Risk Spillover between Bitcoin and Conventional Financial Markets: An Expectile-Based Approach

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Abstract

We challenge the existing literature that points to the detachment of Bitcoin from the global financial system. We use daily data from August 17, 2011 - February 14, 2020 and apply a risk spillover approach based on expectiles. Results show reasonable evidence to imply the existence of downside risk spillover between Bitcoin and four assets (equities, bonds, currencies, and commodities), which seems to be time dependent. Our main findings have implications for participants in both the Bitcoin and the traditional financial markets for the sake of asset allocation, and risk management. For policy makers, our findings suggest that Bitcoin should be monitored carefully for the sake of financial stability.

Keywords: Bitcoin; financial markets; asset classes; downside risk spillover; expectile VaR; CAR-ARCHE

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1. Introduction

Over the last decade, many researches have directed their focus toward the controversial Bitcoin market that has quickly attracted the attention of individual and institutional investors from around the globe. Bitcoin is a leading investment vehicle within the newly emerged digital asset family and eligible for portfolio diversification (e.g., Bouri et al., 2019; Guesmi, 2019; Shahzad et al., 2019, 2020). It is regarded as a hedge against global uncertainties and a shelter during stress periods (Luther and Salter, 2017; Bouri et al., 2017a). However, because the Bitcoin market has grown rapidly[1] and exhibited extreme price volatility, it is a potential source of instability to financial markets (European Central Bank, 2012). It is therefore crucial to understand the linkages between Bitcoin and financial markets for the sake of decisions about asset allocation, risk management, and financial stability. Notably, Bitcoin has gradually become more complex (Antonakakis et al., 2019), suggesting the necessity to apply advanced and refined techniques to uncover time-varying risk spillover from Bitcoin to other assets.

In this paper, we uncover the complexity of the risk spillover between Bitcoin and conventional assets (equities, bonds, currencies, and commodities) via the construction of a time-varying downside risk spillover. The latter is based on the expectile Value-at-Risk (EVaR) approach recently proposed by Zhang and Ma (2019), which integrates the ARCH-Expectile model with embedded Conditional Autoregressive structure (namely CAR-ARCHE model). This would allow for capturing the contribution of market risk factors and measuring the downside of Bitcoin and the four conventional assets under study.

This current paper belongs to the literature on Bitcoin finance and economics and relates to studies on the linkages between Bitcoin and financial markets and their

[1] Bitcoin price increased from around $430 in December 2015 to more than $7000 in December 2019.

various policy implications. However, its contributions are on several fronts. Firstly, we challenge the growing evidence that mostly indicates that Bitcoin is detached from the global financial system (e.g., Baur et al., 2018; Bouri et al., 2019; Corbet et al., 2018; 2019; Li and Huang, 2020), and provide reasonable evidence to suggest the presence of significant downside rsik spillovers between Bitcoin and various asset classes. We find that the risk spillover varies with time, which is generally in line with the existing studies that generally show that the relationship between Bitcoin and other assets classes exbibits some time variation (e.g., Ji et al., 2018; Bouri et al., 2019; Okorie and Lin, 2020)[2]. Secondly, we focus on downside risk spillovers rather than average spillovers or correlations, which represents a shift in the related literature (e.g., Ji et al., 2018; Symitsi and Chalvatzis, 2018; Kurka, 2019; Li and Huang, 2020). Thirdly, for measuring risk spillovers, we employ the EVaR that it is related to the probability of the tail realization of asset returns and allows for describing the risks produced in the entire distribution of asset returns. This has the important consequence that the standard risk measures such as VaR and CVaR that at best can measure the risks produced at the lower tail of the distribution of asset returns are no longer valid because expectile-based spillover measures are more sensitive to the size of extreme value of distribution (Kuan et al., 2009) than quantile-based measures (e.g., VaR and CVaR). Our results show significant time-varying downside risk spillovers from Bitcoin to the conventional assets under study and vice-versa, which has not been previously discovered by the GARCH-based measures adopted in the academic literature (e.g., Symitsi and Chalvatzis, 2018; Bouri et al., 2018). Our analyses have important implications regarding risk management, asset allocation, and regulatory formulation.

The direction of the rest of the paper is as follows. Section 2 reviews the academic literature dealing with the relationship between Bitcoin and financial markets. Section 3 presents the empirical methods, starting with the definitions of Expectile VaR,

[2] Other studies show that the relationship between Bitcoin and uncertainties measures are non-constant and varies with time (e.g., Qin et al., 2020).

moving to the CAR-ARCHE model and the time-varying downside risk spillover test. Section 4 describes the dataset and presents the empirical results. Section 5 concludes.

2. Related studies

The relationship between Bitcoin and financial markets has been the subject of several studies over the last five years, which mostly indicate that Bitcoin is detached from conventional assets like equities, fiat currencies, commodities, and bonds. This is an important finding as investors and portfolio managers tend to switch into alternative investments in order to diversify the risk of their conventional portfolios. While gold maintains a special status as a valuable asset during crisis periods, Bitcoin has emerged as an eligible investment vehicle for portfolio diversification (Bouri et al., 2019; Guesmi, 2019; Shahzad et al., 2019, 2020). In fact, many investors view Bitcoin as a shelter during stress periods (Luther and Salter, 2017; Bouri et al., 2017a). Not surprisingly, Bitcoin is often considered as a safe haven asset because its value is more stable than that of stocks or conventional currencies. It also has a hedging ability against stocks because its price determinants are different from those of stocks and are mostly dependent on Bitcoin's own supply and demand and on other unique factors such as attractiveness, blockchain technology, mining difficulties, as well as other internal factors like security issues and bubbles (e.g., Li and Wang, 2017; Zhou, 2019; Kristoufek, 2020)[3]. Furthermore, Bitcoin has the ability to protect against various types of uncertainties (Bouri et al., 2017a; Demir et sl., 2018; Qin et al., 2020).

In addition to considering Bitcoin market risk measurement (Katsiampa, 2017), several studies focus on the market linkages between Bitcoin and conventional assets like stocks, bonds, currencies, and commodities using used various methodologies such as GARCH models, Granger causality tests, and connectedness measures. Bouri et al. (2017b) apply a univariate GARCH model and find that Bitcoin is volatility is negatively related with the US stock market uncertainty. Symitsi and Chalvatzis

[3] Walther et al. (2019) provide significant evidence on the role of some exogenous factors related to economic and financial variables in driving the volatility of Bitcoin.

(2018) employ multivariate VAR-GARCH model to examine spillovers between Bitcoin and the equity stock indices of energy and information technology. They show one-sided return and volatility spillovers and bidirectional shock effects. Baur et al. (2018) use various regression models and show that Bitcoin is uncorrelated with equities, bonds and commodities during both tranquil and stress periods. Bouri et al. (2019) apply a smooth transition VAR-GARCH model and study the spillovers between Bitcoin and various assets such as equities, commodities, currencies and bonds. They find that Bitcoin returns are somewhat related to commodities, and that Bitcoin mostly receives more volatility shocks than it transfers. Other studies apply several connectedness measures. Ji et al. (2018) use the directed acyclic graph approach and show that the contemporaneous linkages between Bitcoin and financial markets are weak, suggesting the isolation of the Bitcoin market. Corbet et al. (2018) use time and frequency measures of connectedness and report evidence that Bitcoin is segmented from conventional assets, pointing to its diversification benefits. In another study, Corbet et al. (2019) systematically examine the literature and argue that the Bitcoin market is almost independent of conventional assets, indicating a possibility for portfolio diversification. Kurka (2019) examine the relationship between leading cryptocurrencies and other asset classes via the application of connectedness measures. They indicate that information transmission is negligible on aggregate, but there is some indication of significant shocks originating from Bitcoin and propagating to financial markets. Li and Huang (2020) show that Bitcoin and other leading cryptocurrencies are very weakly connected to traditional assets and thus they do not represent an eminent source of risk to the global financial system. Okorie and Lin (2020) consider crude oil cryptocurrency markets and show evidence of some volatility linkages that might disturb potential hedging strategies.

The above literature reveals important aspects of the linkages between Bitcoin and financial markets, mostly pointing to the segmentation of Bitcoin from the global financial system. Furthermore, previous studies apply several modeling techniques for understanding the spillovers between Bitcoin and financial markets such as time-varying correlations, VAR models, Granger causality, connectedness measures, and GARCH-based models. GARCH-based models have been used extensively to model the risk of Bitcoin (e.g., Katsiampa, 2017) and continue to represent the main tool to models asset linkages while accounting for stylized facts of asset returns such as heteroscedasticity and heavy-tails. Specifically, the returns of Bitcoin and other assets exhibit tail dependence (Shahzad et al., 2019) that seem to vary with time and across quantiles. Interestingly, the Bitcoin market has gradually become more complex (Antonakakis et al., 2019), suggesting the necessity to apply more advanced and refined techniques to uncover the extreme risk spillovers between Bitcoin and assets classes for the sake of financial stability and portfolio implications. To properly incorporate such characteristics and cope with the above issues, we use the EVaR approach recently proposed by Zhang and Ma (2019), which emerges as a powerful and appropriate procedure for our study. Notably, the EVaR goes beyond the Value at Risk (VaR) and conditional VaR (CVaR) that at best can measure the risks produced at the lower tail of the distribution of asset returns. Therefore, the EVaR allows for describing the risks produced in the entire distribution of asset returns and conveniently the EVaR is related to the probability of the tail realization of asset returns (Zhang and Ma, 2019).

3. Methods

3.1. The definitions of Expectile VaR (EVaR)

For any $\alpha \in (0,1)$, let $\theta(\alpha)$ be such that $\nu(\theta) = q(\alpha)$. That is, the quantile $q(\alpha)$ of Y at the significance level α is equal to the expectile $\nu(\theta)$ of Y at the prudence level θ, and the relationship between $\theta(\alpha)$ and $q(\alpha)$ is established as Eq. (1) (Yao and Tong, 1996):

$$\theta(\alpha) = \frac{\alpha q(\alpha) - \int_{-\infty}^{q(\alpha)} y dF(y)}{2E(Y) - 2\int_{-\infty}^{q(\alpha)} y dF(y) - (1-2\alpha)q(\alpha)} \tag{1}$$

where $F(y)$ is the distribution function of asset return Y.

3.2. The CAR-ARCHE model

The ARCH-Expectile model with embedded Conditional Autoregressive structure (namely CAR-ARCHE model) is as Eq. (2):

$$\begin{aligned} y_t &= x_t'\beta(\theta) + e_t \\ e_t &= \sigma_t \varepsilon_t \\ \sigma_t^2 &= \kappa_0 + \sum_{i=1}^{p} \kappa_i e_{t-i}^2 \end{aligned} \tag{2}$$

where ε_t represents IID (independently identically distribution) with $E\left[\varepsilon_t\right] = 0, E\left[\varepsilon_{\mathrm{t}}^2\right] = 1$, and p denotes the lag order in the ARCH term, $\kappa_0 > 0, \kappa_i \geq 0, i = 1,2,\cdots,p$. When $x_t = \left(1, y_{t-1}, \left(y_{t-1}^{+}\right)^2, \left(y_{t-1}^{-}\right)^2, \cdots, \left(y_{t-n}^{+}\right)^2, \left(y_{t-n}^{-}\right)^2\right)$ or $x_t = \left(1, y_{t-1}^{+}, y_{t-1}^{-}, \cdots, y_{t-n}^{+}, y_{t-n}^{-}\right)$, the CAR-ARCHE model is marked as the CAR_1-ARCHE(n, p) and CAR_2-ARCHE(n, p), respectively.

Based on the CAR-ARCHE model, it can be argued that the expectile of asset return Y (namely EVaR) satisfies $v_y\left(\theta\right) = x_t'\beta\left(\theta\right)$.

3.3. Time-varying downside risk spillover test

(1) The indicator function of EVaR

Firstly, an indicator function of downside risk based on EVaR series is defined as Eq. (3):

$$Z_{m,t} = I(y_{m,t} < \text{EVaR}_{m,t}), \ m = 1,2 \tag{3}$$

where $y_{m,t}$ and $\text{EVaR}_{m,t}$ are the logarithmic returns and EVaR of asset return m at time t, respectively, and $I(\bullet)$ denotes an indicator function. If the actual loss passes EVaR, $Z_{m,t}=1$; otherwise $Z_{m,t}=0$.

(2) Time-varying downside risk spillover statistics

Let $\mathrm{EVaR}_{m,t}$ show the time series of EVaRs of an asset return m at the significance level of α. Referring to Lu et al. (2014), we set the rolling sample $W=64$ in empirical analyses. To assess the dynamic downside risk spillovers during the subsample $[t-W+1, t]$, suppose $\hat{Z}_{m,t}=I\left(y_{m,t}<\mathrm{EVaR}_{m,t}\right)$ for two return series $\left\{y_{1,t}, y_{2,t}\right\}$, then the lag-$j$ subsample cross covariance function for $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$ is specified as:

$$\hat{C}_t\left(j,W\right)=\begin{cases} W^{-1}\sum_{t=1+j}^{W}\left(\hat{Z}_{1,t}-\hat{f}_1\right)\left(\hat{Z}_{2,t-j}-\hat{f}_2\right), & 0\le j\le W-1 \\ W^{-1}\sum_{t=1-j}^{W}\left(\hat{Z}_{1,t+j}-\hat{f}_1\right)\left(\hat{Z}_{2,t}-\hat{f}_2\right), & 1-W\le j<0 \end{cases} \tag{4}$$

where $\hat{f}_m=W^{-1}\sum_{t=1}^{W}\hat{Z}_{m,t}$. And the lag-$j$ subsample cross correlation function for $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$ is written as Eq. (5):

$$\hat{\rho}_t\left(j,W\right)=\hat{C}_{\mathrm{t}}\left(j,W\right)\Big/\sqrt{\hat{D}_1\hat{D}_2},\ j=0,\pm1,\cdots,\pm\left(W-1\right) \tag{5}$$

where $\hat{D}_{\mathrm{m}}=\hat{f}_m\left(1-\hat{f}_m\right)$ denotes the sample variance of $\hat{Z}_{m,t}$.

To detect the unidirectional and bidirectional time-varying downside risk spillovers for these two assets, referring to Lu et al. (2014), we introduce the Daniell kernel function and corresponding test statistics are written as Eq. (6):

$$H_{1,t}(W)=\left[W\sum_{j=1}^{W-1}k^2\left(\frac{j}{M}\right)\widehat{\rho}_t^2(j,W)-C_{1W}(k)\right]\Big/\sqrt{2D_{1W}(k)}$$
$$H_{2,t}(W)=\left[W\sum_{j=1-W}^{W-1}k^2(j/M)\widehat{\rho}_t^2(j,W)-C_{2W}(k)\right]\Big/\sqrt{2D_{2W}(k)} \tag{6}$$

where $k(x)=\sin(\pi x)/\pi x,\ x\in(-\infty,+\infty)$ is the Daniell kernel function, and M represents the lag order, we set $M=10$ in empirical analyses. Centring factors ($C_{1W}(k)$ and $C_{2W}(k)$) and scaling factors ($D_{1W}(k)$ and $D_{2W}(k)$) can be specified as Eq. (7) (Hong, 2001):

$$C_{1W}(k)=\sum_{j=1}^{W-1}\left(1-\frac{j}{W}\right)k^2\left(\frac{j}{M}\right),\quad D_{1W}(k)=\sum_{j=1}^{W-1}\left(1-\frac{j}{W}\right)\left(1-\frac{j+1}{W}\right)k^4\left(\frac{j}{M}\right)$$
$$C_{2W}(k)=\sum_{j=1-W}^{W-1}\left(1-\frac{|j|}{W}\right)k^2\left(\frac{j}{M}\right),\ D_{2W}(k)=\sum_{j=1-W}^{W-1}\left(1-\frac{|j|}{W}\right)\left(1-\frac{|j|+1}{W}\right)k^4\left(\frac{j}{M}\right) \tag{7}$$

If $\{y_{1,t}\}$ and $\{y_{2,t}\}$ are mutually independent in the subsample, then according to Hong (2001), for $i=1,2$, $H_{i,t}(W)\to N(0,1),\ as\ W\to\infty$, and the time-varying downside risk spillover tests are the one-sided tests. If the significance probability of $H_{i,t}(W)$ is less than the corresponding significance level of α, then the null hypothesis can be rejected, which implies significant downside risk spillover for these two assets at time *t*.

4. Empirical results

4.1. The dataset and some key statistics

This study uses daily data covering Bitcoin price against the US dollar, from one of the largest Bitcoin exchanges, Bitstamp, US dollar index, MSCI world equity index, S&P Goldman Sachs Commodity Index (GSCI), and PIMCO Investment

Grade Corporate Bond Index ETF (Ji et al., 2018). All data series are in USD and come from the DataStream database. The sample period is August 17, 2011 - February 14, 2020, yielding a total of 2,216 daily common observations. The beginning and ending of the sample period are dictated by the availability of data. For all series, returns are computed in a log form.

Table 1 presents the summary statistics of daily return. Except for the GSCI, all the means of returns are positive. Notably, Bitcoin has the largest mean and the largest standard deviation. All return series are negatively skewed and have high values for the kurtosis, implying a departure from the Gaussian distribution. Heteroscedasticity, based on the ARCH-LM statistics of the Engle (1982) test, is significant in all cases, except Bond. Statistics from the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) show that all daily return series are stationary at the 1% level of significance.

Table 1. Summary statistics and key tests of daily returns

	Mean	Max.	Min.	SD	Skewness	Kurtosis	Jarque-Bera	ARCH-LM (20)	ADF
Bitcoin	0.309	48.478	-66.395	5.795	-0.9331	22.9758	37165.47***	18.878***	-48.970***
Dollar index	0.013	2.032	-2.399	0.418	-0.0307	5.0445	386.31***	6.209***	-48.164***
MSCI	0.034	4.112	-5.029	0.755	-0.4498	7.2808	1766.774***	15.571***	-40.914***
GSCI	-0.033	7.617	-6.586	1.147	-0.0536	6.1031	890.187***	6.254***	-49.677***
Bond	0.004	1.123	-3.905	0.285	-1.4303	19.7299	26598.77***	0.264	-49.900***

Notes: The sample period is August 17, 2011 - February 14, 2020, covering 2,215 daily return observations. SD denotes standard deviation. Jarque-Bera statistics are associated with the null hypothesis test of whether the return series are normally distributed. ARCH-LM (20) are statistics for heteroskedasticity ARCH test, up to 20 lags. ADF is augmented Dickey Fuller statistics of the null hypothesis test on the presence of a unit root in the return series. ADF test is conducted with an intercept and lag length of models selected based on the Schwarz information criterion. *** indicates statistical significance at the 1% level.

Results from the pairwise Pearson correlation coefficients are given in Table 2. They show a very weak positive correlation between Bitcoin and each of the other assets, except the US dollar. These results are generally is in line with previous studies (i.e., Ji et al., 2018).

Table 2. Pearson correlation coefficients among daily returns

	Bitcoin	Dollar index	MSCI	GSCI	Bond
Bitcoin	1				
Dollar index	-0.004	1			
MSCI	0.015	-0.233	1		
GSCI	0.005	-0.206	0.427	1	
Bond	0.021	-0.115	-0.069	-0.051	1

Notes: The sample period is August 17, 2011 - February 14, 2020, covering 2,215 daily return observations.

4.2. Selection of CAR-ARCHE model

In the light of the truncated orders of autocorrelation and partial autocorrelation functions, together with the ARCH-LM test and the principle of minimum AIC value, appropriate models are singled out through many attempts under the given α corresponding to expectiles with different θ for the five asset returns, respectively. Table 3 lists their specific model forms and lag orders.

Table 3. Model selection of five asset returns

Return	α	θ	CAR_i-ARCHE(n, p) model
Bitcoin	0.05	0.0327	CAR_2-ARCHE(1, 2)
	0.01	0.0033	CAR_1-ARCHE(1, 1)
Dollar index	0.05	0.0197	CAR_1-ARCHE(1, 1)
	0.01	0.0035	CAR_2-ARCHE(1, 1)
MSCI	0.05	0.0227	CAR_2-ARCHE(1, 1)
	0.01	0.0032	CAR_1-ARCHE(1, 1)
GSCI	0.05	0.0209	CAR_1-ARCHE(2, 1)
	0.01	0.0033	CAR_1-ARCHE(1, 1)
Bond	0.05	0.0172	CAR_1-ARCHE(2, 2)
	0.01	0.0015	CAR_1-ARCHE(2, 1)

4.3. Estimation of EVaRs based on the CAR-ARCHE models

We calculate the downside EVaRs by means of the Eq. $\hat{v}_y(\theta) = x_t'\hat{\beta}(\theta)$ above at corresponding prudence levels for the five asset returns, respectively, and relevant results are shown in Table 4.

Table 4. Summary of EVaRs for five asset returns

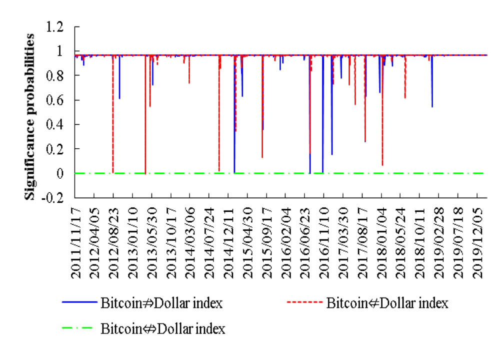
Return	α	θ	Mean	Std.Dev	Failure time	Rate of failure	LR statistic
Bitcoin	0.05	0.0327	-7.3522	1.8922	110	4.97%	0.0054
	0.01	0.0033	-16.8895	5.5854	22	0.99%	0.0010
Dollar index	0.05	0.0197	-0.6515	0.0306	117	5.28%	0.3648
	0.01	0.0035	-1.0217	0.0401	26	1.17%	0.6402
MSCI	0.05	0.0227	-1.1901	0.3205	119	5.37%	0.6322
	0.01	0.0032	-1.9658	0.6903	32	1.44%	3.8898
GSCI	0.05	0.0209	-1.8695	0.2000	120	5.42%	0.8015
	0.01	0.0033	-2.9832	0.1927	25	1.13%	0.3556
Bond	0.05	0.0172	-0.5063	0.1647	105	4.74%	0.3141
	0.01	0.0015	-0.9446	0.5382	22	0.99%	0.0009

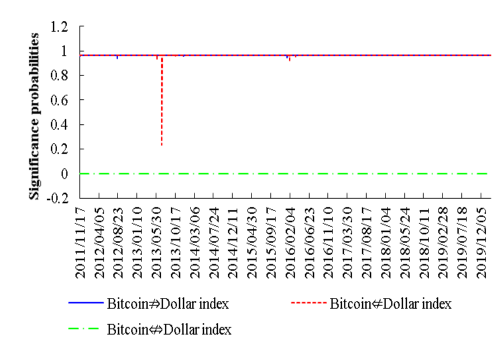
Some findings are identified as follows: ① All *LR*-values are lesser than corresponding critical values (namely 3.84 and 6.64) at the significance levels of 5% and 1%, respectively. Hence, we can say that, at the 5% and 1% significance levels, the CAR-ARCHE models have adequately estimated the downside EVaRs of the five assets.②No matter at the significance levels of 5% or 1%, the mean values of EVaRs of Bitcoin prove far greater than those of other four asset returns. Therefore, in comparison, it is necessary for Bitcoin market participants to prepare more risk reserves.

4.4. Time-varying downside risk spillover between Bitcoin returns and returns of the other four assets

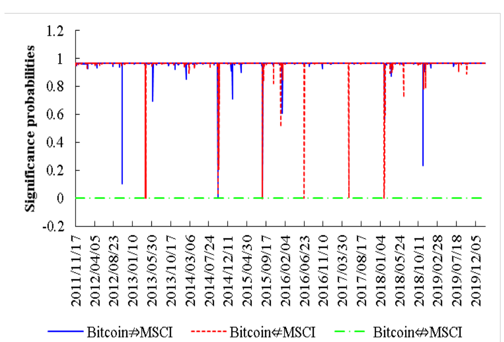
After the EVaR series of the five asset returns are gained, we further calculate the unidirectional and bidirectional time-varying downside risk spillover statistics $H_{i,t}(W), i=1,2$ and the corresponding p-values during the sample period. Subsequently, the bidirectional and unidirectional time-varying downside risk spillovers between Bitcoin returns and the other four asset returns are examined, respectively.

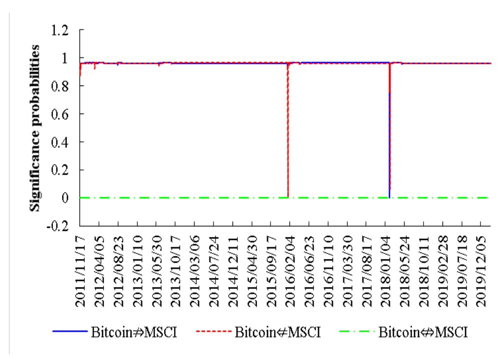
We list the significance probability trends of time-varying downside risk spillover statistics at the 5% and 1% significance levels with $W=64, M=10$ (W is the rolling sample size, M represents the lag order) (see Fig. 1). According to the results in Fig. 1, several findings can be emerged as follows.



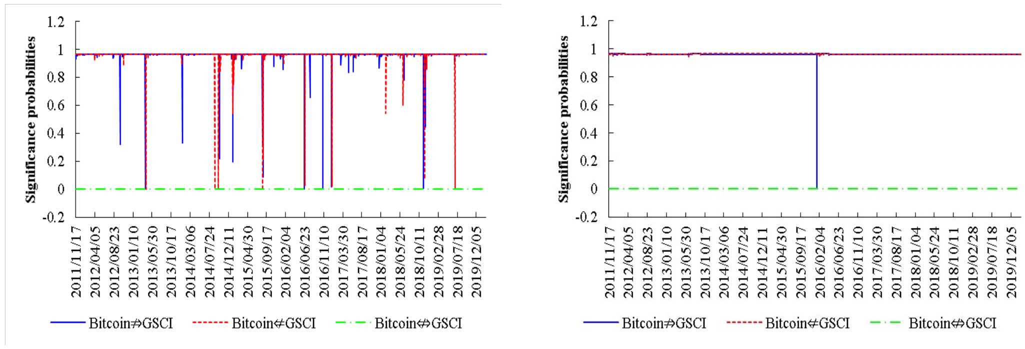


(a1) $\alpha=0.05$ (b1) $\alpha=0.01$

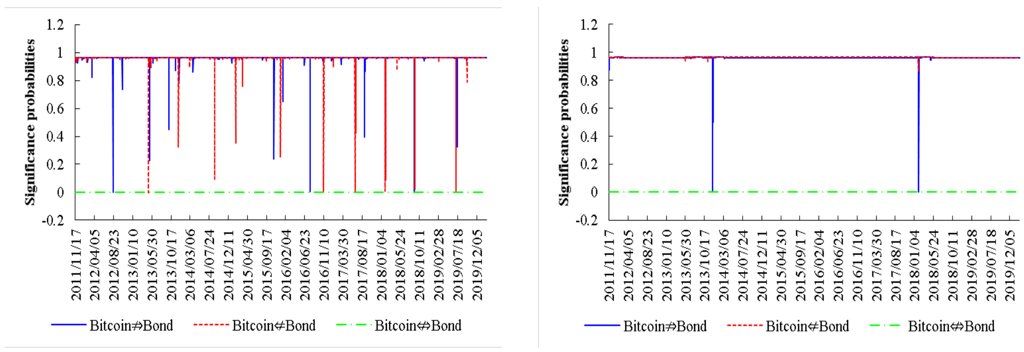




(a2) $\alpha = 0.05$ (b2) $\alpha = 0.01$



(a3) $\alpha = 0.05$ (b3) $\alpha = 0.01$



(a4) $\alpha = 0.05$ (b4) $\alpha = 0.01$

Fig. 1. Significance probabilities of time-varying downside risk spillover statistics for Bitcoin and other four assets at the 5% and 1% significance levels ($W = 64, M = 10$)

(1) During the sample period (November 17, 2011- February 14, 2020), there are significant bidirectional downside risk spillovers between Bitcoin and the other four assets at each time point. At the 5% and 1% significance levels, it can be demonstrated from the trends of significance probabilities of the bidirectional time-varying statistic $H_{2,t}$ that corresponding *p*-values are close to zero at each time point.

(2) With the exception of some special time points, there are no significant unidirectional downside risk spillovers from Bitcoin to the Dollar index, world equities, commodities and bonds and *vice-versa* during the sample period. However, there are highly significant bidirectional downside risk spillover effects between them at each time point. So, it can be found that there exist remarkable synchronising

downside risk spillovers between Bitcoin and other four assets in this paper, that is, the interactions between them are very rapid and direct.

It can also be affirmed from the trends of significance probabilities of statistic in Fig. 1 that the unidirectional time-varying downside risk spillover statistics from Bitcoin to other four assets and vice-versa are not statistically significant for most of sample period, but they are remarkable and present a variation with a jump during some special time points. For example, at the 5% significance level, in late August, 2012, in mid-April, 2013, from late September to early October, 2014, from mid to late August, 2015, in late June, 2016, in early August, 2016, in early November, 2016, in early January, 2017, in early February, 2018, in early September, 2018, as well as in early July, 2019, the unidirectional time-varying downside risk spillover statistics from Bitcoin to other four assets and vice-versa are very statistically significant. While at the 1% significance level, in mid-January, 2016, the unidirectional time-varying downside risk spillover statistics from Bitcoin to commodities and world equities to Bitcoin are very statistically significant; and in early February, 2018, the unidirectional time-varying downside risk spillover statistics from Bitcoin to world equities and bonds are very statistically significant.

Our main results contradict with most of the literature that shows the isolation of Bitcoin from the global financial system (e.g., Baur et al., 2018; Bouri et al., 2019; Corbet et al., 2018; 2019; Li and Huang, 2020). In fact, during certain periods related to major events, the downside risk spillover between Bitcoin and the global financial system is significant, which indicate that the declaration that Bitcoin is a new basket for eggs (e.g., Qin et al., 2020) is not always correct hold true. The Bitcoin market is not segmented, as previously argued. This finding is partially comparable to Bouri et al. (2018) and Kurka (2019) who also uncover periods of significant shock transmission between Bitcoin and traditional assets. In fact, Kurka (2019) indicate that the increasing market value of Bitcoin reinforces the risk spillover from Bitcoin, leading to some disruptions to the financial system. It could be that the time-variation in the risk spillovers reflects not only exogenous shocks related to economic and financial factors (Walther et al., 2019; Matkovskyy et al., 2020) but also security issues (Conti et al., 2018) and bubble risks (Su et al., 2018), both of which might contribute to the significant spillover effects between Bitcoin and conventional assets.

5. Concluding remarks

The advance of Bitcoin and its extreme high volatility have sparked extensive concern over its interplay with the global financial system. To cope with this concern, we provide a valuable tool to uncover the dynamic time-evolution of the complex risk spillover between Bitcoin and various asset classes (stocks, bonds, currencies, and commodities). Overall, the results obtained indicate that downside risk spillovers between Bitcoin and the four assets under study are significant and are a phenomenon that occurs during specific periods.

Our analyses have a number of limitations that open new possibilities for future research. A first limitation relates to the use of aggregate indices of conventional assets, which could mask potential risk spillover between and disaggregated indices related to equity sectors, pairs of currencies, or strategic commodities such as gold and crude oil. Future studies can address this limitation, now our applied methods have successfully uncovered of significant risk spillovers. Another limitation relates to the use of Bitcoin as a representative of the cryptocurrency market. This is because Bitcoin dominates the cryptocurrency market with a market share that amounts to around 70%. Future research can consider some leading cryptocurrencies such as Ethereum and Ripple.

However, despite these limitations, our findings are important and potentially useful to investors and portfolio managers to better comprehend the Bitcoin market and facilitate more refined portfolio allocations and risk management decisions. Our analyses indicate that the risks in one asst can be used to predict the risks in the other assets. In fact, the results also show that expectiles-based measures of risk can be exploited to capture downside risk spillovers in complex markets that are subject to global trade tensions and difficult economic environment. The findings have also implications regarding the design and implementation of procedures for monitoring and maintaining financial stability. Given the ability of Bitcoin risk to alter the risk of conventual assets, regulators and policy makers have to monitor the Bitcoin market for the sake of financial stability. Accordingly, our findings can have an influence on the decisions of governments in in countries that seek to consider Bitcoin as an official cryptocurrency or as part of their foreign reserves.

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