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Semi-strong efficiency of Bitcoin

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ABSTRACT

This research examines the semi-strong efficiency of Bitcoin in the Bitstamp and Mt.Gox markets, showing how the digital currency responds to monetary policy and Bitcoin events. On the one hand, we observe that Bitcoin has become more efficient over time in relation to its own events. On the other hand, Bitcoin is not affected by monetary policy news, highlighting the absence of any kind of control on Bitcoin. These findings are relevant for investors and policymakers since Bitcoin is a financial asset without any connection to the measures of central banks.

1. Introduction

Bitcoin has become one of the most popular and volatile assets in the market in only nine years since it went online in 2009. Despite its remarkable speculative component (Baek and Elbeck, 2015) and with a fundamental value equal to zero (Cheah and Fry, 2015), this cryptocurrency has attracted the attention of many companies and academics from different fields. In particular, research on Bitcoin was first based on computational aspects, given its innovative technology (Swan, 2015). However, the number of publications approaching the topic from an economic perspective has increased in order to gain some insight into the features of Bitcoin. On the one hand, many works have been carried out relating Bitcoin and information queries through Google and Wikipedia, showing the existence of a bidirectional causal relationship between the Bitcoin price and searched queries (Kristoufek, 2013), although the effect on Bitcoin seems to be only relevant in the short run (Ciaian et al., 2016). Regarding transaction costs, Bitcoin is characterised by a cost advantage compared to other retail foreign exchange markets as a consequence of its own infrastructure (Kim, 2017). In relation to price features, Bitcoin is quite similar to other financial markets due to the existence of price clustering (Urquhart, 2017). Moreover, an analysis of 224 cryptocurrencies (Phillip et al., 2017) also shows that this technology is characterised by long memory, leverage, stochastic volatility and heavy-tailedness. In terms of interdependency among cryptocurrencies, Ciaian et al. (2017) contend that Bitcoin and 16 altcoins are interdependent in the short-run, but not in the long-run given the importance of macro variables. With regard to management portfolio issues, some authors (Dyhrberg, 2016a; Dyhrberg, 2016b; Bouri et al., 2017a; Bouri et al., 2017b) state that Bitcoin can be considered as an attractive diversifier. Nevertheless, Cheah and Fry (2015), Baek and Elbeck (2015) and Baur et al. (2017) show that this digital currency should only be used as a speculative asset.

On the other hand, and related to weak market efficiency, Urquhart (2016) was the first author to analyse this form of efficiency in the Bitcoin market, obtaining informational inefficiency regardless of the test. Nadarajah and Chu (2017) review this feature by using power transformations of daily returns, whose outcome underlines the weak efficiency of Bitcoin. Bariviera (2017) demonstrates from a dynamic approach, based on the Hurst exponent, that Bitcoin is inefficient, from 2011 to 2014, and it is characterized by white noise the rest of the period until 2017. With a battery of long-range dependence estimators and allowing for time variation, Tiwari et al. (2017) review informational efficiency from 18 July 2010 to 16 June 2017, whose findings show the efficiency of Bitcoin

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with the exceptions of April-August in 2013 and August-November in 2016. In this line, Jiang et al. (2017) examine time-varying long memory with a new efficiency index, affirming the presence of long memory in the Bitcoin market.

The number of articles that have been produced in relation to the Efficient Market Hypothesis is not surprising given that it is one of the main assumptions in finance. The main consequence of the seminal work written by Fama (1965) is simple and noticeable: stock prices include all new information, and as a result, investors cannot earn abnormal returns. According to the Efficient Market theory, we can consider three different forms of efficiency: weak efficiency (future returns cannot be predicted based on past information since current prices include all past stock prices), semi-strong efficiency (public financial information is included in stock prices) and strong efficiency (prices reflect not only public information but also insider information).

As can be observed, most of the literature has been produced in relation to weak efficiency without a conclusive result. Given this fact, and considering the absence of studies focused on semi-strong efficiency, we contribute to the literature by analysing this form of efficiency with an event study in order to shed more light on Bitcoin's features. In particular, we study how returns behave because of Bitcoin and monetary policy events, thus we can examine if Bitcoin only responds to its own news or if central banks are able to affect Bitcoin's price.

2. Data and methodology

In order to evaluate the semi-strong efficiency hypothesis, we have used the methodology of the event study. This methodology allows us to observe the market response according to each event, quantifying the effect on Bitcoin and determining its significance.

The data that has been used for this study is sourced from the Bitstamp and Mt.Gox markets from 13 September 2011 to 17 December 2017, and from 13 September 2011 to 25 February 2014, respectively.[1] Despite the fact that Mt.Gox went into bankruptcy, this market is considered for the current analysis since it encompassed around 70% of all transactions in 2013. Therefore, the absence of this market could give rise to inexact results due to the lack of information in the Bitstamp market from 2011 to 2014.

We use daily returns calculated as the fraction of the natural logs of prices at time t and $t-1$, $r_{i,t} = \log(P_t/P_{t-1})$. Table 1 shows the descriptive statistics of both markets in which it is possible to observe that Mt.Gox is more volatile than Bitstamp given that there has been a decrease in volatility in recent years.

With regard to the events on Bitcoin, Feng et al. (2017) created a novel indicator to evaluate informed trading on Bitcoin prior to large events. We have used the same events, from 2011 to March 2017, in order to create a consistent database of events that can be used by different authors, adding eight events until 17 December 2017.[2] We have 50 events: 28 negative events and 22 positive events. In relation to monetary policy events, we have collected the main open market operations of each central bank, namely: Federal Reserve System (FED), European Central Bank (ECB), Bank of Japan and Bank of England. Moreover, we have considered those events relevant for the international economy, such as Brexit or bailout programmes in the European Union.[3] As a result, there are 39 events: 27 positive events and 9 negative events.[4] These events have been classified according to the point of view of investors in stock markets. In particular, expansionary policies (lowering the benchmark federal funds rate or bond purchase programmes) have been considered as positive events, while contractionary policies, (raising the benchmark federal funds rate or the end of quantitative easing programmes) are negative events. As special cases, macroeconomic adjustment programmes in the European Union have been considered as positive events while the United Kingdom European Union membership referendum is a negative event.

On the other hand, Katsiampa (2017) has evaluated the goodness-of-fit to Bitcoin price volatility comparing several GARCH-type models, whose outcome highlights the proper performance of the AR(1)-CGARCH(1,1) model. Given this recent research, we model the dynamic behaviour of Bitcoin returns with the AR-CGARCH model along with the corresponding events as exogenous variables, resulting in the following baseline model:

$$r_t = c + \beta_1 r_{t-1} + \beta_2 ne_t + \beta_3 pe_t + u_t; \quad u_t = h_t z_t, \quad z_t \sim \text{i.i.d}(0,1)$$
$$\begin{cases} h_t^2 = q_t + \alpha(u_{t-1}^2 - q_{t-1}) + \gamma(u_{t-1}^2 - q_{t-1})d_{t-1} + \phi(h_{t-1}^2 - q_{t-1}) \\ q_t = \omega + \rho(q_{t-1} - \omega) + \theta(u_{t-1}^2 - h_{t-1}^2) \end{cases} \tag{1}$$

where r_t denotes the return on day t, ne_t denotes the negative events while pe_t is used for positive events on day t, u_t denotes the error term, z_t is a white noise process and h_t^2 is the conditional variance given by the CGARCH model.[5] We examine the effect of each event on Bitcoin returns by analysing the abnormal return on the same day of the event (AR_0), and the cumulative abnormal return with a 1-day window ($CAR_{(-1,1)}$).[6] More specifically, β_2 denotes the $AR_0/CAR_{(-1,1)}$ for negative events, while β_3 denotes the $AR_0/CAR_{(-1,1)}$ for positive events. In addition to this model, we use the AR-CGARCH-M model, adding the standard deviation of residuals $\sigma(u_t)$, with its corresponding coefficient (β_4), in the r_t equation, given its significance in each regression. We show that these models are suitable for

[1] The database can be obtained by any author via Quandl with the following codes: BCHARTS/BITSTAMPUSD (Bitstamp) and BCHARTS/MTGOXCAD (Mt.Gox).

[2] The 8 events have been sourced from coindesk.com, and the title of the news is added in the Appendix.

[3] The source of the events that have been used for this study can be found as supplementary material.

[4] There are three positive events that occur on the same day, so we have 36 positive events on different days.

[5] In regard to the conditional variance, q_t denotes the time varying long-run volatility, d is the dummy variable that denotes the existence of negative shocks, while γ denotes the transitory leverage effects.

[6] Using AR_0, ne_t and pe_t equal to 1 on the day of the event t and 0 for the rest of the days, while using $CAR_{(-1,1)}$, ne_t and pe_t equal to 1/3 on days $t-1$, t and $t+1$ and 0 for the rest of the days. It has not been possible to use more than 1-day window given the overlapping of events.

Table 1
Descriptive statistics.

	N	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Bitstamp	2287	0.0035	0.0024	0.3380	−0.5563	0.0457	−1.4636	26.7352
Mt. Gox	896	0.0034	0.0047	0.5756	−0.6191	0.0681	−1.4465	25.2769

Table 2
Pre- and post-estimation tests.

	Model	Test	Bitstamp	Mt.Gox	Test	Bitstamp	Mt.Gox
Pre-estimation tests		ARCH(5)	5.8852***	96.465***	$Q^2(10)$	627.46***	534.71***
Post-estimation tests	AR-CGARCH	ARCH(5)	0.137	0.1031	$Q^2(10)$	1.649	1.634
Post-estimation tests	AR-CGARCH-M	ARCH(5)	0.135	0.203	$Q^2(10)$	1.539	2.083

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

Table 3
AR-CGARCH model: AR_0 & $CAR_{(-1,1)}$ estimations and p-values.

	Bitcoin events				Monetary policy events			
	Bitstamp		Mt.Gox		Bitstamp		Mt.Gox	
Variable	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$
r_{t-1}, (β_1)	0.1639***	0.1586***	0.2197***	0.2214***	0.1649***	0.1642***	0.2037***	0.2070***
ne_t, (β_2)	−0.0336***	−0.0388***	−0.0589***	−0.0658***	−0.0047	−0.0042	−0.2281***	−0.2376***
pe_t, (β_3)	0.0051***	0.0091	0.0079	−0.0003	0.0027	−0.0021	0.0046	0.0126

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

Bitcoin returns reporting the same pre- and post-estimation tests that have been used by Katsiampa (2017) in Table 2. Both models are appropriate given that heteroskedasticity and autocorrelation tests, ARCH and Ljung-Box Q^2 tests, cannot be rejected.

Finally, given the baseline model, Eq. (1), we show the robustness of our results by analysing two particular cases: in the first case, Eq. (2), we control for the effect of each event on the time varying long-run volatility, q_t, and in the second case, Eq. (3), we control for the effect of each event on the transitory component, $h_t^2 - q_t$.[7]

$$q_t = \omega + \rho(q_{t-1} - \omega) + \theta(u_{t-1}^2 - h_{t-1}^2) + \beta_5 ne_t + \beta_6 pe_t \quad (2)$$

$$h_t^2 - q_t = \alpha(u_{t-1}^2 - q_{t-1}) + \gamma(u_{t-1}^2 - q_{t-1})d_{t-1} + \phi(h_{t-1}^2 - q_{t-1}) + \beta_7 ne_t + \beta_8 pe_t \quad (3)$$

3. Empirical results

We show the main outcome of this study with Tables 3 and 4. The former summarizes the results for the baseline model, Eq. (1), while the latter includes the AR-CGARCH-M model with similar coefficients. First, it is possible to observe, in both tables, that r_{t-1} is always significant at the 1% significance level. This fact represents an initial sign of weak inefficiency, in the same line as Urquhart (2016) or Nadarajah and Chu (2017), obtaining the same result for the autoregressive process of order 1, like Katsiampa (2017). In relation to Bitcoin news, the coefficients for the negative events are always negative and significant at the 1% level, demonstrating that Bitcoin returns are responding quickly to negative situations, both on the same day of the event, AR_0, and in a time window of (-1,1), $CAR_{(-1,1)}$. With regard to positive events, the coefficients are only significant in the case of the Bitstamp market (AR_0), although when including the deviation of residuals, with the AR-CGARCH-M model, it is possible to observe significant coefficients for Bitstamp in both cases, AR_0 and $CAR_{(-1,1)}$. While negative events are significant regardless of the market (Bitstamp or Mt.Gox), positive events are only significant for Bitstamp. This aspect seems to be connected with the increase in popularity of Bitcoin, given that Mt.Gox went into bankruptcy in 2014. Moreover, we cannot connect the bubble around 2013/2014 with positive news given that this kind of news is not significant for the Mt.Gox market (Corbet et al., 2017b). Therefore, Bitcoin has become more efficient over time since investors are responding more quickly to positive news, which can be related to its extraordinary performance during 2016–2017.

[7] We introduce 2 variables in order to control for the effect of the events on the volatility for AR_0 estimation: one variable for negative events and another variable for positive events. These variables are equal to 1 on day t, and 0 otherwise. On the other hand, in the case of $CAR_{(-1,1)}$ estimation, we introduce 6 variables: three variables for positive events and three variables for negative events. These variables are equal to 1 on days $t-1$, t, and $t+1$, respectively, and 0 otherwise. More specifically, each variable represents each day: $t-1$, t, and $t+1$.

Table 4
AR-CGARCH-M model: AR_0 & $CAR_{(-1,1)}$ estimations and p-values.

	Bitcoin events				Monetary policy events			
	Bitstamp		Mt.Gox		Bitstamp		Mt.Gox	
Variable	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$
r_{t-1}, (β_1)	0.170***	0.165***	0.220***	0.224***	0.172***	0.173***	0.210***	0.215***
ne_t, (β_2)	−0.034***	−0.038***	−0.060***	−0.072***	−0.004	−0.003	−0.235***	−0.261***
pe_t, (β_3)	0.005*	0.010*	0.005	−0.003	0.002	−0.002	0.005	0.012
$\sigma(u_t)$, (β_4)	0.094***	0.104***	0.126***	0.137***	0.077*	0.076**	0.111***	0.121***

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

Table 5
AR-CGARCH model: AR_0 & $CAR_{(-1,1)}$ estimations and p-values, after controlling for the effect of each event on the time varying long-run volatility.

	Bitcoin events				Monetary policy events			
	Bitstamp		Mt.Gox		Bitstamp		Mt.Gox	
Variable	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$
r_{t-1}, (β_1)	0.165***	0.170***	0.220***	0.219***	0.165***	0.167***	0.207***	0.241***
ne_t, (β_2)	−0.033***	−0.021**	−0.044***	−0.030	−0.008	0.001	−0.228**	0.364
pe_t, (β_3)	0.005	0.009*	0.008	0.013	0.001	−0.001	0.006	0.006
ne_t, (β_5)	0.0008***	0.0003	0.2253***	0.0005	0.1594***	−0.0002	0.0053	0.0297
pe_t, (β_6)	0.0001	0	0.0016	0.0034	0.0001	0	0	−0.0001

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

Table 6
AR-CGARCH-M model: AR_0 & $CAR_{(-1,1)}$ estimations and p-values, after controlling for the effect of each event on the time varying long-run volatility.

	Bitcoin events				Monetary policy events			
	Bitstamp		Mt.Gox		Bitstamp		Mt.Gox	
Variable	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$
r_{t-1}, (β_1)	0.1754***	0.1652***	0.2233***	0.2173***	0.1697***	0.1722***	0.2125***	0.2328***
ne_t, (β_2)	−0.0348***	−0.0316***	−0.0474***	−0.0468**	−0.0034	−0.0090	−0.239**	0.157
pe_t, (β_3)	0.0051	0.0088	−0.0002	−0.0094	−0.0001	0.0018	0.0053	0.0067
$\sigma(u_t)$, (β_4)	0.0883***	0.0911***	0.1172**	0.1246***	0.0769***	0.0714*	0.1148**	0.1172**
ne_t, (β_5)	0.0009***	0.0019***	0.0017	0.0022	−0.0001	0	0.0057	0.0380
pe_t, (β_6)	0.0001	0	0.0062***	0.0048	−0.0001*	0	0	0

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

In contrast, if we focus on monetary policy events, the Bitcoin market is clearly inefficient. The coefficients are not significant, either for negative or positive events, with the exception of the Mt.Gox market. In this case, negative events are significant, but this result stems from the absence of events since there is only one negative event from 2011 to 2014, thus we should only focus on positive events, which are also not significant. Given this outcome, we can contend that Bitcoin is not responding to international monetary policy, although it does respond to Bitcoin news. In other words, the digital currency is behaving as a consequence of particular news that is only based on Bitcoin without being affected by the policies of central banks.[8] Although this aspect is not surprising, it is interesting to underline that central banks are not able to control the Bitcoin market, unlike the rest of the stock exchanges (Brenner et al., 2009; Pennings et al., 2015). It is possible that this outcome will change in the future, in favour of efficiency, if Bitcoin becomes a widespread means of payment or if investors increasingly use the digital currency as a possible diversifier for portfolio management issues. In fact, this statement is supported by Corbet et al. (2017a) who contend that crypto-currencies become more sensitive to currency monetary policy events as they become larger. On the whole, these results can be related to the spillover literature since Corbet et al. (2017c) also observe that digital currencies (Bitcoin, Lite and Ripple) respond to regulatory changes and technological failures, without any connectedness between cryptocurrencies and other financial markets.

In order to show the robustness of our results, we include the two particular cases of the baseline model. Tables 5 and 6 show the

[8] Although most positive monetary policy events occur in 2012 through 2015 and most negative events thereafter, this fact is not affecting the outcome given that monetary policy events are not significant, regardless of being positive or negative.

Table 7
AR-CGARCH model: AR_0 & $CAR_{(-1,1)}$ estimations and p-values, after controlling for the effect of each event on the transitory component.

	Bitcoin events				Monetary policy events			
	Bitstamp		Mt.Gox		Bitstamp		Mt.Gox	
Variable	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$
r_{t-1}, (β_1)	0.1653***	0.1705***	0.2196***	0.2162***	0.1690***	0.1884***	0.2072***	0.2153***
ne_t, (β_2)	−0.0361***	−0.0219**	−0.0364**	−0.0083	−0.0054	0.0005	−0.2277*	−0.2288
pe_t, (β_3)	0.0053	0.0084	0.0078	−0.0004	0.0029	−0.0040	0.0051	0.0146
ne_t, (β_7)	0.0009***	0.0034**	0.0034	0.0037	−0.0001	0.0002	0.0122	0.0224
pe_t, (β_8)	0	0	0.0011	0.0009	0.0002	−0.0002	0.0010	0.0011

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

Table 8
AR-CGARCH-M model: AR_0 & $CAR_{(-1,1)}$ estimations and p-values, after controlling for the effect of each event on the transitory component.

	Bitcoin events				Monetary policy events			
	Bitstamp		Mt.Gox		Bitstamp		Mt.Gox	
Variable	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$	AR_0	$CAR_{(-1,1)}$
r_{t-1}, (β_1)	0.170***	0.167***	0.219***	0.215***	0.176***	0.194***	0.214***	0.218***
ne_t, (β_2)	−0.037***	−0.026***	−0.044***	−0.019	−0.010*	0.001	−0.239**	−0.219
pe_t, (β_3)	0.005*	0.011*	0.004	−0.005	0.002	0.013	0.002	0.005
$\sigma(u_t)$, (β_4)	0.096***	0.099***	0.118**	0.123**	0.097***	0.059	0.106**	0.105**
ne_t, (β_7)	0.0009***	0.0010***	0.0031***	0.0035	−0.0001***	0.0012**	0.0092	0.0266
pe_t, (β_8)	0	0	0.0010	0.0010	−0.0001	−0.0007***	0.0013**	0.0007

***significance at the 1% level. **significance at the 5% level. *significance at the 10% level.

coefficients for the return regression, after controlling for the effect of the events on the time varying long-run volatility, q_t. Tables 7 and 8 show the coefficients for the return regression, after controlling for the effect of the events on the transitory component, $h_t^2 - q_t$. In relation to the coefficients of the return equation, we always observe that they are significant in the case of negative events, with the exception of the Mt.Gox market ($CAR_{(-1,1)}$), while positive events are generally not significant. However, in the case of the Bitstamp market, it is possible to observe a certain degree of efficiency for the positive events, compared to the Mt.Gox market. In other words, we observe again that the Bitstamp market is more efficient than the Mt.Gox market. In terms of Bitcoin news, we obtain an outcome in line with Feng et al. (2017), who observe abnormal patterns of large trades before negative events in the Bitstamp exchange and state that "the magnitude and influence of the negative events are evidently higher than the positive ones". The variables that have been included in the volatility component support this statement since the volatility on days with negative events is significant, while it is not significant with positive events in the Bitstamp market.[9]

Moving on to monetary policy events, the coefficients β_2 and β_3 are not significant, underlining the absence of an effect of positive and negative news on Bitcoin returns. We can contend that the Bitcoin market is clearly inefficient, from the point of view of monetary policy events, while it is becoming more efficient in relation to its own events, as a result of the increased attention of investors. However, given that it is not possible to observe a clear response in relation to positive news, compared to negative events, we cannot affirm that the Bitcoin market is completely efficient when examining its own news.

4. Conclusion

Efficient Market Hypothesis has been widely analysed in the Bitcoin market from 2016. More specifically, authors have focused on weak efficiency through a huge number of different approaches. However, few studies related to the spillover literature have examined how certain events affect Bitcoin. To the best of our knowledge, this is the first paper analysing semi-strong efficiency in Bitcoin through an event study with monetary policy and Bitcoin news. In particular, the contribution of our research is twofold. On the one hand, we show that Bitcoin is semi-strong form inefficient in the case of monetary policy news since the digital currency is not responding to this kind of news. On the other hand, if we focus on events that are related to the features of Bitcoin, we observe that the digital currency responds to negative events in the Bitstamp and Mt.Gox markets, while it only responds to positive news in the Bitstamp market. In other words, Bitcoin has become more efficient over time in relation to its own events after the bankruptcy of Mt.Gox. This outcome underlines the gap between Bitcoin and the real economy given that Bitcoin responds to its own events, but not because of international monetary policy news. Therefore, investors should be aware that they are trading in an asset that cannot be

[9] For the sake of space, the values and significance level of the variables β_5, β_6, β_7 and β_8 (t-1 and t+1), in the case of $CAR_{(-1,1)}$, have not been reported. This material is available upon request.

controlled by the central banks. Future research could analyse the possible policies and measures that are able to affect the Bitcoin market in order to control a financial asset that is generally characterised by a speculative behaviour.

Disclosure statement

No potential conflict of interest.

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Appendix

Table 9
Monetary policy events.

Date	Effect	Central Bank	Event type
21/09/2011	Positive	FED	Operation Twist.
06/10/2011	Positive	ECB	New covered bond purchase programme (CBPP2).
06/10/2011	Positive	Bank of England	Quantitative easing boosted by Â£75bn by Bank of England.
27/10/2011	Positive	Bank of Japan	Enhancement of Monetary Easing.
08/12/2011	Positive	ECB	Measures to support bank lending and money market activity.
14/02/2012	Positive	Bank of Japan	Enhancement of Monetary Easing.
21/02/2012	Positive	European Union	Second Economic Adjustment Programme for Greece.
27/04/2012	Positive	Bank of Japan	Enhancement of Monetary Easing.
09/06/2012	Positive	European Union	Recapitalisation of Spanish financial institutions.
05/07/2012	Positive	ECB	The interest rate on the main refinancing operations is decreased by 25 basis points to 0.75%.
02/08/2012	Positive	ECB	Outright Monetary Transactions.
13/09/2012	Positive	FED	Quantitative Easing 3.
19/09/2012	Positive	Bank of Japan	Enhancement of Monetary Easing.
30/10/2012	Positive	Bank of Japan	Enhancement of Monetary Easing.
20/12/2012	Positive	Bank of Japan	Enhancement of Monetary Easing.
25/03/2013	Positive	European Union	Agreement on the Cypriot macroeconomic adjustment programme.
04/04/2013	Positive	Bank of Japan	Introduction of the "Quantitative and Qualitative Monetary Easing".
02/05/2013	Positive	ECB	The interest rate on the main refinancing operations is decreased by 25 basis points to 0.50%
07/11/2013	Positive	ECB	The interest rate on the main refinancing operations is decreased by 25 basis points to 0.25%.
18/12/2013	Negative	FED	FED reduces the pace of Quantitative Easing 3.
05/06/2014	Positive	ECB	Monetary policy measures to enhance the functioning of the monetary policy transmission mechanism.
05/06/2014	Positive	ECB	The interest rate on the main refinancing operations is decreased by 10 basis points to 0.15%.
04/09/2014	Positive	ECB	New covered bond purchase programme (CBPP3).
04/09/2014	Positive	ECB	The interest rate on the main refinancing operations is decreased by 10 basis points to 0.05%.
29/10/2014	Negative	FED	FED concludes QE3 programme.
31/10/2014	Positive	Bank of Japan	Expansion of the Quantitative and Qualitative Monetary Easing.
14/08/2015	Positive	European Union	Third Economic Adjustment Programme for Greece.
03/12/2015	Negative	ECB	The interest rate on the main refinancing operations and the interest rate on the marginal lending facility remain unchanged at 0.05% and 0.30% respectively.
16/12/2015	Negative	FED	FED increases its key interest rate, the Federal Funds Rate: 0.25%-0.50%.
18/12/2015	Positive	Bank of Japan	Enhancement of Monetary Easing.
29/01/2016	Positive	Bank of Japan	QQE with a Negative Interest Rate.
10/03/2016	Positive	ECB	The interest rate on the main refinancing operations is decreased by 5 basis points to 0.00%.
23/06/2016	Negative	European Union	United Kingdom European Union membership referendum.
29/07/2016	Positive	Bank of Japan	Enhancement of Monetary Easing.
04/08/2016	Positive	Bank of England	Bank of England cuts Bank Rate to 0.25% and introduces a package of measures designed to provide additional monetary stimulus.
14/12/2016	Negative	FED	FED increases its key interest rate, the Federal Funds Rate: 0.50%-0.75%.
15/03/2017	Negative	FED	FED increases its key interest rate, the Federal Funds Rate: 0.75%-1.00%.
14/06/2017	Negative	FED	FED increases its key interest rate, the Federal Funds Rate: 1.00%-1.25%.
13/12/2017	Negative	FED	FED increases its key interest rate, the Federal Funds Rate: 1.25%-1.50%.

Table 10
Bitcoin events that have been added in relation to Feng et al. (2017).

Date	Event type		Country	Event
31/03/2017	Policy	Positive	Japan	Japan's Bitcoin Law Goes Into Effect Tomorrow
13/04/2017	Policy	Negative	Russia	Russian Central Banker: Bitcoin's Legal Recognition Isn't Guaranteed.
07/07/2017	Policy	Negative	Poland	Polish Regulators Warn Banks and Consumers on Cryptocurrency Risks.
02/08/2017	Policy	Positive	US	Options Exchange CBOE to Launch Cryptocurrency Derivatives in 2017.
12/09/2017	Policy	Negative	US	Bitcoin OTC Service Suspends Trading Citing China Pressure.
13/11/2017	Policy	Positive	US	CME CEO: Bitcoin Futures Could Begin Trading As Soon As December.
01/12/2017	Policy	Positive	US	CME, CBOE to Begin Bitcoin Futures Trading.
04/12/2017	Policy	Positive	US	CBOE to Begin Bitcoin Futures Trading December 10.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2018.03.013.

References

Baek, C., Elbeck, M., 2015. Bitcoins as an investment or speculative vehicle? A first look. Appl. Econ. Lett. 22 (1), 30–34.
Bariviera, A.F., 2017. The inefficiency of bitcoin revisited: a dynamic approach. Econ. Lett. 161, 1–4.
Baur, D.G., Dimpfl, T., Kuck, K., 2017. Bitcoin, gold and the us dollar–a replication and extension. Finance Res. Lett.
Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D., 2017a. Does bitcoin hedge global uncertainty? evidence from wavelet-based quantile-in-quantile regressions. Finance Res. Lett.
Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017b. On the hedge and safe haven properties of bitcoin: is it really more than a diversifier? Finance Res. Lett. 20, 192–198.
Brenner, M., Pasquariello, P., Subrahmanyam, M., 2009. On the volatility and comovement of us financial markets around macroeconomic news announcements. J. Financial Quant. Anal. 44 (6), 1265–1289.
Cheah, E.-T., Fry, J., 2015. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. Econ. Lett. 130, 32–36.
Ciaian, P., Rajcaniova, M., Kancs, d., 2016. The economics of bitcoin price formation. Appl. Econ. 48 (19), 1799–1815.
Ciaian, P., Rajcaniova, M., et al., 2017. Virtual relationships: short-and long-run evidence from bitcoin and altcoin markets. J. Int. Financial Markets Inst. Money.
Corbet, S., Larkin, C., Lucey, B., Meegan, A., Yarovaya, L., 2017a. Cryptocurrency reaction to fomc announcements: Evidence of heterogeneity based on blockchain stack position.
Corbet, S., Lucey, B., Yarovya, L., 2017b. Datestamping the bitcoin and ethereum bubbles. Finance Res. Lett.
Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2017c. Exploring the dynamic relationships between cryptocurrencies and other financial assets.
Dyhrberg, A.H., 2016. Bitcoin, gold and the dollar–a garch volatility analysis. Finance Res. Lett. 16, 85–92.
Dyhrberg, A.H., 2016. Hedging capabilities of bitcoin. is it the virtual gold? Finance Res. Lett. 16, 139–144.
Fama, E.F., 1965. The behavior of stock-market prices. J. Bus. 38 (1), 34–105.
Feng, W., Wang, Y., Zhang, Z., 2017. Informed trading in the bitcoin market. Finance Res. Lett.
Jiang, Y., Nie, H., Ruan, W., 2017. Time-varying long-term memory in bitcoin market. Finance Research Letters.
Katsiampa, P., 2017. Volatility estimation for bitcoin: a comparison of garch models. Econ. Lett. 158, 3–6.
Kim, T., 2017. On the transaction cost of bitcoin. Finance Res. Lett. 23, 300–305.
Kristoufek, L., 2013. Bitcoin meets google trends and wikipedia: quantifying the relationship between phenomena of the internet era. Sci. Rep. 3, 3415.
Nadarajah, S., Chu, J., 2017. On the inefficiency of bitcoin. Econ. Lett. 150, 6–9.
Pennings, S., Ramayandi, A., Tang, H.C., 2015. The impact of monetary policy on financial markets in small open economies: more or less effective during the global financial crisis? J. Macroecon. 44, 60–70.
Phillip, A., Chan, J., Peiris, S., 2017. A new look at cryptocurrencies. Econ. Lett.
Swan, M., 2015. Blockchain: Blueprint for A New Economy. O'Reilly Media, Inc.
Tiwari, A.K., Jana, R., Das, D., Roubaud, D., 2017. Informational efficiency of bitcoin-an extension. Econ. Lett.
Urquhart, A., 2016. The inefficiency of bitcoin. Econ. Lett. 148, 80–82.
Urquhart, A., 2017. Price clustering in bitcoin. Econ. Lett. 159, 145–148.