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Abstract

This paper aims to elucidate the connectedness between major forex currencies and cryptocurrencies using the quantile cross-spectral approach recently proposed by Baruník and Kley (2015). The sample covers six forex currencies and six cryptocurrencies over the period of 1 September 2015 to 29 December 2017. Compared with the results obtained from standard correlations and detrended moving-average cross-correlation analysis (DMCA), the quantile cross-spectral approach provides richer information on the dependence structure across different quantiles and frequencies. The most interesting result is that the intra-group dependencies are positive in the lower extreme quantiles, while inter-group dependencies are negative. This result holds in both the short- and long-term perspectives. Thus, it is worth diversifying between these two currency groups.

Keywords: cryptocurrencies, fiat currencies, quantile dependence, cross-spectral analysis, diversification

JEL classification: G11, G15, F31

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Introduction

Over the past few years, cryptocurrencies have attracted considerable attention from the general public, investors, and policy makers. Some people focus on the new technology; others focus on the tremendous returns. One way or another, cryptocurrencies are and should be of interest to the economics and finance research communities because of their potential to disrupt financial stability, existing payment systems, and, as suggested by Böhme et al. (2015), perhaps even monetary systems.

In 2014, several authorities claimed that cryptocurrencies do not pose a severe risk to financial stability (Mersch, 2014; Ali et al., 2014). However, the price of the most prominent of them – Bitcoin – was only about 300 US Dollars (USD) at the end of 2014. When I started to think about this paper, the price was over 20,000 USD. By the time I downloaded the data at the end of 2017, this price had dropped by half, and when I was finishing writing this paper at the beginning of February 2018, the price was around 7,000 USD and declining. From this perspective, I believe that something this volatile and with such market capitalization could possibly pose some risk, particularly for consumers (the sharp drop on 5 February wiped approximately 60 billion USD off the value of the entire cryptocurrency market in 24 hours). If investors cannot resist investing/speculating in this new asset class, it is a good idea to at least diversify a bit.

Thus, the central question (and the main motivation of this paper) is as follows: should investors diversify solely within forex currencies or solely within cryptocurrencies? Is it also worth diversifying between these two currency groups? On one hand, risk-seeking investors would prefer cryptocurrencies, but even from the perspective of a classical portfolio manager, investors could easily be attracted to the high-yield returns offered on the cryptocurrency market. For both types of investors, it is therefore essential to know whether and to what extent forex currencies and cryptocurrencies are correlated. It is also important to know whether there are only intra-group correlations or also inter-group dependencies. This paper goes beyond the average standard correlations and provides results on the dependence structure in different quantiles and at different frequencies.

Empirical studies have so far suggested that Bitcoin has only a limited correlation with other assets (e.g., Yermack, 2015; Bouri et al., 2017a; Bouri et al., 2017b), although the data utilized end around 2015. The dataset in this paper comprises six cryptocurrencies with the largest market capitalization and a sufficient history of data over the sample period of 1 September 2015 to 29 December 2017. These are complemented with six standard fiat currencies. Starting with simple correlations and detrended moving-average cross-correlation analysis (DMCA), the results indeed show only low inter-group correlations. To fully explore the frequency dependence structure in different quantiles of the joint distribution, I apply a measure recently proposed by Baruník and Kley (2015) called quantile coherency. The main benefit of this measure is that it was designed to detect any general type of dependence structure, and indeed, the picture obtained is far more colorful.

The main results suggest that extreme negative returns tend to occur jointly within both forex currencies and cryptocurrencies but occur separately between the two currency groups. The cryptocurrency whose behavior is most significantly asymmetric to that of forex currencies is Ripple (XRP), especially in the extreme lower quantiles and in the long run. Thus, even for inter-group currency pairs, there are some significant asymmetrical dependencies. This means that it is worth diversifying between forex and cryptocurrencies, especially because these dependencies are also present in the lower quantiles, which is essential for risk management. In addition, cryptocurrencies are not closely connected to one another, contrary to popular belief.

1 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). A large strand of literature therefore aims to analyze the mutual dependencies across various asset classes.

Baur and Lucey (2010) suggested distinguishing between diversifiers, hedges and safe havens. They considered an asset with a weak positive correlation (on average) with another asset to be a diversifier. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset, on average. Finally, a weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset even during times of market turmoil. Of course, most studies so far have provided evidence that gold has good hedge and safe haven properties (e.g., Baur and Lucey, 2010; Reboredo, 2013; Baumöhl and Lyócsa, 2017).

The literature on safe haven currencies is relatively rich. Several studies have addressed the diversification potential of various forex currencies, especially after the recent financial crisis (e.g., Ranaldo and Söderlind, 2010; Habib and Stracca, 2012). For example, Fatum and Yamamoto (2016) found that the Japanese Yen (JPY) is the “safest” of the save haven currencies and that only JPY appreciates during market turmoil. Usually, low-yield currencies appreciate during market turmoil, which leads to a systemic deviation from the uncovered interest parity (Menkhoff et al., 2012). The results of currency interconnectedness have important implications for currency investors in general as well as for central banks, which optimize their relative composition of international currency reserve holdings with respect to returns in USD terms. However, the literature on the safe haven properties of cryptocurrencies is still rather sparse.

In this spirit, Bouri et al. (2017a) applied a standard dynamic conditional correlation model (DCC) to examine the hedge and safe haven properties of Bitcoin[1] in comparison to various assets, such as stock market indices, bonds, oil, gold, commodity index, and USD. Their results indicated that Bitcoin is a poor hedge and can be considered only a diversifier (in the period of July 2011 to December 2015). Similarly, Bouri et al. (2017b) confirmed that Bitcoin had hedge and safe haven properties with respect to general commodity and energy indices[2]; however, after the crash in December 2013, Bitcoin could be viewed only as a diversifier, as it exhibited only weak positive correlations that were close to zero. The period covered was from July 2010 to December 2015.

Yermack (2015) also found Bitcoin prices to be completely separate from other prominent international currencies and from gold (over the period of July 2010 to March 2014). Reporting practically zero correlations, he argued that macroeconomic events that have similar impacts on the value of forex currencies do not seem to affect Bitcoin at all.

Kurka (2017) documented very low connectedness between Bitcoin and other assets, including EUR/USD, JPY/USD, gold, crude oil, S&P 500, and US 2-year Treasury notes. The sample period was from June 2011 to December 2015. He applied the standard Diebold and Yilmaz (2012) methodology with an extension proposed by Baruník et al. (2016) that allows for considering spillovers from good and bad volatility separately.

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[1] This represents a slight deviation from the computer science literature, where Bitcoin with a capital "B" is usually associated with the protocol and payment network, while bitcoin with a lowercase "b" refers to the currency. In this paper, all currencies start with a capital letter.

[2] The general idea behind examining co-movements with energy is that Bitcoin mining (rewards in the form of transaction fees as well as the creation of new Bitcoins) is highly demanding on electricity power. Hayes (2017) empirically confirmed that the marginal cost of mining one Bitcoin is very close to the Bitcoin price. Theoretically, this should always hold (based on the neoclassical microeconomic theory). This is because in a competitive market, the marginal product of mining should equal its marginal cost, which is the cost of electricity – which in fact should also equal the selling price of Bitcoin. However, electricity is always priced on a local market. In the future, after all Bitcoins are mined out, the only reward for the fully equipped miners (individuals or firms) will be in the form of transaction fees. Essentially, this might lead to an arms race of the lowest costs of generating electricity.

Kristoufek (2015), in his wavelet coherence analysis of the main drivers of the Bitcoin price, also did not find any significant sign that Bitcoin is a safe haven, which is (as argued) expected considering the evolution and instability of its price. The data spanned the period from September 2011 to April 2014. He concluded that Bitcoin is a unique asset that possesses the properties of both a standard financial asset and a speculative one. This argument contrasts with that of Yermack (2015), who suggested that Bitcoin behaves more as a speculative investment than a currency, based on the fact that its market capitalization is significantly higher than the economic transactions it facilitates.

One of the most recent studies, Ciaian et al. (2018), addressed the issue of interconnectedness among Bitcoin and other cryptocurrencies. To verify their main hypothesis – that the prices of cryptocurrencies are driven by Bitcoin price development – they used the autoregressive distributed lag (ARDL) model and a sample of 17 cryptocurrencies. The conclusion was that Bitcoin and other cryptocurrencies are interdependent and that the price relationship between Bitcoin and others is significantly stronger in the short run than in the long run.

The review provided is far from exhaustive[3], but three main conclusions can be drawn here:

1. 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.
2. 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).
3. Bitcoin has the longest history, so most of the studies so far have neglected other cryptocurrencies given the limited number of observations.

[3] For further reading, please see the literature on the determinants of Bitcoin price behavior (e.g., Ciaian et al., 2016). The principles of Bitcoin are well explained by Dwyer (2015).

2 Data description

As shown in the previous section, empirical research on the connectedness of cryptocurrencies is limited to Bitcoin. To overcome this deficiency, our dataset comprises six cryptocurrencies with the largest market capitalization and a sufficient history of data over the sample period of 1 September 2015 to 29 December 2017: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Stellar (XLM), and NEM (XEM). These are complemented with forex currencies: Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Swiss Franc (CHF), Canadian Dollar (CAD), and Chinese Yuan (CNY)[4]. Both groups of currencies are against the US Dollar and closing prices are recorded at 00:00 Greenwich Mean Time. All closing prices are extracted from the publicly available source finance.yahoo, and continuous returns are utilized in the entire analysis. Because forex currencies are not traded during weekends, Friday-to-Monday returns are calculated for cryptocurrencies, following Yermack (2015).

Table 1. Descriptive statistics of continuous and cumulative returns

	Continuous returns				***Cumulative returns (%)***			
Variable	*Mean*	*Std*	*Min*	*Max*	*Mean*	*Std*	*Min*	*Max*
EUR	0.000	0.005	-0.026	0.028	-1.178	3.554	-7.995	6.514
JPY	0.000	0.006	-0.022	0.031	7.187	5.490	-3.085	19.827
GBP	0.000	0.007	-0.079	0.028	-11.761	6.387	-21.339	1.723
CHF	0.000	0.005	-0.015	0.025	-2.504	1.817	-6.814	1.620
CAD	0.000	0.005	-0.016	0.019	0.898	3.184	-9.089	9.463
CNY	0.000	0.003	-0.013	0.013	-4.398	2.538	-8.697	0.736
BTC	0.007	0.044	-0.208	0.225	773.555	1384.409	-0.452	8279.011
ETH	0.010	0.084	-0.521	0.511	7294.038	12037.180	-67.790	61145.930
XRP	0.009	0.105	-0.616	1.528	1030.560	2409.643	-47.665	28178.950
LTC	0.007	0.071	-0.395	0.540	730.186	1718.739	-6.738	12607.090
XLM	0.008	0.122	-0.366	1.893	527.348	1562.117	-38.891	13162.460
XEM	0.015	0.116	-0.361	0.996	77527.590	153732.400	-12.000	1059900.000

Note: The first price of XEM is 0.0001, and the last one is 1.06; i.e., the maximal percentage cumulative return for this currency is not a typo.

Just a quick look at the descriptive statistics presented in Table 1 reveals a tremendous affinity for cryptocurrencies in the investor community and in the general public[5]. The group mean of maximal daily continuous returns is almost 40 times larger for cryptocurrencies than

[4] As noted by Ciaian et al. (2018), the Chinese mainland currency (CNY) now makes up nearly 100% of all Bitcoin trading.

[5] In fact, it also explains the recent extensive demand for graphic cards.

for forex currencies. The difference is even more striking in the case of cumulative returns; however, it comes with significantly higher volatility. To obtain a better perspective, cumulative returns are plotted in Figure A.1 (Appendix). The price evolution of cryptocurrencies is remarkably similar to the evolution of the tulip bulb price in the Netherlands almost four centuries ago.

3 Measuring connectedness

First, to take a quick snapshot of the connectedness between forex currencies and cryptocurrencies and to make the results comparable to those of other studies (e.g., Yermack, 2015; Bouri et al., 2017a; Bouri et al., 2017b), I calculate standard Pearson's correlations and the DMCA coefficient proposed by Kristoufek (2014). This coefficient, labeled $\rho_{(\mathrm{DMCA})}(\lambda)$, is based on the detrended moving-average cross-correlation analysis (DMCA, see Vandewalle and Ausloos, 1998; Alessio et al., 2002) and aptly captures the true correlation between two time series regardless of their possible non-stationarity.

Second, the quantile cross-spectral approach proposed by Baruník and Kley (2015) provides a full perspective of connectedness across different frequencies and quantiles.

3.1 Detrended moving-average cross-correlation analysis

In the detrended moving-average procedure (DMA), for two series $\{x_t\}$ and $\{y_t\}$, integrated series are constructed with the length of T (t = 1, 2, …, T): $X_t = \sum_{i=1}^{t} x_i$ and $Y_t = \sum_{i=1}^{t} y_i$. Fluctuation functions $F_{x,DMA}$ and $F_{y,DMA}$ are defined as

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

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

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) $\rho_{(\mathrm{DMCA})}(\lambda)$ coefficient is set to 0.5 (centered one).

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

$$F_{DMCA}^2(\lambda) = \frac{1}{T-\lambda+1} \sum_{i=\lfloor \lambda-\theta(\lambda-1) \rfloor}^{\lfloor T-\theta(\lambda-1) \rfloor} \left(X_t - \widetilde{X}_{t,\lambda}\right)\left(Y_t - \widetilde{Y}_{t,\lambda}\right) \tag{3}$$

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

$$\rho_{DMCA}(\lambda) = \frac{F_{DMCA}^2(\lambda)}{F_{x,DMA}(\lambda) F_{y,DMA}(\lambda)} \tag{4}$$

3.2 Quantile cross-spectral approach

Baruník and Kley’s (2015) recently proposed quantity, quantile coherency, is a measure of the dynamic dependence of the two processes of ($X_{t,j1}$) and ($X_{t,j2}$), defined as

$$\Re^{j_1,j_2}(\omega;\tau_1,\tau_2) = \frac{f^{j_1,j_2}(\omega;\tau_1,\tau_2)}{\left(f^{j_1,j_1}(\omega;\tau_1,\tau_1) f^{j_2,j_2}(\omega;\tau_2,\tau_2)\right)^{1/2}} \tag{5}$$

where for every $j \in \{1,\ldots,d\}$ 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 $X_{t,j1}$, and $X_{t,j2}$, respectively, obtained from the Fourier transform of the matrix of quantile cross-covariance kernels $\Gamma_k(\tau_1,\tau_2) := \left(\gamma_k^{j_1,j_2}(\tau_1,\tau_2)\right)_{j_1,j_2=1,\ldots,d}$, where

$$\gamma_k^{j_1,j_2}(\tau_1,\tau_2) := \mathrm{Cov}\left(I\left\{X_{t+k,j_1} \le q_{j_1}(\tau_1)\right\}, I\left\{X_{t,j_2} \le q_{j_2}(\tau_2)\right\}\right) \tag{6}$$

for $j \in \{1,\ldots,d\}, k \in Z, \tau_1,\tau_2 \in [0,1]$, and I{$A$} is the indicator function of the event A. For continuous cases, this measure corresponds to the difference in the copula of $\left(X_{t+k,j_1}, X_{t,j_2}\right)$ and the independence copula. Thus, as argued by Baruník and Kley (2015), by letting k vary, we can obtain important information about the serial dependence; by choosing $j_1 \ne j_2$, we can obtain important information about the cross-section dependence. In the frequency domain, this yields the so-called *matrix of quantile cross-spectral density kernels*:

$$\mathbf{f}(\omega;\tau_1,\tau_2) := \left(f^{j_1,j_2}(\omega;\tau_1,\tau_2)\right)_{j_1,j_2=1,\ldots,d} \tag{7}$$

where

$$f^{j_1,j_2}(\omega;\tau_1,\tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1,j_2}(\tau_1,\tau_2) \mathrm{e}^{-ik\omega} \tag{8}$$

Quantile coherency is estimated via the smoothed quantile cross-periodograms, as detailed by Barunik and Kley (2015). In this paper, I extract quantile coherency matrices for three quantiles (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). The entire analysis is performed in R. To estimate quantile coherency matrices, I use the *quantspec* package by Kley (2015), and to visualize them, I use *corrplot* by Wei and Simko (2017).

4 Results

4.1 Standard correlations and DMCA

First, let us take a look at the standard correlations (Figure 1) and estimated DMCA coefficients (Table 2). We can see that these measures actually provide very similar results, and they are in line with those of previous empirical research (e.g., Yermack, 2015; Bouri et al., 2017a; Bouri et al., 2017b). The correlations between forex currencies and cryptocurrencies are practically zero; thus, cryptocurrencies could be viewed as a diversifier for foreign exchange investors (neglecting all other factors apart from the correlations).[6]

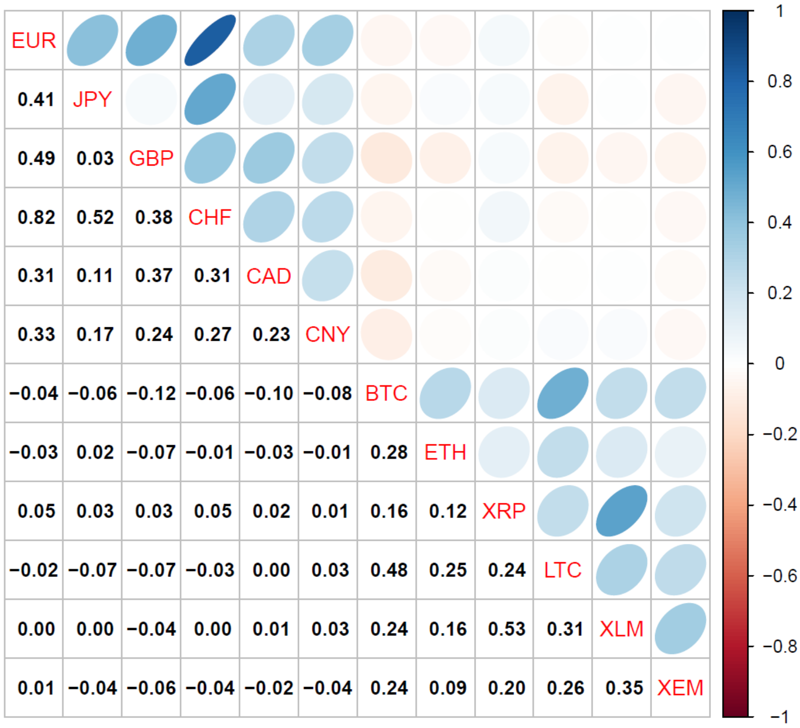

Figure 1. Visualization of Pearson's correlation matrix

Note: The source of the high correlation between EUR and CHF is not induced by the fact that the CHF was fixed at a rate of 1.20 against the EUR until 15 January 2015, as the sample starts in September 2015.

Also interesting are the correlations among the cryptocurrencies. One would assume that the most prominent of them – Bitcoin – would be the driver of the price evolution of other major cryptocurrencies. As we can see, this is not what the results are telling us. Higher

[6] Please note the upper-right quadrant in Figure 1, which corresponds to the inter-group correlations. The results from the quantile coherency analysis are presented in the same way; thus, readers interested in the cross-dependence among forex currencies and cryptocurrencies should look at this part of the coherency matrix.

correlations and DMCA coefficients are found for the pairs BTC-LTC and XRP-XLM (around 0.5). The lower dependence is reported for the second largest cryptocurrency, Ethereum (ETH).

Perhaps now it is worth mentioning that there are significant differences among cryptocurrencies, and calling them “currencies” is somewhat inaccurate. For example, ETH is not just a cryptocurrency (although it is a blockchain-based platform), as it features so-called “smart contracts”, which are basically peer-to-peer contracts that are paid for by the currency ether.[7] LTC is the most similar to BTC, and XRP is similar to XLM, hence the high correlations between these pairs.

Table 2. Detrended moving-average cross-correlation analysis (DMCA)

	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 moving-average window length $\lambda = 2$, above the diagonal to $\lambda = 5$.

4.2 Quantile coherency

The results from the quantile cross-spectral analysis are presented in the form of quantile coherency matrices for three quantiles (0.05, 0.50, 0.95) and all their combinations. Thus, allowing for asymmetries between two assets, we can easily extract information about the dependence between extreme negative and extreme positive returns. The results for different frequencies are shown in Figure 2 (short-term), Figure 3 (mid-term), and Figure 4 (long-term).

The quantile coherency matrix is, of course, symmetric. For example, in Figure 2, the short-term dependence of –0.45 between XLM and LTC in the lower-left sub-matrix (i.e.,

[7] The New York Times described ETH as “a single shared computer that is run by the network of users and on which resources are parceled out and paid for by ether”. Hopefully, the resemblance with the Skynet from the Terminator movies is just a coincidence.

0.05|0.95 quantiles) is the same as that in the upper-right sub-matrix (i.e., 0.95|0.05 quantiles), as both sub-matrices correspond to the connectedness between XLM extreme negative returns and LTC extreme positive returns. That is why I decided to show only significant coherencies in the area above the diagonal; the ones that are not significant are set to zero. Please note that the negative coherency between two pairs in the 0.95|0.05 quantiles simply means that these two currencies move together. In addition, the comparison through different quantiles is not that straightforward. For example, a negative 0.95|0.05 coherency is by default a small number, but its positive counterpart is by construction a higher number, although both of these coherencies reveal the same strength of connection (for details, see Section 2.3 in Baruník and Kley, 2015).

The picture we obtained from quantile cross-spectral analysis is far richer than that extracted from standard correlations. Apart from the abovementioned connectedness between XLM and LTC, there are other eye-catching findings. First, other cryptocurrencies share some joint co-movement. In the previous section, we found a high correlation between BTC and LTC (0.48). Now, we can see that when both BTC and LTC record extreme negative returns (0.05|0.05 quantiles), the coherency is 0.46. When both record extreme positive returns (0.95|0.95 quantiles), the coherency is 0.27. In median dependence (0.50|0.50 quantiles), the coherency is 0.7. Thus, these two cryptocurrencies are connected to some extent in the short-term period, irrespective of the current market situation.

What is interesting is that XEM is on average not associated with any other currency in our sample. However, when we look at the lower quantiles, we find that it is negatively associated with two forex currencies (JPY, CHF) and positively associated with LTC. At the higher quantiles, its extreme positive returns are positively connected to extreme positive returns on EUR, GBP, CAD, and XLM and negatively connected with BTC. Even ETH is significantly positively associated with BTC at the extreme lower quantile and median dependence, even though there are substantial differences between these two cryptocurrencies, as mentioned.

The most significant asymmetric connectedness (0.05|0.95) is found for XRP; this cryptocurrency exhibits remarkable safe haven properties, as defined by Baur and Lucey (2010).

From a mid-term perspective (see Figure 3), the dependence structure is quite different. Most of the cryptocurrency pairs are positively associated with one another, even in extreme quantiles. We can also identify pairs from both the forex and cryptocurrency groups, which could be used for diversification purposes; e.g., at the 0.05|0.05 quantiles, JPY and XRP exhibit a significant negative coherency of –0.18 (extreme negative returns are negatively associated), while at the same time, in the same quantiles and in the same frequency, JPY and LTC have a significant coherency of 0.22.

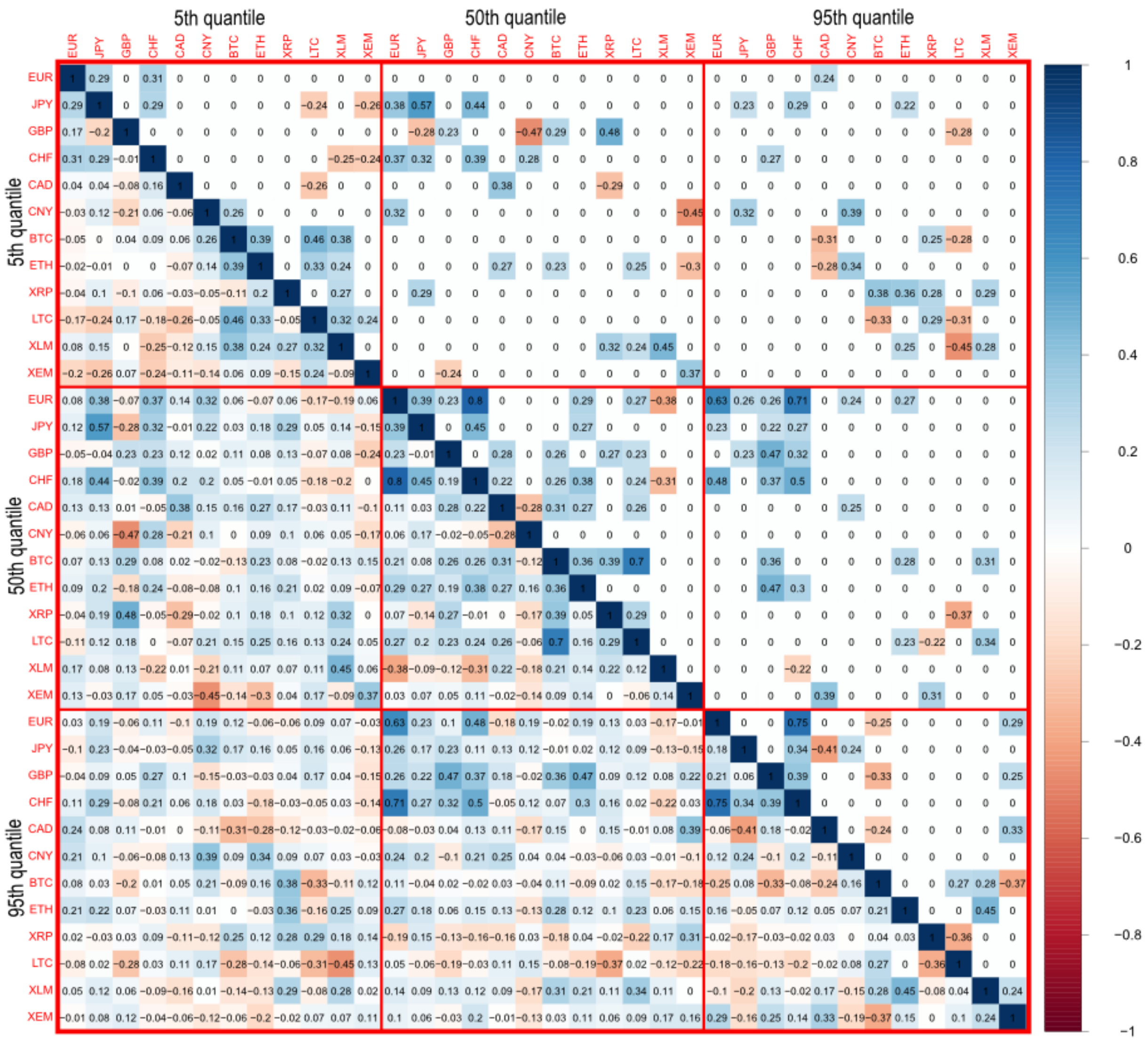

Figure 2. Short-term quantile coherency matrix

Note: Significant coherencies are in the area above the diagonal; the ones that are not significant are set to zero.

In the long run (see Figure 4), the upper diagonal of the coherency matrix is much more colorful; i.e., from longer-term perspective, more coherencies are significant. In particular, the upper-right sub-matrix is full of negative coherencies, meaning that most of the relationships are actually symmetric. This holds for intra-group cryptocurrency coherencies and for some inter-group coherencies. The extreme positive returns on CAD are negatively associated with extreme negative returns on ETH, XRP, and XLM. The same applies for the CNY 0.95|0.05 connectedness with BTC, XRP, LTC, and XLM. However, this finding is not confirmed with positive coherencies at both extreme quantiles. The only asymmetric relationship is the coherency between ETH and XRP. BTC and LTC still share the highest co-movement; this is true especially when the returns on both currencies are negative (coherency of 0.78) but also when the returns are extremely positive (coherency of 0.43).

From the portfolio perspective, one should carefully look at the 0.05|0.05 quantiles in particular. What is quite obvious in both the short- and long-term coherency matrices is that within the extreme negative returns, only inter-group negative dependencies are found. This simply means that it is beneficial to diversify among forex currencies and cryptocurrencies because in times of distress, extremely low returns are negatively associated.

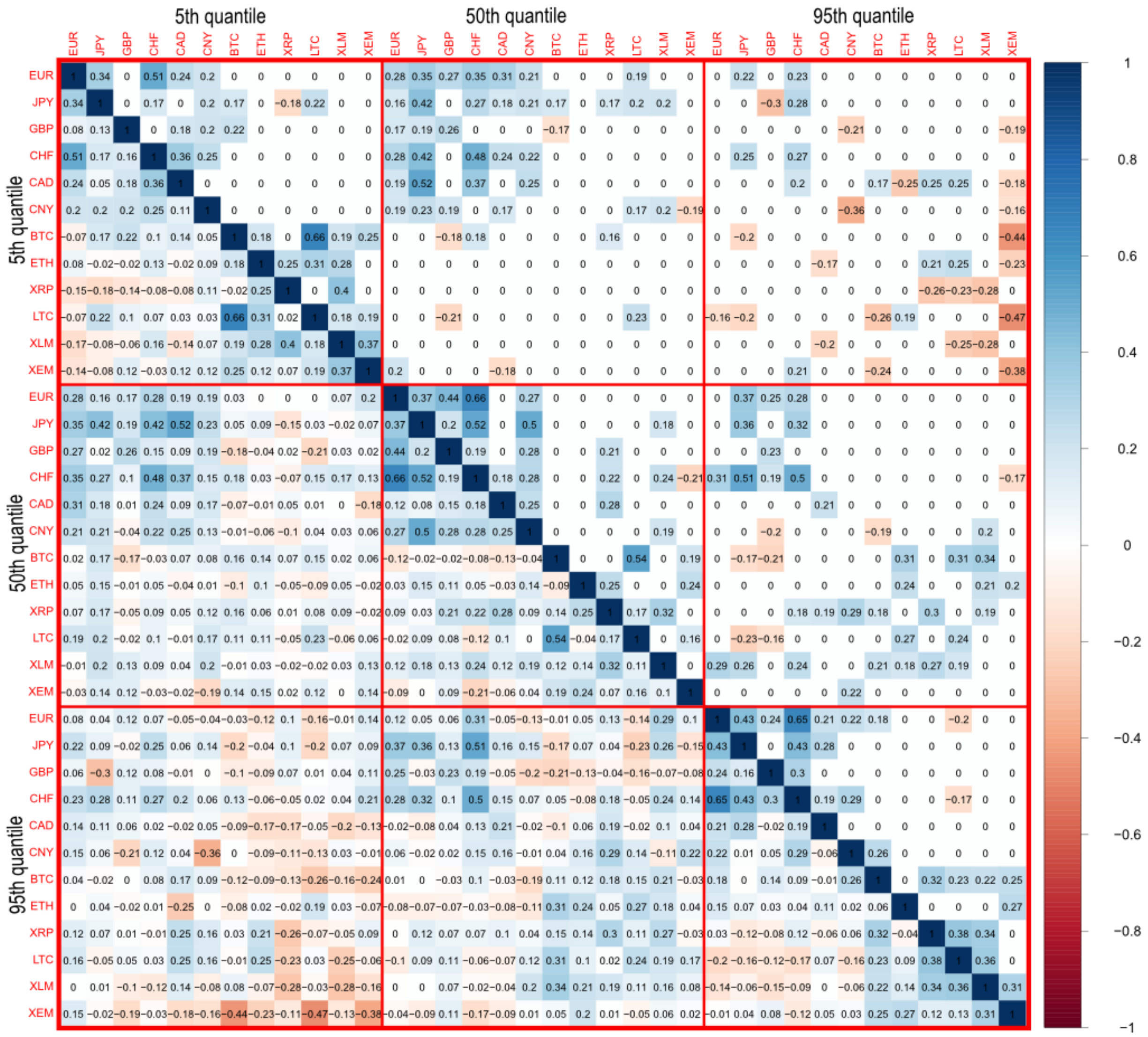

Figure 3. Mid-term quantile coherency matrix

Note: Significant coherencies are in the area above the diagonal; the ones that are not significant are set to zero.

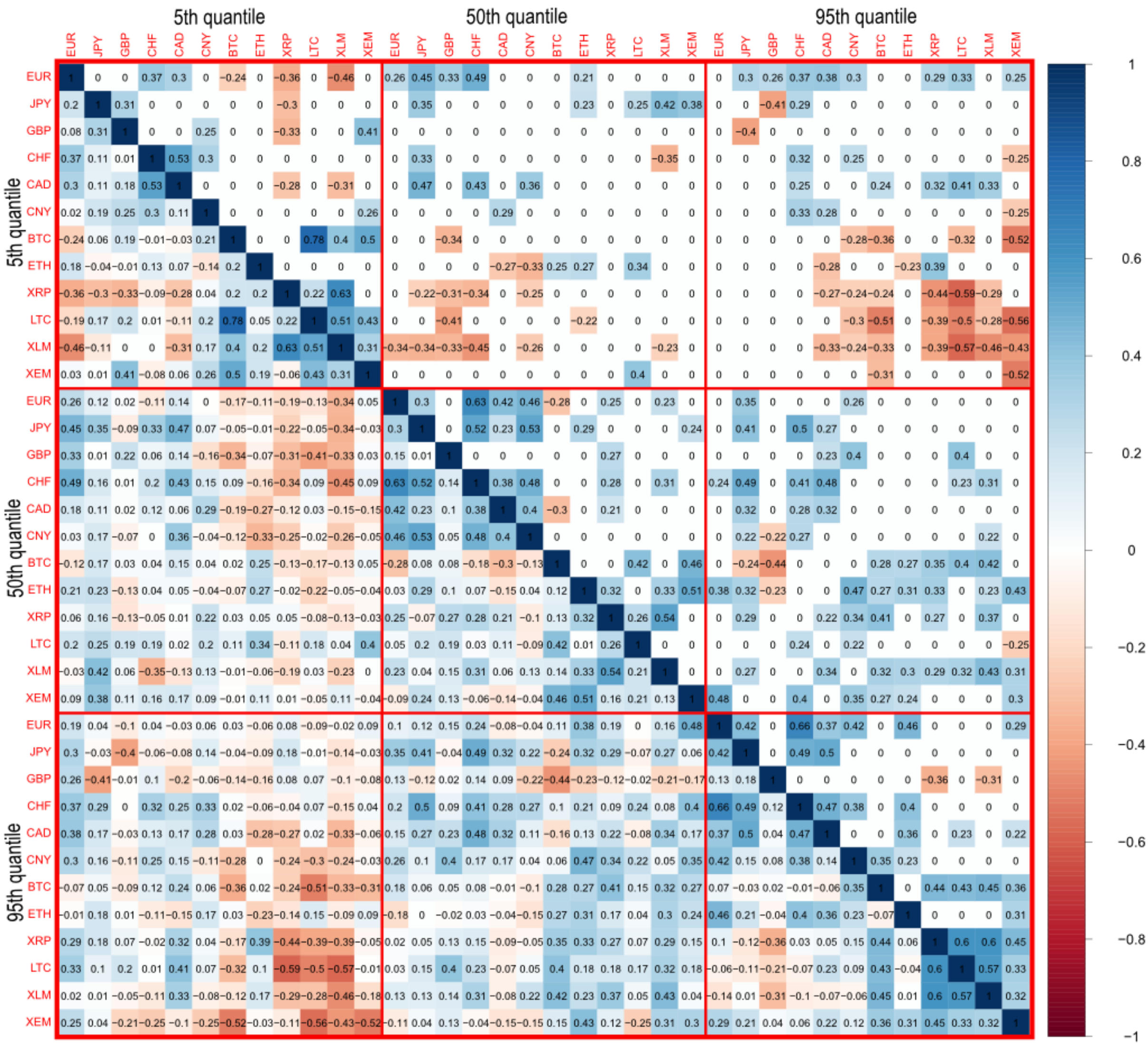

Figure 4. Long-term quantile coherency matrix

Note: Significant coherencies are in the area above the diagonal; the ones that are not significant are set to zero.

5 Concluding remarks

The results demonstrate various types of connectedness between forex and cryptocurrencies, but more importantly, they reveal inter-group asymmetric return co-movement for cryptocurrencies and forex currencies. This is unsurprising because even though the general public views all cryptocurrencies as one and the same ensemble, there are significant differences among them. For example, in contrast to ETH, Bitcoin has no underlying asset. Investors who are thinking about investing (speculating) in cryptocurrencies will benefit from diversifying within the various types of currencies in this new asset class.

Of course, the negative correlation is only one aspect of portfolio performance; given the highly volatile price movements on the cryptocurrency market, investors should carefully consider other aspects as well. However, Brière et al. (2015) showed that the inclusion of even a small proportion of Bitcoin may dramatically improve risk-return portfolio characteristics. Our results suggest that other cryptocurrencies should do this work better.

The results are practically in line with the recent research on cryptocurrencies (e.g., Ciaian et al., 2018) but provide new evidence on connectedness in extreme quantiles. This paper is the first to apply the newly proposed methodology of Baruník and Kley (2015). It would be interesting for further research to see how other assets are connected in quantiles with the new, highly debated cryptocurrency market. Of course, this requires that this new asset class still exists.

What is still unsolved is a sound regulatory framework. As De Filippi (2014) puts it: "Bitcoin is a regulatory nightmare to a libertarian dream". Even the prospect of tougher regulation is currently giving rise to panic behavior at the cryptocurrency market, which is resulting in sharp drops such as the one that occurred at the time I finished writing this paper (5 February 2018).

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Appendix

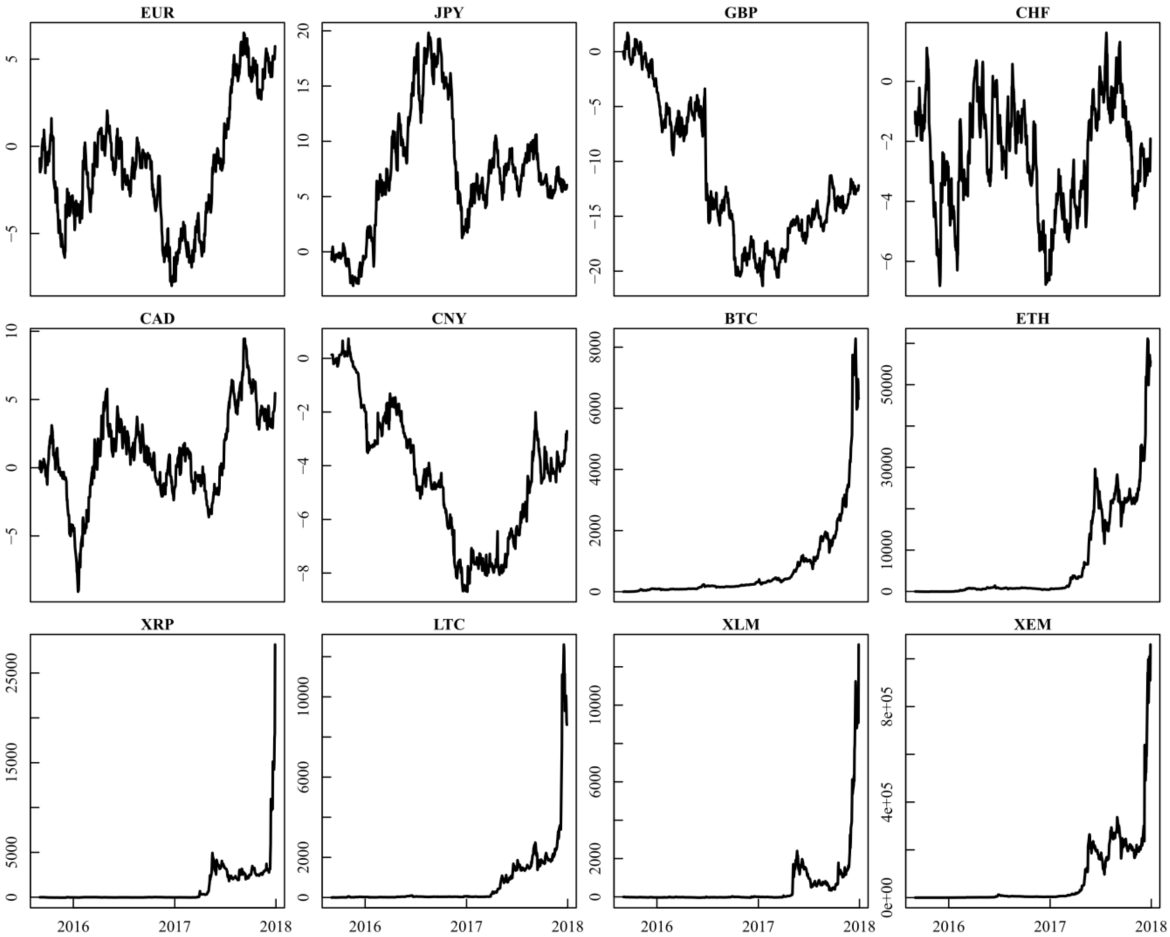

Figure A.1. Cumulative returns (in %)