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When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin

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ABSTRACT

Bitcoin was launched to solve the distrust and uncertainty in the existing financial system. Here we investigate risk spillover effect from economic policy uncertainty (EPU) to Bitcoin using a multivariate quantile model and the Granger causality risk test. We use the US EPU index, equity market uncertainty index, and VIX as proxies for EPU. We find that risk spillover effect from EPU to Bitcoin is negligible in most conditions. Our work provides useful information on building asset portfolios for investors who have investment strategies in Bitcoin, because Bitcoin can be acted as a safe-haven or a diversifier under EPU shocks.

1. Introduction

In the context of distrusting the existing international financial system and facing the extreme economic uncertainty, on 31 October 2008, Nakamoto (2008) released a nine-page white paper describing a new monetary system, i.e., Bitcoin, a fully decentralized cryptocurrency based on the blockchain technology. On 16 December 2008, Satoshi Nakamoto released an early version of Bitcoin network and the first units of the Bitcoin cryptocurrency (called Bitcoin). Since then, Bitcoin has attracted much attention from practitioners, academics and the media due to its unique decentralized payment or trust system that does not rely on the third parties (e.g., financial institutions). Especially during the 2010–2013 European sovereign debt crisis and the 2012–2013 Cypriot banking crisis, many people resorted to Bitcoin as a safe-heaven or hedging asset to avoid risk and market uncertainty (Bouri et al., 2017b).

The current world is full of economic policy uncertainty (EPU), e.g., financial crisis and trade war. In this background, the price of Bitcoin increased sharply from \$0.09 on 18 July 2010 to \$7487.19 on 31 May 2018, and its price and market capitalization reached their record high of \$19343.04 and \$326 billion on 16–17 December 2017, respectively.[1] Thus a natural question is raised: when Bitcoin meets EPU, does EPU affect the behavior of Bitcoin? In the existing literature, few studies have focused on this topic. To the best of our knowledge, Bouri et al. (2017b) and Demir et al. (2018) are the only two works to investigate the impact of EPU on Bitcoin using the ordinary least squares (OLS) and (wavelet-based) quantile-on-quantile regressions. Another closely related work on this

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[1] Source: http://www.coindesk.com/price/ and https://coinmarketcap.com.

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topic is that of Bouri et al. (2018b), who use copula-based techniques to examine the quantile conditional dependence and causality between Bitcoin and the global financial stress index (GFSI), showing that Bitcoin can be a safe-haven against global financial stress. However, their studies are limited to analyzing the relationship between EPU/GFSI and Bitcoin return and ignore the risk spillover effect from EPU to Bitcoin. Here we aim to investigate whether EPU affects the behavior of Bitcoin from a risk spillover perspective. Namely, we study the risk spillover effect from EPU to Bitcoin or the impact of EPU shocks on Bitcoin. Meanwhile, a hypothesis is proposed: if Bitcoin is really independent of the existing economic and financial system, it will be little affected by EPU, i.e., the risk spillover effect from EPU to Bitcoin should be weak or negligible. For this propose, we use two different approaches, i.e., the multivariate quantile model (MVQM) of White et al. (2015) and the Granger causality risk test of Hong et al. (2009), to examine the risk spillover effect from EPU to Bitcoin. The US EPU index and the US equity market uncertainty (EMU) index developed by Baker et al. (2016) are used to represent EPU,[2] and the CBOE volatility index (VIX) is also considered for robustness test. We employ daily and weekly data of Bitcoin price and the US EPU, EMU and VIX indeices during the period from 18 July 2010 to 31 May 2018.

Our work has the following three contributions. First, our study is the first attempt to examine the impact of EPU on Bitcoin from a risk spillover perspective, which complements to the previous research of Bouri et al. (2017b) and Demir et al. (2018).[3] Unlike their research that only uses daily data of either the US EPU index or the VIX index for empirical analysis, we use daily and weekly data of the US EPU, EMU and VIX indices, making our results more comprehensive and robust. Second, our work is the first one using two different approaches. i.e., the MVQM and the Granger causality risk test, to examine the risk spillover effect from EPU to Bitcoin at different quantiles (i.e., risk levels). Based on a conditional autoregressive value-at-risk (CAViaR) model of Engle and Manganelli (2004) using regression quantiles, both of the MVQM and the Granger causality risk test are inherently nonlinear models, which allow us to quantify the risk spillover effect varying across the quantiles (e.g., downside and upside risks). Especially, the Granger causality risk test also allows us to investigate the risk spillover effect at different time-lags, and this is important because the information transmission usually has a time-lag effect. Third, our results confirm the proposed hypothesis that the risk spillover effect from EPU to Bitcoin is negligible. Using the MVQM approach we find that VaRs of Bitcoin at different quantiles are only related to its own lagged volatilities and VaRs, and are independent of both the lagged volatilities and lagged VaR of EPU, meaning that the impact of EPU on Bitcoin is insignificant from the risk spillover view. The results by the Granger causality risk test show that the risk spillover effect from EPU to Bitcoin is negligible or weak varying across quantiles and lags.

In the existing literature, much empirical research (see, e.g., Beckmann and Czudaj, 2017; Chuliá et al., 2017a; 2017b) finds that traditional financial asset markets are somewhat affected by EPU. However, this conclusion does not hold true for the largest digital currency — Bitcoin, based on our investigation on risk spillover effect from EPU to Bitcoin using the MVQM-CAViaR and the Granger causality risk test. Unlike the research conducted by Bouri et al. (2017b) and Demir et al. (2018) who find Bitcoin returns are negatively correlated with EPU and conclude that Bitcoin can act as a hedge against uncertainty, we find negligible or weak risk spillover effect from EPU to Bitcoin, indicating that Bitcoin differs from traditional financial assets and is somewhat isolated from the current economic and financial environment. Our findings provide important information for investors who have an interest in using Bitcoin as an investment or hedging asset in their diversified portfolios, because the negligible risk spillover effect from EPU to Bitcoin means that in an extremely uncertain economic policy situation Bitcoin can be considered as a safe-haven or a diversifier. For example, according to recent media reports (see, e.g., Masters, 2018; Maurya, 2018) and CoinMarketCap, since the Turkish currency and debet crisis sparked and the Lira started plunging, many Turkish investors have shifted their holdings to Bitcoin and other cryptocurrencies, leading to a surge in the cryptocurrency trading volume on Turkey's cryptocurrency exchanges (e.g., Paribu and BtcTurk). Note that regulatory polices on Bitcoin or cryptocurrencies can heavily influence the decision-making behavior of market participants. Currently, different countries or regulatory agencies show different attitudes and views on cryptocurrencies. For example, some counties such as Germany, the UK and the USA are still carefully examining and weighing the regulatory and legal framework for cryptocurrencies. Thus our study on risk spillover effect from EPU to Bitcoin also supplies valuable information for regulatory agencies when they define the positioning of cryptocurrencies in their financial system and set relevant regulatory policies on cryptocurrencies.

2. Methodology

2.1. Multivariate quantile model (MVQM)

The MVQM is a VAR extension to quantile models, also called as VAR for VaR. White et al. (2015) develop a reduced and structural form of the MVQM, i.e., a bivariate MVQM(1,1), which is a multivariate extension of CAViaR models proposed by Engle and Manganelli (2004). Thus MVQM is also called as MVQM-CAViaR model. The MVQM is straightforward, i.e., quantiles (i.e., VaR) of a time series (e.g., Bitcoin returns $r_{1,t}$) distribution depend on the lags of exogenous and endogenous variables, e.g., its own lags and the lags of other related variables (e.g., EPU changes $r_{2,t}$). Mathematically, the MVQM-CAViaR(1,1) we used for examining

[2] Note that in this paper the term "EPU" denotes economic policy uncertainty, and such terms as "the EPU index" and "the US EPU index" refer to the US economic policy uncertainty index developed by Baker et al. (2016).

[3] According to Corbet et al. (2018a) who provide an excellent and systemic review on the topics of Bitcoin and other cryptocurrencies as a financial asset, most of the current literature focuses on diversification benefits by Bitcoin or relationships between Bitcoin and other traditional assets (see, e.g., Brière et al., 2015; Dyhrberg, 2016a, 2016b; Bouri et al., 2017c; 2017d; Baur et al., 2018a, 2018b; Giudici and Abu-Hashish, 2018; Ji et al., 2018; Bouri et al., 2018a, 2018b; Symitsi and Chalvatzis, 2018; Feng et al., 2018; Corbet et al., 2018b; Yi et al. 2018).

impact of EPU on Bitcoin is defined as follows:

$$q_{1,t} = c_1 + a_{11}|r_{1,t-1}| + a_{12}|r_{2,t-1}| + b_{11}q_{1,t-1} + b_{12}q_{2,t-1}, \tag{1}$$

$$q_{2,t} = c_2 + a_{21}|r_{1,t-1}| + a_{22}|r_{2,t-1}| + b_{21}q_{1,t-1} + b_{22}q_{2,t-1}, \tag{2}$$

where $|r_{1,t-1}|$ and $|r_{2,t-1}|$ represent absolute values of returns of Bitcoin and changes of EPU respectively, which can be considered as volatility of Bitcoin and EPU, and $q_{1,\,t}$ and $q_{2,\,t}$ are conditional quantiles of the distributions of Bitcoin returns and EPU changes. The definition of $q_{1,\,t}$ and $q_{2,\,t}$ shows that they actually represent VaRs of the two variables (Shen, 2018), which are defined as

$$q_{i,t} \;=\; \mathrm{VaR}_{i,t} = -Q_\theta(r_{i,t}|I_{t-1}) = -\inf_q\{q \in \mathbb{R}|\Pr(r_{i,t} \le q|I_{t-1}) \ge \theta\}, \quad i = 1, 2, \tag{3}$$

where Q_θ is a quantile function at the confidence level $\theta \in (0, 1)$ and I_{t-1} is the available information set at time $t-1$.

In Eq. (1), quantiles of Bitcoin returns r_{1t} (q_{1t}), at the confidence level θ, depend on itself with a lag ($q_{1,t-1}$) by b_{11}, on its volatility with a lag ($|r_{1,t-1}|$) through a_{11}, on EPU's volatility with a lag ($|r_{2,t-1}|$) via a_{12}, and importantly on the uncertainly-quantiles with a lag ($q_{2,t-1}$) by b_{22}. Eq. (2) holds a similar interpretation for EPU. Since we mainly consider the risk spillover effect from EPU to Bitcoin or the influence of EPU on Bitcoin, here we focus our attention on Eq. (1) by analyzing the four coefficients a_{11}, a_{12}, b_{11} and b_{12}, especially b_{12} that represents the degree of risk spillover effect from EPU to Bitcoin. Thus in our empirical analysis, we follow Chuliá et al. (2017b) and only report the estimated coefficients associated with Eq. (1).

2.2. The Granger causality risk test

The idea behind the Granger causality risk test of Hong et al. (2009) is that given two variables, e.g., Bitcoin and EPU, EPU can be considered as Granger causes risk to Bitcoin if the capacity to predict the future risk information of Bitcoin is improved via adding the past risk information of EPU (Wang et al., 2017). In what follows we briefly introduce the Granger causality risk test.

We first obtain VaR estimation for Bitcoin and EPU using the asymmetric slope model in the CAViaR framework of Engle and Manganelli (2004), and then transform the VaR into a risk indicator, i.e.,

$$Z_{i,t} = \mathbf{1}(r_{i,t} < -\mathrm{VaR}_{i,t}), \quad i = 1, 2, \tag{4}$$

where $\mathbf{1}(\cdot)$ is an indicator function.

The statistic for the Granger causality risk test builds on the cross-correlation function (CCF) between two risk indicators $\hat{Z}_{i,t}$ ($i = 1,2$), and the sample CCF is defined as

$$\hat{\rho}(j) = \frac{\hat{C}(j)}{\hat{S}_1\hat{S}_2}, \tag{5}$$

where $\hat{C}(j)$ is the sample cross-covariance function between two risk indicators at positive lag j, which is defined as

$$\hat{C}(j) \;=\; T^{-1}\sum_{t=1+j}^{T}(\hat{Z}_{1,t} - \hat{\alpha}_1)(\hat{Z}_{2,t-j} - \hat{\alpha}_2), \quad 1 \le j \le T-1, \tag{6}$$

where the sample mean $\hat{\alpha}_i = T^{-1}\sum_{t=1}^{T} Z_{i,t}$, T is the sample length, and the sample variance $\hat{S}_i^2 \;=\; \hat{\alpha}_i(1-\hat{\alpha}_i)$.

Based on the sample CCF, a kernel-based statistic proposed by Hong et al. (2009) for examining the one-way Granger causality in risk from one variable (e.g., EPU) to another variable (e.g., Bitcoin) is defined as

$$Q(M) = \left[T\sum_{j=1}^{T} k^2(j/M)\hat{\rho}^2(j) - C_T(M)\right]/[D_T(M)]^{1/2}, \tag{7}$$

where the centering and standardization constants are defined as

$$C_T(M) = \sum_{j=1}^{T-1}(1-j/T)k^2(j/M), \tag{8}$$

$$D_T(M) = 2\sum_{j=1}^{T-1}(1-j/T)(1-(j+1)/T)k^4(j/M), \tag{9}$$

$k(\cdot)$ is a kernel function assigning weights to various lags, and M is the bandwidth, i.e., the lag order. Common kernel functions include the truncated kernel, the Daniel kernel, the Bartlett kernel, the Parzen kernel and the Quadratic-Spectral kernel. Following Wang et al. (2016, 2017) and Shen (2018), here we use the Daniel kernel, defined as $k(x) = \sin(\pi x)/(\pi x)$. Under the null hypothesis that one variable (e.g., EPU) does not Granger-cause risk to another variable (e.g., Bitcoin), the kernel-based statistic $Q(M)$ obeys an asymptotically standard normal distribution $N(0, 1)$ (Hong et al., 2009). If the null hypothesis is rejected when the value of $Q(M)$ is larger than the right-tailed critical value of $N(0, 1)$ at the significance level β, there is one-way Granger causality in risk from EPU to Bitcoin, namely, there is a risk spillover effect from EPU to Bitcoin.

3. Data

Following Chuliá et al. (2017b) who investigate spillover effects from the US EPU and EMU indices to emerging and developed stock markets using the MVQM-CAViaR and Demir et al. (2018) who study whether the US EPU index can predict the Bitcoin returns using the three approaches (e.g., the quantile regression), we use the US EPU and EMU indices developed by Baker et al. (2016) as two proxies for EPU. We obtain daily data of the US EPU and EMU indices from the website of Economic Policy Uncertainty Index (http://www.policyuncertainty.com) developed by Baker et al. (2016). We also follow Bouri et al. (2017b), who examine whether Bitcoin can hedge EPU, and use the VIX index as an alternative proxy for EPU. We collect daily prices of the VIX index from Yahoo Finance (https://finance.yahoo.com). Like Bouri et al. (2017b) and Demir et al. (2018), we collect daily price data of Bitcoin in USD from the website of CoinDesk (https://www.coindesk.com/price/). The reason why we use Bitcoin price data from CoinDesk is that its Bitcoin price index is an average of Bitcoin prices across major Bitcoin exchanges in the world and thus it can well reflect the overall trend of the Bitcoin market. The sample period for the above data is from 18 July 2010 to 31 May 2018. Following Demir et al. (2018), we consider the logarithmic returns of Bitcoin or changes of the EPU, EMU, and VIX indices, i.e., $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, where $P_{i,\ t}$ is Bitcoin price or the value of the three indices at time t.

About data frequency, we mainly use daily data of the above variables for empirical analysis and also consider weekly data for robustness test. Note that data of Bitcoin and the US EPU and EMU indices are based on calendar days (including weekdays, weekends and holidays), thus their daily returns or changes have 2874 observations during the entire period from 19 July 2010 to 31 May 2018. Because the VIX data are based on business days (with 1981 observations), in order to study the risk spillover effect from the VIX to Bitcoin, we match Bitcoin data with the VIX data by removing weekend and holiday data of Bitcoin. Thus the data set can be divided two groups, group I (Bitcoin, EPU and EMU) with calendar-day observations and group II (Bitcoin and VIX) with business-day observations. We transform the daily prices into weekly prices by averaging prices of the whole week. Similar to daily data, weekly data of Bitcoin in group I and group II are different (see Table 1).

Previous research has different conclusions on market efficiency of Bitcoin and relations between Bitcoin and other assets before and after the December 2013 Bitcoin price crash. For example, Urquhart (2016) obtains evidence of the inefficiency of Bitcoin during the entire sample period, but he finds that the Bitcoin market has moved toward an efficient market since the latter half of 2013. Bouri et al. (2017c) find that the hedge and safe-haven properties of Bitcoin against commodities during the pre-crash period and the post-crash period are significantly different. Bouri et al. (2017a) show that there exist differences in the return-volatility relationship of Bitcoin before and after the crash. Thus, to figure out whether structural breakpoints (e.g., the December 2013 Bitcoin price crash) in Bitcoin returns affect the risk spillover effect from EPU to Bitcoin, we check the robustness over the sample period by using multiple structural change models of Bai and Perron (2003) to detect breakpoints in Bitcoin returns. The detection results point

Table 1
Descriptive statistics on returns of Bitcoin and changes of the US EPU, EMU and VIX indices during the entire period and two subperiods.

	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque–Bera	ADF	Observations
Panel A: The entire period (Daily observations)										
BTC[a]	0.0039	0.0014	0.4246	− 0.4915	0.0585	− 0.3486	14.6854	16409.74***	− 52.25***	2874
EPU	− 0.0003	− 0.0070	2.6025	− 3.1483	0.4961	− 0.0479	4.6511	327.57***	− 25.11***	2874
EMU	− 0.0004	− 0.0492	4.2257	− 4.1866	1.0237	0.0408	3.4428	24.28***	− 23.92***	2874
BTC[b]	0.0058	0.0020	0.4997	− 0.4700	0.0664	− 0.0319	11.7345	6297.63***	− 18.96***	1981
VIX	− 0.0003	− 0.0045	0.7682	− 0.3141	0.0766	1.1791	11.1477	5938.53***	− 47.46***	1981
Panel B: The entire period (Weekly observations)										
BTC[a]	0.0283	0.0120	0.6782	− 0.4508	0.1291	1.0522	7.2292	381.22***	− 12.50***	410
EPU	− 0.0023	− 0.0102	0.9581	− 0.9417	0.2645	− 0.0499	4.2020	24.85***	− 16.61***	410
EMU	− 0.0024	− 0.0305	2.0781	− 2.1360	0.6341	0.1627	3.0601	1.87	− 14.60***	410
BTC[b]	0.0057	0.0027	0.1561	− 0.1645	0.0323	0.5155	8.6041	556.04***	− 17.44***	410
VIX	− 0.0003	− 0.0015	0.2281	− 0.1198	0.0333	1.3725	11.6181	1400.94***	− 15.44***	410
Panel C: Subperiod I										
BTC[a]	0.0077	0.0006	0.4246	− 0.4915	0.0744	− 0.3918	11.6987	3925.30***	− 33.76***	1235
EPU	− 0.0004	− 0.0114	2.2326	− 3.1483	0.4402	− 0.2592	6.6475	698.46***	− 16.27***	1235
EMU	− 0.0009	0.0288	3.1326	− 3.7556	1.0647	0.0070	2.9236	0.31	− 27.10***	1235
BTC[b]	0.0112	0.0021	0.4997	− 0.4700	0.0834	− 0.0881	9.4757	1489.78***	− 14.62***	852
VIX	− 0.0007	− 0.0042	0.4055	− 0.3141	0.0697	0.7517	6.9187	625.38***	− 20.48***	852
Panel D: Subperiod II										
BTC[a]	0.0011	0.0016	0.2908	− 0.2696	0.0426	− 0.4158	9.9130	3310.86***	− 41.06***	1639
EPU	− 0.0002	− 0.0031	2.6025	− 1.9826	0.5345	0.0417	3.7521	39.11***	− 18.90***	1639
EMU	0.0001	− 0.0849	4.2257	− 4.1866	0.9920	0.0723	3.9276	60.18***	− 28.73***	1639
BTC[b]	0.0058	0.0020	0.4997	− 0.4700	0.0664	− 0.0319	11.7345	6297.63***	− 18.96***	1129
VIX	− 0.0003	− 0.0045	0.7682	− 0.3141	0.0766	1.1791	11.1477	5938.53***	− 47.46***	1129

Notes: The entire period is from 19 July 2010 to 31 May 2018, subperiod I is from 19 July 2010 to 4 December 2013, and subperiod II is from 5 December 2013 to 31 May 2018. [a] and [b] indicate Bitcoin data with calendar-day observations and with business-day observations, respectively. Jarque–Bera statistic tests for the null hypothesis of normal distribution. The ADF (Augmented Dickey–Fuller) statistic tests for a unit root. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 2
Estimated coefficients associated with Eq. (1) of MVQM-CAViaR(1,1) using the US EPU and EMU indices during the entire period.

θ	EPU					EMU				
	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_1	a_{11}	a_{12}	b_{11}	b_{12}
Panel A: The entire period (Daily observations)										
0.01	− 0.049	− 0.548**	− 0.005	0.790***	− 0.032	− 0.012	− 0.464***	− 0.007	0.847***	− 0.005
	(0.045)	(0.223)	(0.013)	(0.073)	(0.038)	(0.060)	(0.087)	(0.008)	(0.031)	(0.028)
0.05	0.000	− 0.153***	0.004	0.924***	0.002	− 0.003	− 0.147***	− 0.001	0.931***	− 0.002
	(0.005)	(0.026)	(0.005)	(0.017)	(0.007)	(0.007)	(0.022)	(0.005)	(0.012)	(0.006)
0.95	0.005	0.406***	− 0.004	0.767***	0.001	0.000	0.399**	0.005	0.768***	0.001
	(0.008)	(0.042)	(0.004)	(0.027)	(0.011)	(0.179)	(0.176)	(0.038)	(0.135)	(0.122)
0.99	0.000	0.427***	− 0.014	0.848***	0.009	0.002	0.417***	0.008	0.841***	− 0.001
	(0.026)	(0.100)	(0.010)	(0.037)	(0.022)	(0.405)	(0.147)	(0.006)	(0.129)	(0.169)
Panel B: The entire period (Weekly observations)										
0.01	0.000	− 0.436***	− 0.011	0.811***	0.005	− 0.121	− 0.624	0.024	0.369	0.000
	(0.014)	(0.061)	(0.020)	(0.033)	(0.022)	(0.211)	(0.672)	(0.101)	(0.527)	(0.154)
0.05	0.010	− 0.146*	− 0.004	0.917***	0.016	− 0.534***	0.008	0.060**	− 1.141***	− 0.183
	(0.011)	(0.081)	(0.034)	(0.053)	(0.037)	(0.148)	(0.117)	(0.027)	(0.269)	(0.112)
0.95	0.179*	1.073***	− 0.056	0.285***	− 0.241	0.075	1.140***	0.016	0.286**	− 0.032
	(0.096)	(0.170)	(0.040)	(0.096)	(0.180)	(0.085)	(0.198)	(0.018)	(0.126)	(0.071)
0.99	0.109***	1.111***	− 0.128***	0.452***	− 0.040	0.155	1.190***	0.048	0.394	− 0.072
	(0.033)	(0.040)	(0.014)	(0.045)	(0.044)	(0.113)	(0.137)	(0.042)	(0.281)	(0.030)

Notes: Here we only report estimated coefficients in Eq. (1), mainly representing the impact of the US EPU and EMU indices on Bitcoin, but the estimated results of Eq. (2) can be available upon request. The entire period is from 19 July 2010 to 31 May 2018. Numbers in parentheses are standard errors of the corresponding estimated coefficients. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

toward a structural breakpoint on 5 December 2013 in Bitcoin returns,[4] which approaches to the December 2013 Bitcoin price crash. This is also consistent with the results on structural breakpoint testing by Cheah and Fry (2015) and Bouri et al. (2017a), even though our sample length differs from (i.e., is larger than) their sample lengths. Thus we divide the entire period into (i) subperiod I from 19 July 2010 to 4 December 2013 and (ii) subperiod II from 5 December 2013 to 31 May 2018.

In Table 1 we show descriptive statistics on daily and weekly Bitcoin returns and changes of the US EPU, EMU and VIX indices during the entire period. We also present descriptive statistics for daily data during two subperiods. Note that for all periods including the entire periods (with daily observations and weekly observations) and two subperiods, there are two groups for the data set, meaning that there are two data sets for Bitcoin during each period in Table 1. For all periods, Bitcoin has the positive average return and large standard deviation (SD), showing an attractive investment opportunity in Bitcoin but with high risk. The changes of three proxies for EPU (i.e., the US EPU, EMU and VIX indices) show negative mean values and very high SDs during all periods (except for the EMU index in subperiod II with positive mean value), suggesting that economic policy has extreme uncertainty and large fluctuation. Except for the EMU index during the entire period (weekly observations) and subperiod I, all returns or changes are skewed and have a kurtoisis value in excess of the critical value (i.e., three) of a normal distribution, and their Jarque–Bera statistics reject the null hypothesis at 1% significance level, suggesting that all returns or changes disobey the normal distribution and are fat-tailed. This finding supports our decision on using CAViaR and its extension to estimate VaRs or conditional quantiles, which do not need any assumption on the distributions of Bitcoin returns and EPU changes. The ADF statistic show that all returns or changes are a stationary series without unit root and are suitable for the further modeling.

4. Empirical results

4.1. Results from MVQM-CAViaR(1,1)

Here we investigate Bitcoin's reaction to EPU, i.e., risk spillover effects from EPU to Bitcoin using the reduced and structural form VAR-quantile, i.e., MVQM-CAViaR(1,1). We consider four quantiles (or confidence levels), including $\theta = 0.01$, 0.05, 0.95, and 0.99. Especially, VaRs at the former two quantiles and the latter two quantiles represent downside risk and upside risk, respectively.

In Table 2 we report estimated coefficients associated with Eq. (1) at four quantiles during the entire period, where Panels A and B show the results based on daily and weekly data, respectively. Both Panels A and B show that the estimated coefficients b_{12} at different quantiles, representing the impact level of the US EPU and EMU indices on Bitcoin in VaR, are very small (close to zero) and statistically insignificant. This finding suggests that downside and upside risk spillover effects from EPU to Bitcoin are statistically negligible during the entire period. Almost all estimated coefficients a_{12}, measuring the influence level of the volatility of the US EPU index or EMU index on Bitcoin's VaR, are also small and statistically insignificant, except for the two cases of the weekly EPU index at the 99th percentile ($\theta = 0.99$) and the weekly EMU index at the 5th percentile ($\theta = 0.05$). This means that the influence of the volatility of EPU on Bitcoin's VaR is negligible. Almost all estimated autoregressive coefficients b_{11} are statistically significant, except

[4] Detailed results on the structural breakpoint testing are not reported here but available from the authors.

Table 3
Estimated coefficients associated with Eq. (1) of MVQM-CAViaR(1,1) using the US EPU and EMU indices during two subperiods.

θ	EPU					EMU				
	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_1	a_{11}	a_{12}	b_{11}	b_{12}
Panel A: Subperiod I										
0.01	− 0.055	− 0.981	0.010	0.611	− 0.011	0.333	− 0.684	0.007	0.751	0.146
	(1.761)	(13.295)	(1.443)	(6.021)	(0.355)	(1.427)	(0.637)	(0.013)	(0.316)	(0.601)
0.05	− 0.006	− 0.318***	0.011	0.833***	− 0.001	0.007	− 0.321***	0.002	0.828***	0.005
	(0.004)	(0.059)	(0.007)	(0.027)	(0.008)	(0.017)	(0.059)	(0.004)	(0.028)	(0.010)
0.95	0.000	0.575***	− 0.009	0.654***	0.022	0.001	0.343***	0.002	0.832***	0.000
	(0.017)	(0.085)	(0.010)	(0.056)	(0.025)	(0.044)	(0.072)	(0.009)	(0.051)	(0.026)
0.99	0.048	0.951	− 0.030	0.503***	0.009	0.024	0.842	0.043	0.442	0.001
	(0.179)	(0.829)	(0.038)	(0.163)	(0.202)	(329.100)	(48.504)	(8.431)	(872.430)	(65.519)
Panel B: Subperiod II										
0.01	0.002	− 0.355	− 0.013	0.885***	0.000	0.002	− 0.216	0.000	0.910	0.003
	(0.088)	(0.547)	(0.053)	(0.215)	(0.073)	(47.301)	(29.765)	(2.376)	(451.730)	(33.869)
0.05	0.003	− 0.181***	0.014	0.905***	0.012	− 0.019	− 0.461	0.000	0.679*	− 0.007
	(0.007)	(0.060)	(0.005)	(0.030)	(0.010)	(0.027)	(0.342)	(0.008)	(0.365)	(0.011)
0.95	− 0.001	0.370***	0.006	0.739***	0.005	0.046	0.289	0.014	0.420	− 0.017
	(0.015)	(0.064)	(0.009)	(0.045)	(0.021)	(0.675)	(0.940)	(0.075)	(0.271)	(0.418)
0.99	0.010	0.482***	− 0.001	0.755***	0.001	0.039	0.726	0.004	0.183	0.010
	(0.016)	(0.098)	(0.013)	(0.072)	(0.015)	(0.168)	(0.216)	(0.060)	(0.337)	(0.061)

Notes: Here we only report estimated coefficients in Eq. (1), mainly representing the impact of the US EPU and EMU indices on Bitcoin, but the estimated results of Eq. (2) can be available upon request. Subperiod I is from 19 July 2010 to 4 December 2013 and subperiod II is from 5 December 2013 to 31 May 2018. Numbers in parentheses are standard errors of the corresponding estimated coefficients. *** and * indicate statistical significance at 1% and 10% level, respectively.

for the weekly EMU index at 1st percentile ($\theta = 0.01$), suggesting that the VaR of Bitcoin is autocorrelated. The estimated coefficients a_{11} are statistically significant except for two cases of the weekly EMU index at the 1st and 5th percentiles, which indicates that the VaR of Bitcoin is affected by its lagged volatility.[5] In summary, we have the following findings: (i) the risk spillover effect from EPU to Bitcoin is insignificant, and (ii) the VaR of Bitcoin is affected by its lagged VaR and volatility. These findings suggest that the risk of Bitcoin price is independent of the changes of EPU and is related to its previous risk and volatility information.

For robustness test, we also estimate coefficients associated with Eq. (1) at four quantiles during two subperiods (subperiods I and II) to check whether the December 2013 Bitcoin price crash affects our results. In Table 3 we report the estimated results for the two subperiods. Both Panels A and B of Table 3 show that the estimated coefficients b_{12} at different quantiles are statistically insignificant, suggesting that the December 2013 Bitcoin price crash does not change our finding on the negligible risk spillover effect from EPU to Bitcoin.

We further use the VIX index instead of the US EPU and EMU indices for examining the risk spillover effect from EPU to Bitcoin. In Table 4 we present estimated coefficients associated with Eq. (1) at four quantiles during the entire period and two subperiods. Based on the daily and weekly data of Bitcoin and the VIX index during the entire period and the daily data of Bitcoin and the VIX index during two subperiods (i.e., before and after the December 2013 Bitcoin price crash), the estimated coefficients b_{12} at different quantiles confirm that there is no risk spillover effect from EPU to Bitcoin, or the impact of EPU on Bitcoin is negligible. The empirical results based on the VIX index also confirm (i) that the effect of volatility of EPU on Bitcoin is insignificant and (ii) that the risk of Bitcoin (in terms of VaR) is observably affected by its own lagged risk and volatility.

4.2. Results from the Granger causality risk test

In this section, we estimate statistics $Q(M)$ associated with Eq. (7) and the corresponding p-values of one-way Granger causality in risk for measuring risk spillover effect from EPU to Bitcoin at different lags. We follow Hong et al. (2009) and Wang et al. (2016) and examine risk spillover effects with the lag orders $M = 5$, 10 and 20 days/weeks. Like the MVQM-CAViaR analysis in Section 4.1, we also consider four quantiles (or confidence levels), i.e., $\theta = 0.01$, 0.05, 0.95, and 0.99, and three periods including the entire period and two subperiods.[6]

In Table 5 we show estimated statistics $Q(M)$ for measuring risk spillover effect from the US EPU and EMU indices to Bitcoin during the entire period. Panel A based on daily data shows that almost all estimated statistics across different quantiles and lags

[5] It is not difficult to understand that the VaR is related to the volatility. For example, we usually use variance-covariance approaches (e.g., RiskMetrics and GARCH-type) to estimate the VaR of financial asset, but this type of approaches needs to know the distribution of returns.

[6] Note that both Bouri et al. (2017b) and Demir et al. (2018) find negative relations between Bitcoin and EPU, which are built on contemporaneous or instantaneous correlations between Bitcoin and the EPU or VIX index. To figure out whether contemporaneous or instantaneous correlations affect our finding, we follow Wang et al. (2016) and also use a modified statistic of one-way Granger causality in risk by adding a CCF with a lag order of zero. We find that contemporaneous or instantaneous correlations do not change our central finding on the insignificant risk spillover effect from EPU to Bitcoin. The detailed results can be obtained from the authors.

Table 4
Estimated coefficients associated with Eq. (1) of MVQM − CAViaR(1,1) using the VIX index during the entire period and two subperiods.

θ	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_1	a_{11}	a_{12}	b_{11}	b_{12}
Panel A: The entire period (Daily observations)						*Panel B: The entire period (Weekly observations)*				
0.01	0.005	− 0.166***	− 0.110	0.946***	0.005	− 0.001	− 0.444**	− 0.103	0.856***	− 0.034
	(0.008)	(0.044)	(0.131)	(0.028)	(0.079)	(0.059)	(0.223)	(0.188)	(0.099)	(1.057)
0.05	0.000	− 0.187***	− 0.001	0.916***	0.006	− 0.072***	0.033	− 0.102	− 0.968***	0.107
	(0.003)	(0.030)	(0.054)	(0.021)	(0.044)	(0.026)	(0.039)	(0.092)	(0.082)	(0.474)
0.95	0.007	0.389***	− 0.061	0.788***	0.009	0.052	1.107***	− 0.184*	0.304	− 0.686
	(0.022)	(0.088)	(0.097)	(0.055)	(0.225)	(0.073)	(0.408)	(0.111)	(0.496)	(1.285)
0.99	0.018***	0.347***	− 0.106	0.879***	− 0.023	0.021	0.781***	− 0.315***	0.591**	0.026
	(0.006)	(0.062)	(0.057)	(0.042)	(0.022)	(0.035)	(0.266)	(0.049)	(0.065)	(0.243)
Panel C: Subperiod I						*Panel D: Subperiod II*				
0.01	− 0.013	− 0.429*	− 0.578	0.694***	0.023	− 0.002	− 0.483*	− 0.164	0.810***	− 0.003
	(0.072)	(0.250)	(1.147)	(0.145)	(0.754)	(0.092)	(0.250)	(0.863)	(0.200)	(0.970)
0.05	0.004	− 0.198***	− 0.027	0.897***	0.039	− 0.003	− 0.207**	− 0.004	0.878***	− 0.010
	(0.006)	(0.059)	(0.093)	(0.042)	(0.088)	(0.005)	(0.097)	(0.130)	(0.053)	(0.099)
0.95	0.015	0.458***	0.021	0.697***	− 0.010	0.007	0.269***	− 0.054	0.839***	− 0.003
	(0.031)	(0.071)	(0.155)	(0.060)	(0.363)	(0.006)	(0.050)	(0.022)	(0.035)	(0.068)
0.99	0.052	0.618*	− 0.137	0.787***	− 0.138*	0.007	0.291***	− 0.103*	0.902***	0.007
	(0.021)	(0.329)	(0.150)	(0.125)	(0.073)	(0.016)	(0.062)	(0.054)	(0.021)	(0.076)

Notes: Here we only report estimated coefficients in Eq. (1), mainly representing the impact of the US EPU and EMU indices on Bitcoin, but the estimated results of Eq. (2) can be available upon request. The entire period is from 19 July 2010 to 31 May 2018, subperiod I is from 19 July 2010 to 4 December 2013, and subperiod II is from 5 December 2013 to 31 May 2018. Numbers in parentheses are standard errors of the corresponding estimated coefficients. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 5
Estimated statistics $Q(M)$ associated with Eq. (7) for measuring extreme risk spillover effects from the US EPU and EMU indices to Bitcoin using the Granger causality risk test during the entire period.

θ	EPU⇒BTC			EMU⇒BTC		
	$M = 5$	$M = 10$	$M = 20$	$M = 5$	$M = 10$	$M = 20$
Panel A: The entire period (Daily observations)						
0.01	− 0.653	0.289	1.522*	− 0.700	− 0.157	0.542
	[0.743]	[0.386]	[0.064]	[0.758]	[0.562]	[0.294]
0.05	− 0.765	− 0.714	− 0.059	− 0.810	− 1.203	− 1.230
	[0.778]	[0.762]	[0.523]	[0.791]	[0.886]	[0.891]
0.95	0.598	0.756	1.229	− 0.202	− 0.037	0.546
	[0.275]	[0.225]	[0.110]	[0.580]	[0.515]	[0.293]
0.99	− 0.891	− 0.942	− 1.103	− 0.905	− 1.254	− 1.752
	[0.813]	[0.827]	[0.865]	[0.817]	[0.895]	[0.960]
Panel B: The entire period (Weekly observations)						
0.01	− 0.044	0.058	0.906	− 0.294	− 0.623	− 0.862
	[0.518]	[0.477]	[0.183]	[0.616]	[0.733]	[0.806]
0.05	− 0.786	− 1.056	− 1.247	0.113	0.635	0.949
	[0.784]	[0.855]	[0.894]	[0.455]	[0.263]	[0.171]
0.95	2.452***	1.362*	0.797	− 0.106	− 0.232	− 0.718
	[0.007]	[0.087]	[0.213]	[0.542]	[0.592]	[0.764]
0.99	− 1.182	− 1.537	− 2.159	4.364***	8.670***	6.440***
	[0.881]	[0.938]	[0.985]	[0.000]	[0.000]	[0.000]

Notes: "EPU⇒BTC" and "EMU⇒BTC" represent one-way Granger causality in risk from the US EPU index to Bitcoin and from the US EMU index to Bitcoin, respectively. The entire period is from 19 July 2010 to 31 May 2018. Numbers in brackets are p-values of the corresponding estimated coefficients. *** and * indicate statistical significance at 1% and 10% level, respectively.

are insignificant, except for a case of the EPU index at 10% significant level when the confidence level $\theta = 0.01$ and lag order $M = 20$, suggesting the absence of risk spillover effect from EPU to Bitcoin. Panel B shows that most of estimated statistics based on weekly data support the above finding. But there are some exceptions, including that estimated statistics are significant from the EPU index to Bitcoin when $\theta = 0.95$ and $M = 5$ and 10 and from the EMU index to Bitcoin when $\theta = 0.99$ and $M = 5$, 10 and 20. When the US EPU index or EMU index shows extreme upside risk representing that the uncertainty shock increases sharply, EPU has an upside risk spillover effect on Bitcoin, leading to Bitcoin price increases. But note that this result only holds up in certain cases for weekly data.

For robustness check, in Table 6 we report estimated statistics $Q(M)$ for measuring risk spillover effect from the US EPU and EMU indices to Bitcoin during two subperiods. Panel A for subperiod I shows that most of estimated statistics support the finding on negligible risk spillover effect from EPU to Bitcoin. There are three exceptions, including the existence of risk spillover effect

Table 6
Estimated statistics $Q(M)$ associated with Eq. (7) for measuring extreme risk spillover effects from the US EPU and EMU indices to Bitcoin using the Granger causality risk test during two subperiods.

θ	EPU⇒BTC			EMU⇒BTC		
	M = 5	M = 10	M = 20	M = 5	M = 10	M = 20
Panel A: Subperiod I						
0.01	− 0.349	2.615***	6.687***	− 0.696	1.128	3.164***
	[0.636]	[0.005]	[0.000]	[0.757]	[0.130]	[0.000]
0.05	− 0.477	− 0.932	0.256	0.152	− 0.196	− 0.764
	[0.683]	[0.824]	[0.399]	[0.440]	[0.578]	[0.778]
0.95	− 0.277	− 0.457	1.209	0.340	0.141	− 0.025
	[0.609]	[0.676]	[0.113]	[0.367]	[0.444]	[0.510]
0.99	− 1.256	2.588***	6.382***	− 1.077	− 1.488	− 2.047
	[0.895]	[0.005]	[0.000]	[0.859]	[0.932]	[0.980]
Panel B: Subperiod II						
0.01	− 0.683	− 0.846	− 1.174	− 0.734	− 0.636	− 0.641
	[0.753]	[0.801]	[0.880]	[0.769]	[0.738]	[0.739]
0.05	− 0.745	− 0.787	− 0.805	− 0.730	− 0.894	− 0.380
	[0.772]	[0.784]	[0.790]	[0.767]	[0.814]	[0.648]
0.95	− 0.262	0.265	0.164	− 0.536	− 0.834	− 0.502
	[0.604]	[0.396]	[0.435]	[0.704]	[0.798]	[0.692]
0.99	− 0.469	0.035	0.244	− 0.846	− 1.129	− 1.076
	[0.680]	[0.486]	[0.404]	[0.801]	[0.871]	[0.859]

Notes: "EPU⇒BTC" and "EMU⇒BTC" represent one-way Granger causality in risk from the US EPU index to Bitcoin and from the US EMU index to Bitcoin, respectively. Subperiod I is from 19 July 2010 to 4 December 2013 and subperiod II is from 5 December 2013 to 31 May 2018. Numbers in brackets are p-values of the corresponding estimated coefficients. *** indicates statistical significance at 1% level.

from the US EPU index to Bitcoin (i) when $\theta = 0.99$ and $M = 10$ and 20, and (ii) when $\theta = 0.01$ and $M = 10$ and 20, and (iii) from the US EMU index to Bitcoin when $\theta = 0.01$ and $M = 20$. The latter two exceptions can be interpreted as follows: when the US EPU index or EMU index shows extreme downside risk meaning that the uncertainty shock decreases steeply, EPU has a downside risk spillover effect on Bitcoin, and this results in a decrease of Bitcoin price. However, after the December 2013 Bitcoin price crash, the above exceptions all disappear in subperiod II, confirming again the inexistence of risk spillover risk effect from EPU to Bitcoin.

In Table 7 we present estimated statistics $Q(M)$ for measuring risk spillover effect from the VIX index to Bitcoin during the entire period and two subperiods. Panel A based on daily data during the entire period shows evidence of downside risk spillover effect from the VIX index to Bitcoin, because estimated statistics $Q(M)$ are significant when $\theta = 0.01$ and $M = 5$, 10, and 20 and when $\theta = 0.05$ and $M = 5$ and 10. But this evidence disappears when examining weekly data during the entire period (see Panel B), meaning the

Table 7
Estimated statistics $Q(M)$ associated with Eq. (7) for measuring risk spillover effect from the VIX index to Bitcoin using the Granger causality risk test during the entire period and two subperiods.

θ	M = 5	M = 10	M = 20	M = 5	M = 10	M = 20
Panel A: The entire period (Daily)				*Panel B: The entire period (Weekly)*		
0.01	1.369*	2.296*	3.329***	0.176	− 0.312	− 0.419
	[0.086]	[0.011]	[0.000]	[0.430]	[0.622]	[0.662]
0.05	2.037**	1.302*	1.074	− 0.954	− 0.519	− 0.686
	[0.021]	[0.096]	[0.141]	[0.830]	[0.698]	[0.754]
0.95	0.857	0.104	0.163	− 0.319	− 0.646	− 0.979
	[0.196]	[0.459]	[0.435]	[0.625]	[0.741]	[0.836]
0.99	− 0.872	− 1.063	− 0.545	− 1.074	− 1.538	− 0.461
	[0.809]	[0.856]	[0.707]	[0.859]	[0.938]	[0.678]
Panel C: Subperiod I				*Panel D: Subperiod II*		
0.01	2.306**	3.789***	3.737***	0.905	1.829**	3.419***
	[0.011]	[0.000]	[0.000]	[0.183]	[0.034]	[0.000]
0.05	0.777	0.190	− 0.240	0.186	0.002	− 0.280
	[0.219]	[0.425]	[0.595]	[0.426]	[0.499]	[0.610]
0.95	0.396	− 0.113	− 0.193	− 0.422	− 0.999	− 1.465
	[0.346]	[0.545]	[0.576]	[0.664]	[0.841]	[0.929]
0.99	0.184	0.820	0.893	− 0.757	0.431	1.063
	[0.427]	[0.206]	[0.186]	[0.775]	[0.333]	[0.144]

Notes: The entire period is from 19 July 2010 to 31 May 2018, subperiod I is from 19 July 2010 to 4 December 2013, and subperiod II is from 5 December 2013 to 31 May 2018. Numbers in brackets are p-values of the corresponding estimated coefficients. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

inexistence of risk spillover effect from the VIX index to Bitcoin. For subperiods I and II in Panels C and D, only when $\theta = 0.01$ estimated statistics $Q(M)$ are significant, and the insignificant risk spillover effect from the VIX to Bitcoin holds in other conditions. On the whole, Table 7 shows that estimated statistics $Q(M)$ for the VIX index in most conditions are statistically insignificant, confirming that risk spillover effect from EPU to Bitcoin is insignificant.

5. Conclusions

We have investigated the risk spillover effect from the US EPU, EMU and VIX indices to Bitcoin using two different approaches, i.e., the MVQM-CAViaR and the Granger causality risk test. We have examined risk spillover effect using daily and weekly data during the entire period and also checked whether the December 2013 Bitcoin price crash influences the spillover results by splitting the sample period into two subperiods. We have further studied whether contemporaneous or instantaneous correlations impact risk spillover effect. The empirical results based on the MVQM-CAViaR approach show that the impact of the US EPU, EMU and VIX shocks on Bitcoin's risk is negligible, while the Granger causality risk test shows that risk spillover effect from the US EPU, EMU and VIX indices to Bitcoin is insignificant in most conditions (i.e., different quantiles and time-lags). Our results are robust to data frequency, the influence of the December 2013 Bitcoin price crash, and contemporaneous or instantaneous correlations. Our finding on the inexistence risk spillover effect from EPU to Bitcoin provides new information for investors when they construct asset portfolios, e.g., Bitcoin can be used as a safe-haven or a diversifier in condition of extreme EPU shocks. In the future, our work can be extended to examine the impact of economic policy uncertainty on more cryptocurrencies (e.g., Ethereum, Ripple and Litecoin) for checking whether the cryptocurrency market is immune from EPU shocks.

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