.09	0.12
	(0.76)	(0.90)	(0.91)	(0.85)	(0.91)	(0.91)	(0.78)	(0.91)	(0.77)	(0.72)
LB(15)	9.84	7.81	7.33	7.49	7.61	7.37	8.03	7.24	10.68	13.47
	(0.83)	(0.93)	(0.95)	(0.94)	(0.93)	(0.95)	(0.92)	(0.95)	(0.77)	(0.57)
JB	5,753***	5,927***	6,842***	6,641***	6,353***	6,777***	8,099***	6,568***	5,361.64***	4,868***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Skewness	-0.02	-0.11	-0.15	-0.05	-0.06	-0.15	-0.27	-0.14	-0.01	0.06
Kurtosis	10.21	7.31	10.86	7.74	7.57	10.82	11.54	7.69	9.96	6.63
Negative sign bias test	0.09	0.09	0.11	0.07	0.08	0.04	0.06	0.01	0.40	0.12
	(0.93)	(0.93)	(0.91)	(0.95)	(0.93)	(0.97)	(0.95)	(0.99)	(0.69)	(0.90)
Poistive sign bias test	1.12	1.21	1.03	1.21	1.07	1.18	1.22	1.07	0.82	1.14
	(0.26)	(0.23)	(0.30)	(0.23)	(0.29)	(0.24)	(0.22)	(0.29)	(0.41)	(0.25)
Joint effect test	1.28	1.51	1.10	1.64	1.17	1.41	1.50	1.17	1.09	1.43
	(0.73)	(0.68)	(0.78)	(0.65)	(0.76)	(0.70)	(0.68)	(0.76)	(0.78)	(0.70)

Notes: Sample from 16 March 2011 – 21 June 2018. ***, **, * indicator significance at 1%, 5% and 10% levels respectively. For the parameters t-values robust to heteroscedasticity are given in parentheses. For the residual tests prob-values are given in parentheses. LB(15) is the Ljung-Box Q-statistic for 15 lags. ARCH(1) is the LM-test for 1st order ARCH effects. JB ist the Jarque-Bera test for normality. The sign bias test examines the asymmetric impact of positive and negative shocks upon the conditional variance. The positive and negative size bias tests examine whether the magnitude of positive respectively negative shocks affects the conditional variance. The joint effect test examines the simultaneous presence of sign and size bias. Diagnostic tests are carried out on the standardized residuals. The models are estimated in R, using the package *rugarch* and the nonlinear solver algorithm *SOLNP*.

The opposite phenomenon can be observed in the performance of ln(EPU) and $(\ln(EPU))^2$. While ln(EPU) exerts a negative force on the Bitcoin's exchange rate, the impact of $(\ln(EPU))^2$ is positive. Differentiation of Bitcoin's return with respect to ln(EPU) shows that Bitcoin's negative relationship to the EPU becomes positive if the EPU assumes a value higher than about 83. Since the median of the EPU is around 85, this result suggests that while Bitcoin tends to move with the markets when the uncertainty of economic policy is low, a higher degree of uncertainty in economic policy will cause some investors to buy Bitcoin, pulling up the exchange rate and thus fulfilling its role as a safe haven against economic uncertainty. One possible explanation for the negative relationship between Bitcoin and the EPU in a context of low economic uncertainty could be that those investors who bought Bitcoin will sell it again when economic policy returns to normal. Overall the results regarding these two measures confirm the non-linear relationship between Bitcoin and global uncertainty. In fact, Bitcoin can serve as a hedge in times of tranquil financial markets but is not a safe haven in times of financial market distress. Its role as a safe haven is only fulfilled in times when economic policy becomes insecure.

Regarding the global financial markets variables in Model VI-VIII, their impact on the exchange rate of Bitcoin is consistently negative. Although the impact is comparably small, as the size of their parameter estimates of $\Delta\%$SPG1200, $\Delta\%$MSCI World, and $\Delta\%$MSCI EM suggest, the result indicates that Bitcoin can be used to hedge against stock market losses at a global level, which applies to both developed and developing countries. However, taking the previous results into consideration, Bitcoin's hedging ability is only likely when financial markets are rather calm.

Summarizing the results of Table 5, the findings stress the importance of news coverage in driving the volatility of Bitcoin and also provide some support of the Bitcoin's hedge capability. While the results suggest that Bitcoin can serve as a hedge against falling stock markets, it is also likely that it will move downwards with the markets if global financial volatility is higher than usual. Therefore, the characterisation of Bitcoin as a hedging instrument should be treated with caution. Although Bitcoin can serve as a safe haven against high economic policy uncertainties, this is not the case in times of distressed financial markets.

In Model IX, all variables enter into the estimation simultaneously. The results are mostly robust compared to previous models. However, Δ%Gold correlatively collides with Δ%MSCI EM, and, not surprisingly, Δ%MSCI World shows high correlation with Δ%SPG 1200 and Δ%MSCI EM. In the last model, the variables responsible for multicollinearity and the insignificant variable NOTX are removed, and the remaining variables perform robustly and evenly fall in line with expectations.

The performance of the non-explanatory variables is generally robust throughout the models. The ARCH effect is well captured by the parameters γ, and the GARCH effect suggested by the parameters β have almost diminished upon the entry of explanatory variables. In the last model, the half-life of volatility shocks have gone down from 99 days to 1 day, and the leverage parameters have become insignificant, pointing to the ability of the explanatory variables to capture the volatility persistence and the leverage effect. In comparison to the Model I without explanatory variable in Table 4, the skewness fell by 1 - (| 0.06 | / | -0.86 |) = 93%, the kurtosis by 1 - (6.63/13.48) = 51%, and the JB test statistic by 1 - (4,868/12,428) = 61% in the final model in Table 5. This result confirms that the use of explanatory variables has also significantly reduced the fat tail behaviour of standardised residuals, which eventually stresses the role of the variables used in this analysis in explaining Bitcoin's exchange rate dynamics.

Rounding up the analysis, the empirical findings contrast with those that find that the Bitcoin market is completely isolated from the world economy, as reported by Kristoufek (2013), Baek and Elbeck (2015), and Ciaian et al. (2016). The findings also contrast these of Vidal-Tomás and Ibañez (2018) which claim that Bitcoin is not affected by the international monetary policy. Moreover, the results disagree on the conclusions of Walther et al. (2018) which find Bitcoin cannot serve as a hedge against a stock market downturn. Regarding the non-linear relationship between Bitcoin and global uncertainties, the findings are at odds with these of Bouri et al. (2017b) and Bouri et al. (2018b) which find that Bitcoin act as a hedge against global financial uncertainty at higher quantiles.

Indeed, the findings support the findings of Walther et al. (2018) which states that Bitcoin tends to move downwards with the financial markets in times of market distress due to flight-to-quality. The findings also indicate Bitcoin's role as a safe haven against economic uncertainties, to some degree consistent with Demir et al. (2018) which find a positive relationship between Bitcoin and EPU at their lower and higher quantiles. Also, the findings are to some degree consistent with those of Corbet et al. (2017) which find significant evidence of Bitcoin's exchange rate dynamics being driven by international monetary policy announcements, albeit they focus on the volatility of Bitcoin rather than its level, as done in this study. However, as the estimated impact of monetary policy announcements is rather unpronounced, the results do not support the idea that the global expansionary monetary policy over the years has inflated the exchange rate of Bitcoin as it may have done on traditional asset prices. The findings of the role of news coverage in driving Bitcoin's volatility is somewhat consistent with those of Polasik et al. (2015), who find that Bitcoin's return is driven by newspaper sentiments. Moreover, the results fall more in line with those of Ciaian et al. (2016), Baek and Elbeck (2015), Koutmos (2018) which state that fundamentals and Bitcoin-related specific do have a significant impact on the exchange rate of Bitcoin. To the author's best knowledge, this is the first paper to examine the impact of regulation-related events on Bitcoin's exchange rate and provide some implications for policymakers and regulators regarding the sentiment of Bitcoin investors towards market regulation.

5 Conclusion

In this paper, we have examined the Bitcoin exchange rate and the associated volatility by using an EGARCH framework with a wide range of explanatory variables. The main findings of the paper can be summarised as follows. First, the results emphasise the role of fundamentals and Bitcoin-related specific events in the exchange rate formation of Bitcoin. Second, regulation-related events play a significant role in driving the exchange rate of Bitcoin. Third, results also stress the importance of news coverage in driving the volatility of Bitcoin. Fourth, Bitcoin may be a hedge against in times of tranquil markets but is likely to expose to flight-to-quality as global financial uncertainty increases, therefore not acting as a safe haven against stock market crashes. Fifth, Bitcoin's ability to provide a safe haven seems to be given in times of uncertain economic policy. Overall, the empirical findings of this paper suggest that the Bitcoin market is not entirely isolated from the world economy.

To some extent, the random walk behaviour of the Bitcoin's exchange rate return due to its near-zero level memory and its quick reaction to singular news events support the findings of Bartos et al. (2015) which state that the Bitcoin market follows the hypothesis of an efficient market in its weak form. However, the assumption of a weak-efficient market is contrasted with the existence of bubbles in the Bitcoin market which may question the rational expectation of the investors, as being a fundamental assumption of the hypothesis of efficient market. Although Bitcoin's volatility clustering behaviour has been sufficiently explained by fundamentals, much of the fat tail of Bitcoin's exchange rate is still unexplored, suggesting that more significant explanatory variables should be considered to increase the overall explanatory power of a GARCH-type model in future research. To explore further the link between Bitcoin and the world economy, multivariate GARCH-type models can be employed to extract the conditional time-varying correlations between Bitcoin and the global financial markets. The relationship between Bitcoin and monetary policy can also be further examined by analysing conditional time-varying correlations between Bitcoin and Wu-Xia or Krippner shadow short rates. Overall, these correlations may be low due to Bitcoin's current strong isolation from the world economy, but it would be interesting to see how they would evolve in the future.

As a payment system, Bitcoin is still immature. Understanding the exchange rate formation mechanism provides a basis for further economic discussion on the future development of Bitcoin. In its current form, Bitcoin is unable to compete with established payment systems due to its volatility and limited scale. From the author's point of view, a transformation of Bitcoin from an object of speculation to a stable online currency will be inevitably connected to a vast expansion of Bitcoin's supply. Whether Bitcoin will survive in the long term is uncertain but its underlying technology, the blockchain, could permanently change the financial system.

References

Al-Khazali, O., Elie, B., Roubaud, D., et al. (2018). The impact of positive and negative macroeconomic news surprises: Gold versus bitcoin. *Economics Bulletin*, 38(1):373–382.

Ali, R., Barrdear, J., Clews, R., and Southgate, J. (2014). The economics of digital currencies. *Bank of England Quarterly Bulletin*, 54(3): 276–286.

Allison, P. D. (2002). Missing data: Quantitative applications in the social sciences. *British Journal of Mathematical and Statistical Psychology*, 55(1): 193–196.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1): 31–56.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *Journal of International Economics*, 73(2): 251–277.

Ané, T. and Geman, H. (2000). Order flow, transaction clock, and normality of asset returns. *Journal of Finance*, 55(5): 2259–2284.

Aouadi, A., Arouri, M., and Teulon, F. (2013). Investor attention and stock market activity: Evidence from france. *Economic Modelling*, 35(C): 674–681.

Baek, C. and Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, 22(1): 30–34.

Baker, S. R., Bloom, N., and Davis, S. J. (2015). Measuring economic policy uncertainty. NBER Working Paper No. 21633, National Bureau of Economic Research.

Balcilar, M., Bouri, E., Gupta, R., and Roubaud, D. (2017). Can volume predict bitcoin returns and volatility? a quantiles-based approach. *Economic Modelling*, 64:74–81.

Balcilar, M., Gupta, R., and Segnon, M. (2016). The role of economic policy uncertainty in predicting U.S.

recessions: A mixed-frequency Markov-switching vector autoregressive approach. Discussion Paper No. 2016-14, Kiel Institute for the World Economy.

Bank, M., Larch, M., and Peter, G. (2011). Google search volume and its influence on liquidity and returns of german stocks. *Financial Markets and Portfolio Management*, 25(3): 239–264.

Bank of Canada (2014). Bank of Canada Review Spring 2014.

Bank of England (2015). One Bank Research Agenda. Discussion Paper February 2015.

Bariviera, A. F. (2017). The inefficiency of bitcoin revisited: A dynamic approach. *Economics Letters*, 161:1–4.

Bartos, J. et al. (2015). Does Bitcoin follow the hypothesis of efficient market? *International Journal of Economic Sciences*, 4(2): 10–23.

Baur, D. and Glover, K. (2016). The destruction of a safe haven asset? *Applied Finance Letters*, 1(1):8–15.

Baur, D. G. and Lucey, B. M. (2010). Is gold a hedge or a safe haven? an analysis of stocks, bonds and gold. *Financial Review*, 45(2):217–229.

Baur, D. G. and McDermott, T. K. (2010). Is gold a safe haven? international evidence. *Journal of Banking & Finance*, 34(8):1886–1898.

Berry, T. D. and Howe, K. M. (1994). Public information arrival. *Journal of Finance*, 49(4): 1331–1346.

Bitpay (2017). BitPays Bitcoin Transactions Reach an All-Time High. Retrieved from `https://www.ccn.com/bitpays-bitcoin-transactions-reach-time-high/`. Last accessed on 16 Jul 2018.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3): 623–685.

Blundell Wignall, A. (2014). The Bitcoin Question: Currency versus Trust-less Transfer Technology. Technical report, OECD Working Paper on Finance, Insurance and Private Pensions No. 37, OECD Publishing.

Böhme, R., Christin, N., Edelman, B., and Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives*, 29(2): 213–238.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3): 307–327.

Bouoiyour, J. and Selmi, R. (2015a). Bitcoin price: Is it really that new round of volatility can be on way? MPRA Paper No. 65580, University Library of Munich, Germany.

Bouoiyour, J. and Selmi, R. (2015b). What Does Bitcoin Look Like? *Annals of Economics and Finance*, 16(2): 449–492.

Bouoiyour, J., Selmi, R., et al. (2015). Greece withdraws from Euro and runs on Bitcoin; April Fools Prank or Serious Possibility? MPRA Paper No. 65317, University Library of Munich, Germany.

Bouri, E., Azzi, G., and Dyhrberg, A. H. (2017a). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics - The Open-Access, Open-Assessment E-Journal*, 11:1–16.

Bouri, E., Das, M., Gupta, R., and Roubaud, D. (2018a). Spillovers between bitcoin and other assets during bear and bull markets. Working Papers 201812, University of Pretoria, Department of Economics.

Bouri, E., Gupta, R., Lau, C. K. M., Roubaud, D., and Wang, S. (2018b). Bitcoin and global financial stress: A copula-based approach to dependence and causality in the quantiles. *The Quarterly Review of Economics and Finance*.

Bouri, E., Gupta, R., Tiwari, A. K., and Roubaud, D. (2017b). Does bitcoin hedge global uncertainty? evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23:87–95.

Brière, M., Oosterlinck, K., and Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, 16(6): 365–373.

Buchholz, M., Delaney, J., Warren, J., and Parker, J. (2012). Bits and Bets, Information, Price Volatility, and Demand for Bitcoin. *Economics*, 312.

Buuren, S. v. and Groothuis-Oudshoorn, K. (2010). mice: Multivariate imputation by chained equations in r. *Journal of statistical software*, pages 1–68.

Capie, F., Mills, T. C., and Wood, G. (2005). Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions and Money*, 15(4):343–352.

Caporale, G. M., Spagnolo, F., and Spagnolo, N. (2017). Macro news and commodity returns. *International Journal of Finance & Economics*, 22(1):68–80.

Cheah, E.-T. and Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, 130: 32–36.

Cheah, E.-T., Mishra, T., Parhi, M., and Zhang, Z. (2018). Long memory interdependency and inefficiency in bitcoin markets. *Economics Letters*, 167:18–25.

Choi, H. and Varian, H. (2012). Predicting the present with Google Trends. *Economic Record*, 88(S1): 2–9.

Ciaian, P., Rajcaniova, M., and Kancs, d. (2016). The economics of BitCoin price formation. *Applied Economics*, 48(19): 1799–1815.

Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. *Econometrica*, 41(1): 135–155.

Corbet, S., McHugh, G., and Meegan, A. (2017). The influence of central bank monetary policy announcements on cryptocurrency return volatility. *Investment Management and Financial Innovations*, 14(4):60–72.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., and Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165:28–34.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *Journal of Finance*, 66(5): 1461–1499.

Demir, E., Gozgor, G., Lau, C. K. M., and Vigne, S. A. (2018). Does economic policy uncertainty predict the bitcoin returns? an empirical investigation. *Finance Research Letters. Forthcoming*.

Ding, R. and Hou, W. (2015). Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions and Money*, 37(C): 12–26.

Doornik, J. A. and Ooms, M. (2008). Multimodality in GARCH regression models. *International Journal of Forecasting*, 24(3): 432–448.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters*, 16: 85–92.

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. is it the virtual gold? *Finance Research Letters*, 16:139–144.

Easley, D. and O'hara, M. (1992). Time and the process of security price adjustment. *Journal of Finance*, 47(2): 577–605.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4): 987–1007.

European Central Bank (2012). Virtual Currency Schemes.

Feng, W., Wang, Y., and Zhang, Z. (2017). Informed trading in the bitcoin market. *Finance Research Letters*.

Funke, M., Shu, C., Cheng, X., and Eraslan, S. (2015). Market Segmentation, Fundamentals or Contagion? Assessing Competing Explanations for CNH-CNY Pricing Differentials. *Journal of International Money and Finance*, 59(C): 245–262.

Gallant, A. R., Rossi, P. E., and Tauchen, G. (1992). Stock prices and volume. *Review of Financial Studies*, 5(2): 199–242.

Garcia, D. and Schweitzer, F. (2015). Social signals and algorithmic trading of bitcoin. *Royal Society Open Science*, 2(9).

Ghalanos, A. (2018). Introduction to the rugarch package.(version 1.4-0). Technical report.

Ghosh, D., Levin, E. J., Macmillan, P., and Wright, R. E. (2004). Gold as an inflation hedge? *Studies in Economics and Finance*, 22(1):1–25.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., and Siering, M. (2014). Bitcoin-Asset or Currency? Revealing Users' Hidden Intentions. *Revealing Users' Hidden Intentions (April 15, 2014). ECIS*.

Glouderman, L. (2014). Bitcoin's Uncertain Future in China. *USCC Economic Issue Brief*, (4).

Goldman Sachs (2014). All about Bitcoin. *Top of Mind*.

Gomez Gonzalez, J. E. and Parra Polania, J. A. (2014). Bitcoin: something seems to be 'fundamentally' wrong. Working Paper No. 819, Banco de la Republica.

Goodhart, C. A., Hall, S. G., Henry, S. B., and Pesaran, B. (1993). News effects in a high-frequency model of the sterling-dollar exchange rate. *Journal of Applied Econometrics*, 8(1): 1–13.

Gronwald, M. (2014). The Economics of Bitcoins-Market Characteristics and Price Jumps. CESifo Working Paper No. 5121, CESifo Group Munich.

Härdle, W. K. and Trimborn, S. (2015). CRIX or evaluating blockchain based currencies. Discussion Paper

SFB649DP2015-048, Humboldt University, Collaborative Research Center 649.

He, D., Habermeier, K. F., Leckow, R. B., Haksar, V., Almeida, Y., Kashima, M., Kyriakos-Saad, N., Oura, H., Saadi Sedik, T., Stetsenko, N., and Verdugo Yepes, C. (2016). Virtual Currencies and Beyond: Initial Considerations. IMF Staff Discussion Notes 16/3, International Monetary Fund.

Jones, C. M., Kaul, G., and Lipson, M. L. (1994). Transactions, volume, and volatility. *Review of Financial Studies*, 7(4): 631–651.

Jones, C. M. and Seguin, P. J. (1997). Transaction Costs and Price Volatility: Evidence from Commission Deregulation. *American Economic Review*, 87(4): 728–37.

Joy, M. (2011). Gold and the us dollar: Hedge or haven? *Finance Research Letters*, 8(3):120–131.

Karnizova, L. and Li, J. C. (2014). Economic policy uncertainty, financial markets and probability of U.S. recessions. *Economics Letters*, 125(2): 261–265.

Karpoff, J. M. (1987). The Relation between Price Changes and Trading Volume: A Survey. *Journal of Financial and Quantitative Analysis*, 22(01): 109–126.

Katsiampa, P. (2017). Volatility estimation for bitcoin: A comparison of garch models. *Economics Letters*, 158:3–6.

Khuntia, S. and Pattanayak, J. (2018). Adaptive market hypothesis and evolving predictability of bitcoin. *Economics Letters*, 167:26–28.

Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters*, 167:81–85.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific reports*, 3(3415).

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one*, 10(4): e0123923.

Little, R. J. and Rubin, D. B. (1989). The analysis of social science data with missing values. *Sociological Methods & Research*, 18(2-3): 292–326.

Lumsdaine, R. L. and Papell, D. H. (1997). Multiple trend breaks and the unit-root hypothesis. *Review of Economics and Statistics*, 79(2): 212–218.

Luther, W. J. and Olson, J. (2013). Bitcoin is memory. *Journal of Prices & Markets*, 3(3): 22–33.

MacDonell, A. (2014). Popping the Bitcoin bubble: An application of log-periodic power law modeling to digital currency. Working Paper, University of Notre Dame.

Mainelli, M. and Milne, A. (2016). The Impact and Potential of Blockchain on the Securities Transaction Lifecycle. SWIFT Institute Working Paper No. 2015-007, SWIFT Institute.

Mishkin, F. S. (2016). *The economics of money, banking, and financial markets*. Pearson education, Harlow, England, Eleventh global edition.

Mitchell, M. L. and Mulherin, J. H. (1994). The impact of public information on the stock market. *Journal of Finance*, 49(3): 923–950.

Mody, A. (2009). From Bear Stearns to Anglo Irish; How Eurozone Sovereign Spreads Related to Financial Sector Vulnerability. IMF Working Papers No. 09/108, International Monetary Fund.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. *Journal of Econometrics*, 80(2): 355–385.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., and Lightfoot, G. (2015). Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry. *International Journal of Electronic Commerce*, 20(1): 9–49.

Preis, T., Moat, H. S., and Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific reports*, 3(1684).

Roache, S. K. and Rossi, M. (2010). The effects of economic news on commodity prices. *The Quarterly Review of Economics and Finance*, 50(3):377–385.

Rubin, D. B. (1987). The calculation of posterior distributions by data augmentation: Comment: A noniterative sampling/importance resampling alternative to the data augmentation algorithm for creating a few imputations when fractions of missing information are modest: The sir algorithm. *Journal of the American Statistical Association*, 82(398): 543–546.

Scott, S. L. and Varian, H. R. (2015). Bayesian Variable Selection for Nowcasting Economic Time Series. In Goldfarb, A., Greenstein, S., and Tucker, C., editors, *Economic Analysis of the Digital Economy,* 119-135. University of Chicago Press.

Tauchen, G. E. and Pitts, M. (1983). The price variability-volume relationship on speculative markets. *Econometrica*, 51(2): 485–505.

Urquhart, A. (2016). The inefficiency of bitcoin. *Economics Letters*, 148:80–82.

Van Wijk, D. (2013). What can be expected from the BitCoin. Working Paper No. 345986, Erasmus Rotterdam Universiteit.

Vidal-Tomás, D. and Ibañez, A. (2018). Semi-strong efficiency of bitcoin. *Finance Research Letters*.

Walther, T., Klein, T., Thu, H. P., et al. (2018). Bitcoin is not the new gold-a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59:105–116.

Wang, L. and Liu, Y. (2015). Exploring Miner Evolution in Bitcoin Network. In *Passive and Active Measurement,* 290-302. Springer International Publishing.

Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. *Economics Letters*, 168:21–24.

Yermack, D. (2013). Is Bitcoin a real currency? An economic appraisal. NBER Working Paper No. 19747, National Bureau of Economic Research.

A Appendix

Table 6: Regulation-related events

Date	Effect	Country/Region	Event type
2013-06-29	Positive	US	The US Financial Crimes Enforcement Network (FinCEN) issued license to Mt. Gox the largest Bitcoin exchange at that time.
2013-11-18	Positive	US	The US Senate held a hearing on Bitcoin. The general consensus is summed up by the director of the FinCEN We want to operate in a way that does not hinder innovation.
2013-12-05	Negative	CN	The Peoples Bank Of China (PBOC) declared prohibiting financial institutions from handling Bitcoin transactions which led to a market panic.
2014-01-27	Negative	RU	The Russia Central Bank recommended that Russians and legal entities refrain from dealing with Bitcoins.
2014-03-26	Negative	US	The US Internal Revenue Service (IRS) declared that Bitcoin is a property subject to tax.
2014-04-07	Negative	EU	The European Banking Authority (EBA) recommended that national supervisory authorities discourage financial institutions from dealing visual currencies.
2014-07-03	Negative	JP	The Japanese government made a cabinet decision, prohibiting banks and securities companies from dealing Bitcoins.
2014-08-01	Positive	CN	The Financial Services and the Treasury of Hong Kong addressed that Hong Kong at present has no legislation directly regulating Bitcoin and other similar virtual currencies.
2014-10-04	Negative	CN	The People Bank of China's restrictions against Bitcoin finally pressured some Chinese banks to issue a deadline against several Bitcoin exchanges.
2015-03-06	Positive	US	New York State announced to release BitLicense application.
2015-09-22	Positive	US	New York State Department of Financial Services (NYDFS) approved the first BitLicense application to Circle Internet Financial.
2015-10-22	Positive	EU	European Court of Justice (ECJ), the highest court in Europe, ruled that Bitcoin is a payment method not a property; buying and selling Bitcoin are tax free.
2016-02-24	Positive	JP	Japanese legislators officially proposed virtual currencies to be payment methods.
2016-05-25	Positive	JP	Japan officially recognized Bitcoin and digital currencies as means of payment that is not a legal currency.
2016-11-29	Positive	RU	Russias Federal Tax Service stated that there is no legal prohibition of cryptocurrencies in a document.
2017-03-24	Positive	JP	The Japan's Financial Services Agency (FSA) announced that a new law will be implemented from April.1 2017, which categorizes Bitcoin as a legal payment method.
2017-03-31	Positive	JP	Japans Bitcoin Law Goes Into Effect Tomorrow.
2017-04-13	Negative	RU	Russian Central Banker: Bitcoins Legal Recognition Isnt Guaranteed.
2017-07-07	Negative	PL	Polish Regulators Warn Banks and Consumers on Cryptocurrency Risks.
2017-08-02	Positive	US	Options Exchange CBOE to Launch Cryptocurrency Derivatives in 2017.
2017-09-02	Negative	CN	Department of Business Administration of the PBOC stated four banning rules on the Bitcoin exchanges. Multiple Chinese Bitcoin exchanges delayed or paused Bitcoin withdraw services.
2017-09-12	Negative	US	Bitcoin OTC Service Suspends Trading Citing China Pressure.
2017-10-03	Negative	US	The US Securities and Exchange Commission (SEC) rejected the Winklevoss Bitcoin ETF application.
2017-12-06	Positive	MX	Mexican Senate passes crypto-related fintech law.
2017-12-11	Positive	EU	The European Central Bank (ECB)'s board member Coeure doesn't see macroeconomic risks from bitcoins
2017-12-13	Negative	KR	South Korea's government has called an emergency meeting to discuss the trading of cryptocurrencies.

Table 7: Regulation-related events - Continued

Date	Effect	Country/Region	Event type
2017-12-14	Negative	UK	UK regulator warns on Bitcoin risks.
2017-12-15	Negative	EU	European Union states and legislators agreed on stricter rules to prevent money laundering and terrorism financing on exchange platforms for Bitcoin.
2017-12-17	Negative	FR	France's finance minister calls for Bitcoin regulation debate at G20 summit.
2017-12-19	Negative	SG	Bitcoin warnings grow more strident as Singapore's central bank urges 'extreme caution'.
2017-12-20	Negative	EU	European Commission warns of risks for investors and consumers from Bitcoin.
2017-12-20	Positive	US	US banking regulator said on Wednesday that Bitcoin does not currently pose a threat to the country's banking system.
2017-12-21	Negative	KR	South Korea's central bank chief warns of 'irrational exuberance' in virtual coin frenzy
2017-12-25	Negative	IL	Israel regulator seeks to ban Bitcoin firms from stock exchange.
2017-12-28	Negative	KR	South Korea's government said on Thursday it will impose additional measures to regulate speculation in cryptocurrency trading within the country.
2017-12-29	Negative	IN	India's finance ministry likens cryptocurrencies to Ponzi scheme.
2018-01-04	Negative	US	US SEC warns bitcoin, cryptocurrency investors at risk.
2018-01-08	Negative	KR	South Korea inspects six banks over virtual currency services to clients.
2018-01-12	Negative	BR	Brazil regulator bans funds from buying cryptocurrencies.
2018-01-18	Negative	SI	Slovenia's central bank warns about virtual currency risks.
2018-01-19	Negative	US	US CFTC sues three virtual currency operators for fraud.
2018-01-23	Negative	KR	South Korea to ban cryptocurrency traders from using anonymous bank accounts.
2018-01-25	Negative	UK	UK's PM says that UK should examine criminal use of cryptocurrencies .
2018-01-31	Positive	KR	South Korea's finance minister says no plans to ban cryptocurrency exchanges.
2018-02-06	Negative		BIS chief says Bitcoin is a strong case for policy intervention.
2018-02-08	Negative	EU	ECB's Executive Board member Mersch says that virtual currencies need firm regulation.
2018-02-09	Positive	CN	Hong Kong's regulator to crackdown on cryptocurrency exchanges without a license or violate local securities laws.
2018-02-15	Negative	US	US regulator warns of cryptocurrency 'pump-and-dump' schemes.
2018-02-21	Positive	KR	South Korean regulator hopes to see South Korea normalise the virtual coin business in a self-regulatory environment.
2018-02-27	Positive	KR	South Korea struggles to regulate cryptocurrency market.
2018-03-02	Negative	UK	Bank of England's chief says that cryptocurrencies are failing as money.
2018-03-08	Negative	JP	Japan's FSA punishes seven cryptocurrency exchanges over regulatory lapses.
2018-03-09	Negative	CN	People Bank of China's governor says Bitcoin not a legitimate method of payment.
2018-03-20	Positive		G20 agrees to monitor cryptocurrencies but no action yet.
2018-04-11	Negative	AU	Australian money-laundering watchdog moves to regulate Bitcoin providers.
2018-05-14	Negative	EU	ECB board member Mersch wants banks to segregate any virtual currency business.
2018-06-17	Negative		BIS warns about the rise of virtual currencies.
2018-06-18	Positive	US	NYDFS approved the BitLicense application to the payments company Square

Table 8: International monetary policy events

Date	Effect	Central Bank	Event type
2011-04-07	Negative	ECB	The interest rate on the main refinancing operations is increased by 25 basis points to 1.25%.
2011-07-07	Negative	ECB	The interest rate on the main refinancing operations is increased by 25 basis points to 1.50%.
2011-09-21	Positive	Fed	Operation Twist.
2011-10-06	Positive	ECB	New covered bond purchase programme (CBPP2).
2011-10-06	Positive	BoE	Quantitative easing boosted by £75bn by Bank of England.
2011-10-27	Positive	BoJ	Enhancement of Monetary Easing.
2011-11-03	Positive	ECB	The interest rate on the main refinancing operations is dcreased by 25 basis points to 1.25%.
2011-12-08	Positive	ECB	Measures to support bank lending and money market activity.
2012-02-14	Positive	BoJ	Enhancement of Monetary Easing.
2012-04-27	Positive	BoJ	Enhancement of Monetary Easing.
2012-07-05	Positive	ECB	The interest rate on the main refinancing operations is decreased by 25 basis points to 0.75%.
2012-08-02	Positive	ECB	Outright Monetary Transactions.
2012-09-13	Positive	Fed	Quantitative Easing 3.
2012-09-19	Positive	BoJ	Enhancement of Monetary Easing.
2012-10-30	Positive	BoJ	Enhancement of Monetary Easing.
2012-12-20	Positive	BoJ	Enhancement of Monetary Easing.
2013-04-04	Positive	BoJ	Introduction of the Quantitative and Qualitative Monetary Easing.
2013-05-02	Positive	ECB	The interest rate on the main refinancing operations is decreased by 25 basis points to 0.50%.
2013-11-07	Positive	ECB	The interest rate on the main refinancing operations is decreased by 25 basis points to 0.25%.
2013-12-18	Negative	Fed	Fed reduces the pace of Quantitative Easing 3.
2014-06-05	Positive	ECB	Monetary policy measures to enhance the functioning of the monetary policy transmission mechanism.
2014-06-05	Positive	ECB	The interest rate on the main refinancing operations is decreased by 10 basis points to 0.15%.
2014-08-22	Positive	ECB	Draghi strongly hints at start of a QE program in the euro area.
2014-09-04	Positive	ECB	New covered bond purchase programme (CBPP3).
2014-09-04	Positive	ECB	The interest rate on the main refinancing operations is decreased by 10 basis points to 0.05%.
2014-10-29	Negative	Fed	Fed concludes QE3 programme.
2014-10-31	Positive	BoJ	Expansion of the Quantitative and Qualitative Monetary Easing.
2015-01-22	Positive	ECB	Announcement of Expanded Asset Purchase Programme (APP).
2015-09-03	Positive	ECB	Draghi announces increase in APP purchase limit.
2015-12-03	Negative	ECB	The interest rate on the main refinancing operations and the interest rate on the margginal lending facility remain unchanged at 0.05% and 0.30% respectively.
2015-12-16	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 0.25%-0.50%.
2015-12-18	Positive	BoJ	Enhancement of Monetary Easing.
2016-01-29	Positive	BoJ	QQE with a Negative Interest Rate.
2016-03-10	Positive	ECB	The interest rate on the main refinancing operations is decreased by 5 basis points to 0.00% and the pace of APP is to be increased by adding Corporate Sector Purchase Programme to the APP.
2016-07-29	Positive	BoJ	Enhancement of Monetary Easing.
2016-08-04	Positive	BoE	Bank of England cuts Bank Rate to 0.25% and introduces a package of measures designed to provide additional monetary stimulus.
2016-12-08	Negative	ECB	ECB announces tapering of the APP.
2016-12-14	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 0.50%-0.75%.
2017-03-15	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 0.75%-1.00%.
2017-06-14	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 1.00%-1.25%.
2017-10-26	Negative	ECB	ECB announces further tapering of the APP.
2017-11-02	Negative	BoE	Bank of England increases Bank Rate to 0.50%.
2017-12-13	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 1.25%-1.50%.
2018-03-21	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 1.50%-1.75%.
2018-06-13	Negative	Fed	Fed increases its key interest rate, the Federal Funds Rate: 1.75%-2.00%.
2018-06-14	Negative	ECB	ECB announces end of the APP.

Table 9: Bitcoin-related specific events

Date	Event	Type	Country	Event
19.12.2011	Market	Positive	US	The Good Wife announced to air a Bitcoin-themed TV episode Bitcoin for Dummies, after which investors bet big on the show and drive prices to new highs.
01.03.2012	Hacking	Negative	US	Linode, an American privately owned virtual private server provider company, was Hacked. Over 46,000 BTC was stolen.
17.08.2012	Crime	Negative	US	Bitcoins Savings & Trust, halted payments, which turned out to be a Ponzi scheme.
05.09.2012	Hacking	Negative	US	Bitfloor, which was the fourth largest exchange dealing in US dollars, announced to be hacked. 24,000 BTC was stolen.
12.03.2013	Technologie	Negative		Bitcoin 0.8 caused a feather hard fork of Bitcoin.
14.05.2013	Investigation	Negative	US	The US Homeland Security Investigations (DHS) seized $2,915,507.40 from an account owned by a Mt. Gox subsidiary, with the warrant.
02.10.2013	Investigation	Negative	US	The US FBI seized around 26,000 BTC from Silk Road, an online black market, during the arrest of its owner Ross William Ulbricht.
23.10.2013	Hacking	Negative	AU	Inputs.io, an Australian Bitcoin wallet provider, was hacked. 4100 Bitcoins (worth over a million USD) was stolen.
18.12.2013	Market	Negative	CN	Chinas biggest Bitcoin exchange at that time, BTCChina, announced to stop accepting deposits in RMB.
07.02.2014	Hacking	Negative		Mt. Gox, Bitstamp, and BTC-e all experienced a stoppage of trading due to massive DDoS attacks.
24.02.2014	Hacking	Negative	JP	Mt. Gox Closed. An alleged leaked internal document showed that over 744,000 BTC were lost by the company.
18.07.2014	Market	Positive	US	Dell announced to accept Bitcoin.
11.12.2014	Market	Positive	US	Microsoft announced to accept Bitcoin.
04.01.2015	Hacking	Negative	LU	Bitstamps operational hot wallets were hacked, and 18,866 BTC was stolen (roughly $5.2 million).
26.01.2015	Market	Positive	US	Coinbase Launched an US Licensed exchange.
14.02.2015	Hacking	Negative	CN	BTER, a Chinese top ranking Bitcoin exchange, was hacked. 7170 BTC (roughly $2.1million) was stolen.
01.08.2015	Investigation	Negative	JP	Mark Karpeles, the CEO of the failed Bitcoin exchange Mt. Gox, was arrested in Japan on charges of fraud and embezzlement in relation to the collapse of Mt. Gox.
15.08.2015	Technologie	Negative		Bitcoin XT Fork Released and caused market fear.
31.10.2015	Market	Positive	UK	Bitcoin featured on the front page of the magazine The Economist.
14.01.2016	Market	Negative	CH	Mike Hearn, who had been heavily involved in the Bitcoin community since the beginning of Bitcoin, announced to quit Bitcoin.
27.04.2016	Market	Positive	US	Steam, a popular gaming platform, announced to accept Bitcoin.
02.08.2016	Hacking	Negative	CN	Bitfinex was hacked, announcing that 119,756 BTC (around 72 million) was stolen.
11.01.2017	Investigation	Negative	CN	Chinese authorities announced plans to investigate Bitcoin exchanges.
02.08.2017	Markt	Positive	US	US Options Exchange CBOE to Launch Cryptocurrency Derivatives in 2017.
13.11.2017	Markt	Positive	US	US CME CEO: Bitcoin Futures Could Begin Trading As Soon As December.
01.12.2017	Markt	Positive	US	US CME, CBOE to Begin Bitcoin Futures Trading.
04.12.2017	Markt	Positive	US	US CBOE to Begin Bitcoin Futures Trading December 10.
07.12.2017	Hacking	Negative	SK	Hackers steal $64 million from cryptocurrency firm NiceHash
19.12.2017	Hacking	Negative	KR	South Korean cryptocurrency exchange to file for bankruptcy after hacking
21.12.2017	Markt	Positive	US	Goldman Sachs Is Setting Up A Trading Bitcoin Desk.
18.01.2018	Market	Positive	US	NYSE-parent ICE to launch cryptocurrency data feed.
27.01.2018	Hacking	Negative	JP	Coincheck cryptocurrency exchange hacked, losing $530 million.
31.01.2018	Market	Positive	JP	Japan's Line to launch cryptocurrency exchange amid hacking fears.
05.02.2018	Market	Negative	US/UK	Banks in Britain and U.S. ban Bitcoin buying with credit cards
26.02.2018	Market	Positive	US	Goldman-backed startup Circle buys major crypto exchange Poloniex
12.03.2018	Market	Positive		Thomson Reuters launches bitcoin sentiment gauge.
14.03.2018	Market	Negative		Google bans cryptocurrency advertising.
26.03.2018	Market	Negative		Twitter to ban cryptocurrency advertising.
06.04.2018	Market	Negative	KR	South Korean cryptocurrency executives detained over alleged embezzlement.
25.04.2018	Market	Positive	US	Nasdaq CEO says Nasdaq is open to cryptocurrency exchange in future.
15.05.2018	Market	Positive	US	Internet entrepreneurs Winklevoss' Bitcoin exchange wins NY approval to expand.
20.06.2018	Hacking	Negative	KR	South Korea's Bithumb loses $32 million in digital money heist.