The Overall And Extremely Low Return Spillovers Among Cryptocurrencies and Stock Markets: Evidence from the COVID-19 Pandemic

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Abstract

Employing spillover index and cross-quantilogram techniques, we measures the overall and extremely low return spillovers among three representative cryptocurrencies (Bitcoin, Ethereum, and Litecoin) and three major stock market indices (the S&P 500, the FTSE 100, and the SZSE 300). The results demonstrate that the overall spillover effects have sharply enhanced and maintained at high level during the COVID-19 pandemic, and all the cryptocurrencies are net transmitters of shocks. Return spillover effects are observed stronger in short-term (a trading week) than in the medium-term (a trading month) and in the long-term (a trading quarter). Under extreme downturn condition, the lowest return dependence between a cryptocurrency and a stock market is not significantly negative or positive, but the dependence relationship between a pair of cryptocurrencies or between a pair of stock indices is significantly positive. This suggests a weak form safe-haven role of cryptocurrencies against stock markets during the COVID-19 pandemic.

Keywords: Spillover; Cryptocurrency; Safe-haven; COVID-19

1. Introduction

As a potential safe haven asset against stocks, cryptocurrency has received great attention due to its unique characteristics, such as non-political attributes, no central authority, no cash-flows and produced by “mining” (Baur et al., 2018). Multiple studies have employed various techniques to examine the integration of the cryptocurrency with traditional financial assets and provided valuable insights into portfolio diversification (Bouri et al., 2017; Corbet et al., 2018; Trabelsi, 2018; Bouri et al., 2019; Shahzad et al., 2020; Conlon et al., 2020; Mariana et al., 2021). They come to the conclusion that the connectedness between cryptocurrency and conventional assets is weak, but with a rising trend (Zeng et al., 2020) or with time vary characteristics (Ji et al., 2018; Charfeddine et al., 2020; Corbet et al., 2018). Studies point out that cryptocurrency is relatively isolated from traditional assets during the cryptocurrency bull market (Ji et al., 2018; Shahzad et al., 2019), but the diversification benefits tend to be lower during the cryptocurrency bear market (Corbet et al., 2018; Feng et al., 2018; Zhang et al., 2021; Wang et al., 2021). Some researches even provide evidence that in time of serious financial and economic disruption some assets do not act as hedges, or safe havens, but perhaps rather as amplifiers of contagion(Corbet et al., 2020; Conlon and McGee, 2020).

Notably, the majority of the financial markets are greatly affected by the COVID-19 in 2020. Both cryptocurrency and stock market became extremely volatile and experienced a sharp decline. For cryptocurrencies, Bitcoin, Ethereum and Litecoin experienced a record price declined of 36%, 42% and 36%, respectively, on March 12,

2020. For stock indices, the S&P 500 and FTSE 100 sharply fell more than 20% from February to March in 2020. Therefore, we cannot assume that the connectedness between cryptocurrency and the stock market remains stable during the COVID-19 pandemic.

As the European Central Bank said, “there is a need for a continuous monitoring of the Bitcoin’s integration into the global financial system” (European Central Bank, 2012). It is a way to implement this principle that we study the spillover effects among the three representative cryptocurrencies (Bitcoin, Ethereum, and Litecoin) and three major stock market indices (S&P 500, FTSE 100, and SZSE 300) and discuss the diversification opportunities during the COVID-19 pandemic.

In order to achieve our research purposes, we adopt three techniques to conduct the analysis: the time-domain spillover framework designed by Diebold and Yilmaz (2009, 2012, 2014), frequency decomposition of spillover designed by Barunik and Krehlik (2015), and the cross-quantilogram designed by Han et al. (2016). These three measuring methods allow us to not only study the strength of connectedness between cryptocurrencies and stock market indices in average but also focus on the extreme market conditions, and permit measuring multivariate and bivariate connections at different time scales, which is more indicative of market behavior. To the best of our knowledge, no previous study has combined the spillover index and cross-quantilogram to investigate the spillover effects among cryptocurrencies and stock market indices during the COVID-19 pandemic.

2. Methodologies

2.1 The time- and frequent-domain spillover index

The time-domain spillover framework by Diebold and Yilmaz (2009, 2012, 2014) is built upon a generalized forecast error variance decomposition (GFEVD) of a vector autoregressive (VAR) model. The p-order VAR model can be expressed as:

$$y_t = \sum_{i=1}^{p} \Phi_i \, y_{t-i} + \varepsilon_t \tag{1}$$

where y_t is an $N \times 1$ vector, represents the return vectors of N variables, each Φ_i denotes an $N \times N$ coefficient matrix, and $\varepsilon_t \sim (0, \Sigma)$. The moving average representation is $y_t = \sum_{\mathrm{i}=0}^{\infty} A_i \varepsilon_{t-i}$, where A_i satisfies the recursion $A_i = \sum_{j=1}^{p} \Phi_j \, A_{t-j}$ with A_0 is an $N \times N$ identity matrix. Let $\theta_{ij}(H)$ be the contribution of variable j to the generalized forecast error variance of variable i, the H-step ahead generalized forecast error variance decomposition can be calculated as follows:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_j\right)} \tag{2}$$

Where σ_{jj} denotes the standard deviation of the error term ε of j^{th} equation, A_h denotes coefficient matrix of moving average representation for VAR(p) model, Σ is the covariance matrix of error term ε, and e_i is the selection vector with the i^{th} equaling to one and zeros otherwise.

To compare different pairwise connectedness of any two variables, let $PS_{i \leftarrow j}(H)$ denote the pairwise directional spillover from variable j to variable i (i.e., spillover from variable j to variable i), we standardize the results by the row sum as

$$PS_{i \leftarrow j}(H) = \tilde{\theta}_{ij} = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{3}$$

Then, the directional spillover from variable i to all other variables can be defined as

$$DS_{\cdot\leftarrow i}(H) = \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ji}(H) \tag{4}$$

It measures the proportion of return impact received from other variables in the total forecast error variance for variable i. Analogously, the directional spillover from all other variables to variable i can be calculated as

$$DS_{\cdot\leftarrow i}(H) = \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}(H) \tag{5}$$

Then the net directional spillover from variable i to all other variables is

$$NS_i(H) = DS_{\cdot\leftarrow i}(H) - DS_{i\leftarrow\cdot}(H) \tag{6}$$

To measure the system-wide spillovers, we add up all the non-diagonal $\tilde{\theta}_{ij}(H)$ to calculate the total spillover index as follows

$$TS(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \tag{7}$$

Furthermore, under the frequent-domain spillover framework of Baruník and Křehlík (2018), the spillovers described above can be decomposed across different frequencies, based on spectral representations of the variance decomposition. Thus, at a given frequency, we can investigate the duration of the spillovers among cryptocurrencies and stock market indices. Let $\left(f(\omega)\right)_{j,k}$ denote the generalized causation spectrum over frequency $\omega(\omega \in (-\pi, \pi))$, which represents the portion of the generalized variance decomposition of the j^{th} variable at a given frequency ω due to shocks in the k^{th} variable. The spillover index on frequency band $d = (a, b)$: $a, b \in (-\pi, \pi)$, $a < b$ can be computed as

$$(\theta_d)_{j,k} = \frac{1}{2\pi} \int_d \Gamma_j(\omega) \left(f(\omega)\right)_{j,k} d\omega \tag{8}$$

where $\Gamma_j(\omega)$ denotes frequency share of the variance of the j^{th} variable. Therefore, the generalized variance decomposition on the frequency band d can be scaled as

$$\left(\tilde{\theta}_d\right)_{j,k} = (\theta_d)_{j,k} \Big/ \sum_k (\theta_\infty)_{j,k} \tag{9}$$

where $(\theta_\infty)_{j,k} = \sum_{d_s} \left(\theta_{d_s}\right)_{j,k}$, d_s denotes an interval on the real line from the set of intervals D. When $d \to \infty$, $(\theta_\infty)_{j,k}$ is equal to $\theta_{j,k}(h)$ in time domain. We can define the total frequency spillover on the frequency band d as

$$S_d^F = 100 \times \left(\frac{\sum \tilde{\theta}_d}{\sum \tilde{\theta}_\infty} - \frac{TR\left(\tilde{\theta}_d\right)}{\sum \tilde{\theta}_\infty} \right) \tag{10}$$

Similarly, we can derive the calculation formulas of frequency directional spillover.

In this paper, to estimate the time-domain spillover index, the lag length of the VAR system is set to be two and we perform the variance decomposition in the predictive horizon of 100 days, which are consistent with settings in Baruník and Kˇrehlík (2018). In further estimation of the frequent-domain spillover index, following Pham (2021), we consider three frequency bands: short-term, medium-term and long-term, corresponding to 1-5 days (a trading week), 5-22 days (a trading month) and 22-66 days (a trading quarter).

2.2 The cross-quatilogram

The cross-quantilogram quantifies the bivariate connections between variables, considering two stationary time series as $\{x_{i,t}, t \in Z\}$, $i = 1, 2$. In this paper, $x_{1,t}$ and $x_{2,t}$ represent any combination of cryptocurrency and stock market index return time series. Let $f_i(\cdot)$ and $F_i(\cdot)$ be the distribution and density functions of series $x_{i,t}$, $i = 1,2$. The corresponding quantile function is represented as $q_{it}(\tau_i) = inf\{v: F_i(v) \geq$

$\tau_i\}$ for $\tau_i \in (0,1)$. The cross-quantilogram for a pair of τ_1 and τ_2 with k lags between two events $\{x_{1,t} \le q_{1,t}(\tau_1)\}$ and $\{x_{2,t-k} \le q_{2,t-k}(\tau_2)\}$ can be expressed as:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}\left(x_{1,t} - q_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(x_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau_1}^2\left(x_{1,t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau_2}^2\left(x_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}} \tag{11}$$

where $\psi_{\tau_i}(\mu) = 1\,[\mu < 0] - \tau$ is the quantile-hit process. In the case of two events: $\{x_{1,t} \le q_{1,t}(\tau_1)\}$ and $\{x_{2,t-k} \le q_{2,t-k}(\tau_2)\}$, $\rho_\tau(k) = 0$ indicates no directional predictability from event $\{x_{2,t-k} \le q_{2,t-k}(\tau_2)\}$ to event $\{x_{1,t} \le q_{1,t}(\tau_1)\}$, implies that the returns of variable $i = 2$ below or above a quantile $q_{2,t}(\tau_2)$ at time t, does not provide useful information for predicting whether the returns of variable $i = 1$ will be lower or higher than the quantile $q_{1,t}(\tau_1)$ on the next k^{th} trading day.

The sample cross-quantilogram can be estimated as:

$$\widehat{\rho_\tau}(k) = \frac{\sum_{t=k+1}^{T}\psi_{\tau_1}\left(x_{1,t} - \hat{q}_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(x_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_1}^2\left(x_{1,t} - \hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_2}^2\left(x_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}} \tag{12}$$

Where $\hat{q}_{i,t}(\tau_i)$ denotes the unconditional sample quantile of $x_{i,t}$. We use a Ljung-Box type test to test the statistical significance of $\rho_\tau(k)$, the test statistic can be calculated as:

$$\hat{Q}_\tau(p) = \frac{T(T+2)\sum_{k=1}^{p}\hat{\rho}_\tau^2(k)}{T-k} \tag{13}$$

Following Han et al. (2016), we employ stationary bootstrap to approximate the null distribution of the cross-quantilograms and the Q-statistic above.