MUNI
ECON

SUPTECH WORKSHOP III

Are cryptocurrencies connected to forex? A quantile cross-spectral approach

Related literature

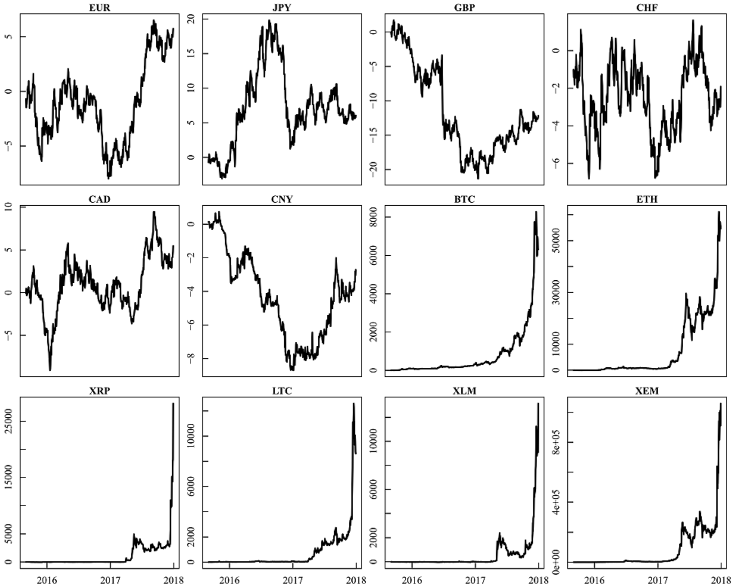
- Connectedness among asset classes is important (i) for investors, as portfolio selection and its performance are associated with the dependence structure of portfolio components, and (ii) for policy makers, because if information is transmitted across assets, policy decisions will likely have cross-market influence (Ciner et al., 2013)
- Baur and Lucey (2010) suggested distinguishing between diversifiers, hedges and safe havens.
- The literature on safe haven currencies is relatively rich (Ranaldo and Söderlind, 2010; Habib and Stracca, 2012; Menkhoff et al., 2012).
- The literature on the safe haven properties (connectedness) of cryptocurrencies is still rather sparse (Yermack, 2015; Bouri et al., 2017a,b; Kurka, 2017; Corbet et al., 2018; Ciaian et al., 2018).

Three main conclusions can be drawn:

- The general consensus in empirical research (although many studies so far are in the form of a working paper) is that Bitcoin returns are not closely related to returns on any other asset classes.
- Most of the studies on cryptocurrencies utilized Bitcoin as a benchmark, which is understandable considering its dominant role in the field. All existing 1500 cryptocurrencies have a market capitalization of 536 billion as of the end of January 2018, while the top 20 cryptocurrencies yield a market capitalization of more than 463 billion (almost 180 billion of which is a share of Bitcoin).
- Bitcoin has the longest history, so most of the studies so far have neglected other cryptocurrencies given the limited number of observations.

Data coverage (vs USD)

- Forex: Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Swiss Franc (CHF), Canadian Dollar (CAD), and Chinese Yuan (CNY).
- Cryptocurrencies: Bitcoin (BTC), Ether (ETH), Ripple (XRP), Litecoin (LTC), Stellar Lumens (XLM), and NEM (XEM).
- Daily data from 1 September 2015 to 29 December 2017 (607 obs).
- Closing prices are recorded at 00:00 Greenwich Mean Time.
- Continuous returns.


EUR
JPY
GBP
CHF
CAD
CNY
BTC
ETH
XRP
LTC
XLM
XEM
2016
2017
2018

Methodology at-a-glance:

- Standard Pearson's correlations.
- DMCA (detrended moving-average cross-correlation analysis) coefficient proposed by Kristoufek (2014).
- Quantile cross-spectral approach proposed by Baruník and Kley (2019).

Detrended moving-average cross-correlation analysis

Fluctuation functions $F_{x,DMA}$ and $F_{y,DMA}$ are defined as:

$$F^2_{x,DMA}(\lambda) = \frac{1}{T-\lambda+1} \sum_{i=\lfloor \lambda - \theta(\lambda-1) \rfloor}^{\lfloor T - \theta(\lambda-1) \rfloor} (X_t - \tilde{X}_{t,\lambda})^2$$

$$F^2_{y,DMA}(\lambda) = \frac{1}{T-\lambda+1} \sum_{i=\lfloor \lambda - \theta(\lambda-1) \rfloor}^{\lfloor T - \theta(\lambda-1) \rfloor} (Y_t - \tilde{Y}_{t,\lambda})^2$$

where λ is the moving-average window length, and θ is a factor of moving-average type (forward, centered and backward), which for the purpose of Kristoufek's (2014) $\rho_{(DMCA)}(\lambda)$ coefficient is set to 0.5 (centered one).

Detrended moving-average cross-correlation analysis

He and Chen (2011) proposed DMCA as a combination of detrended cross-correlation analysis (DCCA) and DMA. The bivariate fluctuation is defined as:

$$F^2_{DMCA}(\lambda) = \frac{1}{T-\lambda+1} \sum_{i=\lfloor \lambda-\theta(\lambda-1)\rfloor}^{\lfloor T-\theta(\lambda-1)\rfloor} (X_t - \tilde{X}_{t,\lambda})(Y_t - \tilde{Y}_{t,\lambda})$$

The DMCA coefficient (actually bounded in [−1, 1]) is then defined as (Kristoufek, 2014):

$$\rho_{(DMCA)}(\lambda) = \frac{F^2_{DMCA}(\lambda)}{F_{x,DMA}(\lambda) F_{y,DMA}(\lambda)}$$

Quantile coherency

Baruník and Kley's (2019) recently proposed quantity - **quantile coherency** - is a measure of the dynamic dependence of the two processes of (X_{t,j_1}) and (X_{t,j_2}), defined as:

$$\Re^{j_1,j_2}(\omega,\tau_1,\tau_2) = \frac{f^{j_1,j_2}(\omega,\tau_1,\tau_2)}{(f^{j_1,j_1}(\omega,\tau_1,\tau_1)f^{j_2,j_2}(\omega,\tau_2,\tau_2))^{1/2}}$$

where for every $j \in \{1,2,...d\}$ and $\tau \in [0,1]$, f^{j_1,j_2}, f^{j_1,j_1} and f^{j_2,j_2} are quantile cross-spectral, and the quantile spectral densities of processes X_{t,j_1}, and X_{t,j_2}, respectively, are obtained from the Fourier transform of the matrix of quantile cross-covariance kernels $\Gamma_k(\tau_1,\tau_2) := (\gamma_k^{j_1,j_2}(\tau_1,\tau_2))_{j_1,j_2=1,2,...,d}$, where

$$\gamma_k^{j_1,j_2}(\tau_1,\tau_2) := \text{Cov}\Big(I\{X_{t+k,j_1} \le q_{j_1}(\tau_1)\}, I\{X_{t,j_2} \le q_{j_2}(\tau_2)\}\Big)$$

Quantile coherency

For continuous cases, this measure corresponds to the difference in the copula of (X_{t+k,j_1}, X_{t,j_2}) and the independence copula. Thus, by letting k vary, we can obtain important information about the serial dependence; by choosing $j_1 \neq j_2$, we can obtain important information about the cross-sectional dependence. In the frequency domain, this yields the so-called matrix of quantile cross-spectral density kernels:

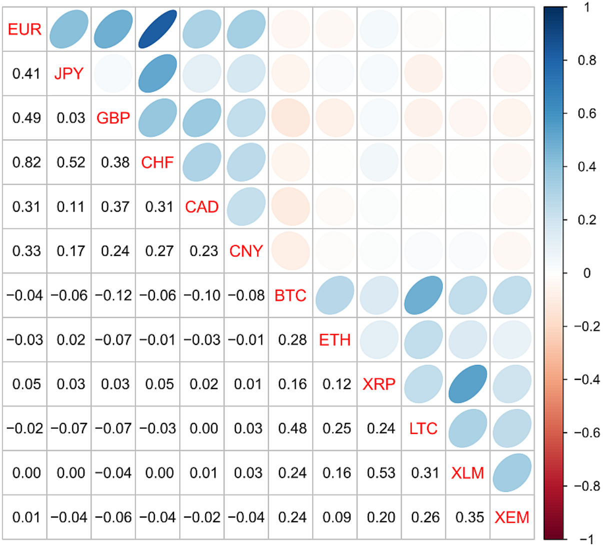
$$\mathbf{f}(\omega, \tau_1, \tau_2) := \left(f^{j_1,j_2}(\omega, \tau_1, \tau_2) \right)_{j_1,j_2=1,2,\dots,d}$$

where

$$f^{j_1,j_2}(\omega, \tau_1, \tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1,j_2}(\tau_1, \tau_2) e^{-ik\omega}$$

Quantile coherency is estimated via the smoothed quantile cross-periodograms. We will extract quantile coherency matrices for three percentiles (0.05, 0.50, 0.95) and all their combinations. Moreover, three frequencies are considered: short-term (2 days), mid-term (22 days), and long-term (250 days).

Standard correlations



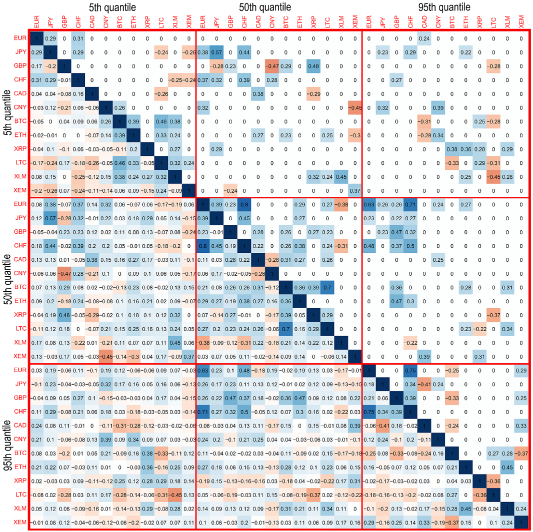
DMCA coefficients

Table 2 Detrended moving-average cross-correlation analysis

	EUR	JPY	GBP	CHF	CAD	CNY	BTC	ETH	XRP	LTC	XLM	XEM
EUR	1	0.381	0.513	0.816	0.358	0.336	-0.051	-0.063	0.036	-0.027	-0.013	-0.012
JPY	0.415	1	0.041	0.486	0.126	0.142	-0.066	-0.016	0.012	-0.086	0.005	-0.061
GBP	0.486	0.034	1	0.409	0.386	0.284	-0.158	-0.108	0.042	-0.105	-0.073	-0.079
CHF	0.822	0.517	0.382	1	0.346	0.270	-0.104	-0.031	0.034	-0.037	-0.010	-0.060
CAD	0.319	0.111	0.369	0.312	1	0.236	-0.108	-0.028	0.022	0.005	-0.009	-0.002
CNY	0.335	0.172	0.241	0.270	0.234	1	-0.098	-0.037	-0.001	0.004	-0.004	-0.050
BTC	-0.037	-0.053	-0.120	-0.059	-0.099	-0.085	1	0.263	0.152	0.469	0.220	0.254
ETH	-0.031	0.023	-0.076	-0.009	-0.024	-0.013	0.289	1	0.073	0.260	0.146	0.054
XRP	0.048	0.032	0.027	0.053	0.021	0.013	0.170	0.126	1	0.220	0.522	0.150
LTC	-0.017	-0.064	-0.070	-0.029	-0.001	0.027	0.488	0.257	0.251	1	0.266	0.242
XLM	0.004	0.003	-0.046	-0.005	0.007	0.028	0.248	0.165	0.534	0.319	1	0.334
XEM	0.009	-0.040	-0.059	-0.041	-0.022	-0.041	0.259	0.105	0.211	0.270	0.354	1

Note: Coefficients under the diagonal correspond to the moving-average window length $\lambda = 2$, and those above the diagonal correspond to $\lambda = 5$.

Quantile coherency (short-term)



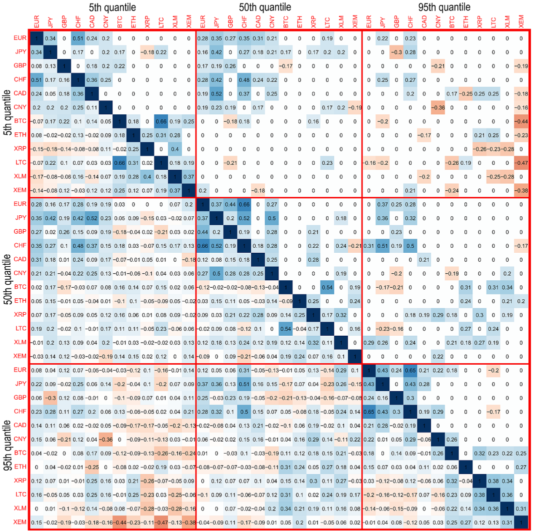
Quantile coherency (short-term - extreme negative returns)

5th quantile

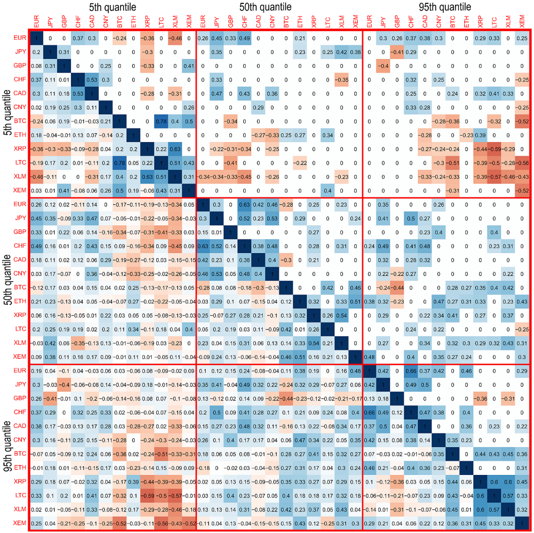
5th quantile

	EUR	JPY	GBP	CHF	CAD	CNY	BTC	ETH	XRP	LTC	XLM	XEM
EUR	1	0.29	0	0.31	0	0	0	0	0	0	0	0
JPY	0.29	1	0	0.29	0	0	0	0	0	−0.24	0	−0.26
GBP	0.17	−0.2	1	0	0	0	0	0	0	0	0	0
CHF	0.31	0.29	−0.01	1	0	0	0	0	0	0	−0.25	−0.24
CAD	0.04	0.04	−0.08	0.16	1	0	0	0	0	−0.26	0	0
CNY	−0.03	0.12	−0.21	0.06	−0.06	1	0.26	0	0	0	0	0
BTC	−0.05	0	0.04	0.09	0.06	0.26	1	0.39	0	0.46	0.38	0
ETH	−0.02	−0.01	0	0	−0.07	0.14	0.39	1	0	0.33	0.24	0
XRP	−0.04	0.1	−0.1	0.06	−0.03	−0.05	−0.11	0.2	1	0	0.27	0
LTC	−0.17	−0.24	0.17	−0.18	−0.26	−0.05	0.46	0.33	−0.05	1	0.32	0.24
XLM	0.08	0.15	0	−0.25	−0.12	0.15	0.38	0.24	0.27	0.32	1	0
XEM	−0.2	−0.26	0.07	−0.24	−0.11	−0.14	0.06	0.09	−0.15	0.24	−0.09	1

Quantile coherency (mid-term)



Quantile coherency (long-term)



Concluding remarks

- General public tends to view all cryptocurrencies as a single entity, there are significant differences between them.
- On average, correlations among cryptos and forex are close to zero – in line with the previous research (Yermack, 2015; Bouri et al., 2017a; Bouri et al., 2017b; Corbet et al., 2018).
- However, the intra-group dependencies are positive in the lower extreme quantiles, while inter-group dependencies are negative.
- The connection between cryptocurrencies is not as strong as is widely believed.