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Stablecoins as a crypto safe haven? Not all of them!

Stablecoins as a crypto safe haven? Not all of them!

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Abstract

We test the safe haven properties of the largest stablecoins (USDT, USDC, TUSD, PAX, DAI, GUSD) against the standard "nonstable" coins (BTC, ETH, XRP, BCH, LTC). Our dataset comprises high-frequency 1-minute data calculated as volume-weighted averages across 18 exchanges where these cryptocurrencies are traded, thus capturing the entire price movement around the world. Using a quantile coherency cross-spectral measure, we find that only TUSD, PAX, and GUSD can serve as safe havens.

Keywords: cryptocurrencies, stablecoins, quantile dependence, cross-spectral analysis, diversification, safe haven

JEL classification: G11, G15, F31

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Highlights

- We use high-frequency data calculated as volume-weighted averages across 18 exchanges.
- The diversification properties of stablecoins against “nonstable” coins are examined.
- Cryptocurrency returns are not closely related to each other, as is widely believed.
- Some stablecoins have safe haven properties; some do not.
- DAI and USDC cannot be considered a diversifier nor a hedge and definitely not a safe haven.

1 Introduction

Given that the volatility of cryptocurrencies is extreme (e.g., Corbet et al., 2018a), investors naturally seek to hedge their positions in other asset classes. Numerous studies have recently shown a very low level of connectedness between a cryptocurrency's returns and the returns of other (traditional) asset classes (*inter alia*, Bouri et al., 2017a; Bouri et al., 2017b, Corbet et al., 2018b, Kurka, 2019). Such results imply that cryptocurrencies may offer diversification benefits for investors.

In the spirit of Baur and Lucey (2010)[1], who suggested distinguishing between diversifiers, hedges and safe havens, a low correlation on average might not be a sufficient condition for considering an asset to be a hedge or a safe haven but a diversifier at best. Such properties should be included in the so-called stablecoins. ECB's Internal Crypto-Assets Task Force (2019) classifies the recent development of stablecoins as an attempt to overcome the volatility drawback of existing crypto assets by claiming to exhibit a stable value – usually by pegging the crypto asset to a (relatively) stable asset. They also noted that stablecoins appear to be used mostly by crypto asset traders to hedge against market movements.

According to our knowledge, only one recent work by Baur and Hoang (2020) challenged the diversification opportunities of the largest stablecoins against Bitcoin and concluded that stablecoins pose safe haven properties.

Our paper presents a follow-up study to Baur and Hoang (2020)—we analyze the dependence in the extreme tails of the return distribution to assess whether stablecoins can serve as a diversifier, hedge or safe haven for standard nonstable cryptocurrencies. However, our approach is different for several reasons: (i) from a methodological perspective, as we have applied the quantile coherency measure to analyze cross-spectral tail dependence; (ii) we use a unique dataset – prices are volume-weighted averages across 18 exchanges, thus capturing the entire price movement of a given cryptocurrency worldwide; and (iii) we consider the five largest cryptocurrencies, not only Bitcoin.

All these differences lead to new findings, particularly that DAI and USDC cannot be considered to be either diversifiers or hedges and definitely not safe havens. By contrast, TUSD, PAX, and GUSD all have negative coherencies with nonstable coins, even in the lower extreme

[1] 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.

quantiles, i.e., we report negative return dependence in times of market turmoil. These three stablecoins appear to have good safe haven properties.

2 Data and methodology

In our analysis, we use high-frequency data on the five largest cryptocurrencies and six largest stablecoins (based on market capitalization):

- Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), and Litecoin (LTC)
- Tether (USDT), USD Coin (USDC), TrueUSD (TUSD), Paxos Standard Token (PAX), Dai (DAI) and Gemini Dollar (GUSD).

Prices at a 1-minute frequency for the entire year of 2019 are obtained from altfins.com. The uniqueness of the dataset is based on the availability of high-frequency data obtained not from a single exchange but from a wide set of exchanges, namely, BINANCE, COINBASE, QUOINE, KRAKEN, BITSTAMP, POLONIEX, GEMINI, BITFLYER, BITSO, BINANCEJE, HITBTC, BITFINEX, BITTREX, BINANCEUS, BITZ, ZB, COINEX, and OKCOIN USD. The final price is calculated as a volume-weighted average across the exchanges. All prices are reported against the USD. If no trade occurred within a given minute in the set of all exchanges, the last known price was imputed. This procedure of handling the possible nonsynchronicity of returns resulted in 525,599 observations per time series.

Table 1: Descriptive statistics (1-minute returns)

	N	Mean	Std. dev.	Min	Max	Skew	Kurtosis
BTC	525599	0.000	0.010	-0.800	0.800	0.620	2053.150
ETH	525599	0.000	0.030	-2.560	2.570	-0.160	6386.370
XRP	525599	0.000	0.010	-0.160	0.170	-0.010	12.600
BCH	525599	0.000	0.000	-0.470	0.490	1.610	4932.590
LTC	525599	0.000	0.010	-0.070	0.070	0.000	13.830
USDT	525599	0.000	0.010	-0.070	0.070	0.020	77.860
USDC	525599	0.000	0.000	-0.060	0.060	-0.030	32.460
TUSD	525599	0.000	0.000	-0.080	0.070	0.010	76.020
PAX	525599	0.000	0.000	-0.050	0.050	0.300	55.820
DAI	525599	0.000	0.010	-0.070	0.070	-0.010	12.130
GUSD	525599	0.000	0.000	-0.090	0.080	0.010	13.750

Basic descriptive statistics of the 1-minute continuous returns (computed from the log of the prices) are available in Table 1. Note that the min-max range of nonstable coins is larger than that of stablecoins; however, DAI has a standard deviation comparable to that of nonstable coins. We highlight this fact later in the results section.

The level of dependence between two cryptocurrency groups is realized via a novel approach recently proposed by Baruník and Kley (2019), the so-called quantile coherency.[2] This measure allows us to uncover the frequency dependence structure in different quantiles of the joint distribution.

Let $\boldsymbol{X}_t = (X_{t,1}, X_{t,2})$, $t \in Z$ be a bivariate, strictly stationary process. For $j_1, j_2, j \in \{1,2\}$, define the quantile function $q_j(\tau) = inf\{\, q \in R : \tau \leq F_j(q)\}$ for any chosen quantile $\tau$and a marginal distribution function F_j. The dependence measure at quantiles τ_1, τ_2 (for $X_{t,1}$ and $X_{t,2}$, respectively) is based on the quantile cross-covariance kernels

$$\gamma_k^{j_1,j_2}(\tau_1,\tau_2) = \mathrm{Cov}\big(I\{X_{t+k,j_1} \leq q_{j_1}(\tau_1)\}, I\{X_{t,j_2} \leq q_{j_2}(\tau_2)\}\big) \tag{1}$$

where $k \in Z$and I is the indicator function. Equation (1) allows for flexibility in estimating either serial dependence $(j_1 = j_2, k \neq 0)$ or cross-dependence$(j_1 \neq j_2)$ at chosen quantiles.

To establish the estimator of quantile cross-spectral density, Baruník and Kley (2019) use rank-based copula cross-periodograms, which are defined for $j \in \{1,2\}$ as

$$d_{n,R}^{j}(\omega,\tau) = \sum_{t=0}^{n-1} I\{\hat{F}_{n,j}(X_{t,j}) \leq \tau\} e^{-i\omega t} = \sum_{t=0}^{n-1} I\{R_{n\,;\,t,j} \leq n\tau\} e^{-i\omega t} \tag{2}$$

where $\hat{F}_{n,j}(x)$ is the empirical distribution function of $X_{t,j}$ and $R_{n;t,j}$ is the maximum rank of $X_{t,j}$ over its past observations.

The estimator for the quantile cross-spectral density then becomes

$$I_{n,R}^{j_1,j_2}(\omega,\tau_1,\tau_2) = \frac{1}{2\pi n} d_{n,R}^{j_1}(\omega,\tau_1) d_{n,R}^{j_2}(-\omega,\tau_2) \tag{3}$$

As $I_{n,R}^{j_1,j_2}(\omega,\tau_1,\tau_2)$ itself is not a consistent estimate of the cross-spectral density kernel (see Kley et al., 2016), smoothed cross-periodograms $\hat{G}_{n,R}^{j_1,j_2}(\omega,\tau_1,\tau_2)$ are calculated using a weighting scheme on $I_{n,R}^{j_1,j_2}(\omega,\tau_1,\tau_2)$ across different frequencies (for technical details, see Baruník and Kley, 2019). Finally, the estimators of quantile coherency are given by

$$\hat{c}_{n,R}(\omega,\tau_1,\tau_2) = \frac{\hat{G}_{n,R}^{j_1,j_2}(\omega,\tau_1,\tau_2)}{\sqrt{\hat{G}_{n,R}^{j_1,j_1}(\omega,\tau_1,\tau_1)\hat{G}_{n,R}^{j_2,j_2}(\omega,\tau_2,\tau_2)}} \tag{4}$$

[2] Thus far applied by only a few studies, e.g. Baumöhl (2019), Baumöhl and Shahzad (2019).

3 Results

To obtain a quick snapshot of the connectedness between stablecoins and nonstable coins and to make the results comparable to those of other studies (e.g., Yermack, 2015; Bouri et al., 2017a; Bouri et al., 2017b), we first show the standard Pearson's correlations in Figure 1. Clearly, at the 1-minute frequency, the connectedness between returns of cryptocurrencies is very low, practically zero.

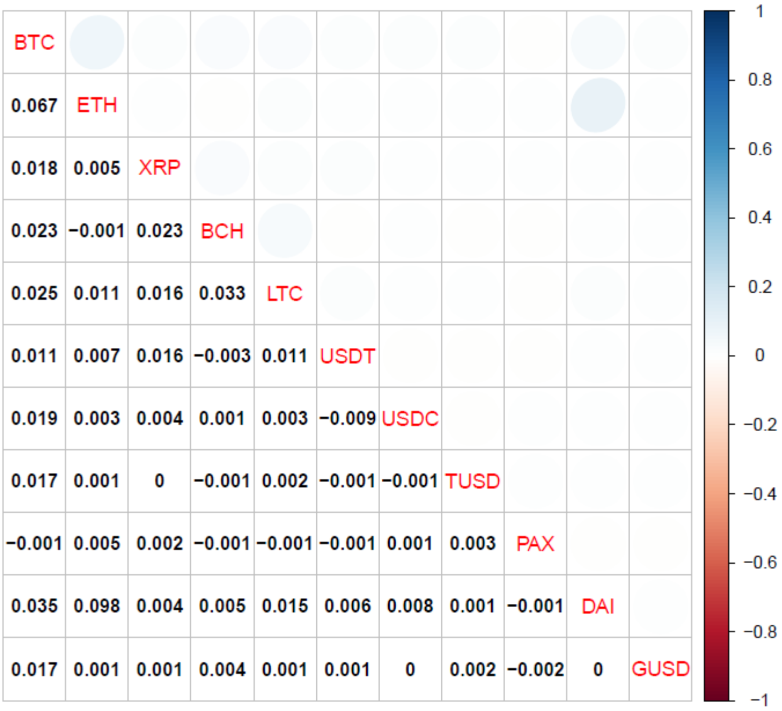

Figure 1: Correlations of returns at a 1-minute frequency

3.1 Extreme negative comovement

Despite the fact that the unconditional correlations between returns are practically zero, the coherencies at extreme lower quantiles provide a much more colorful picture. Figure 2 presents the results of the 5^{th}-to-5^{th} quantile dependence at 1-minute frequency (Panel A) and at 1-hour frequency (Panel B).

A strong dependence is observed among the nonstable coins when we look at their extreme negative return comovement at a 1-minute frequency (e.g., the BTC-ETH coherency is 0.917). As expected, the dependence between stablecoins is significantly weaker and in some cases even negative, meaning that stablecoins can serve as safe haven for standard cryptocurrencies. However, this is not the case for all stablecoins. The intergroup dependencies show some surprising results. The dependence between extreme negative returns among USDC and DAI with nonstable coins is notably high, ranging from 0.477 (DAI-BCH) to 0.881 (DAI-

ETH). A safe haven asset should not be correlated in times of market turmoil; thus, DAI and USDC cannot be considered to be diversifiers or hedges and definitely not safe havens. This result is in strong contrast with TUSD, PAX, and GUSD, which all have negative dependence on nonstable coins: these three stablecoins appear to have good safe haven properties.

For the 1-hour frequency, all the relationships appear to vanish. Baur and Hoang (2020) noted that investors might react to extreme changes with a time delay, so they expected the safe haven properties to strengthen as the return frequency decreased (from 1-minute to daily returns). Our analysis revealed that even at a lower frequency (daily), some significant reactions occur, as the returns are closely related (positively or negatively). Dependence on a daily basis is practically identical to that of 1-minute returns.[3]

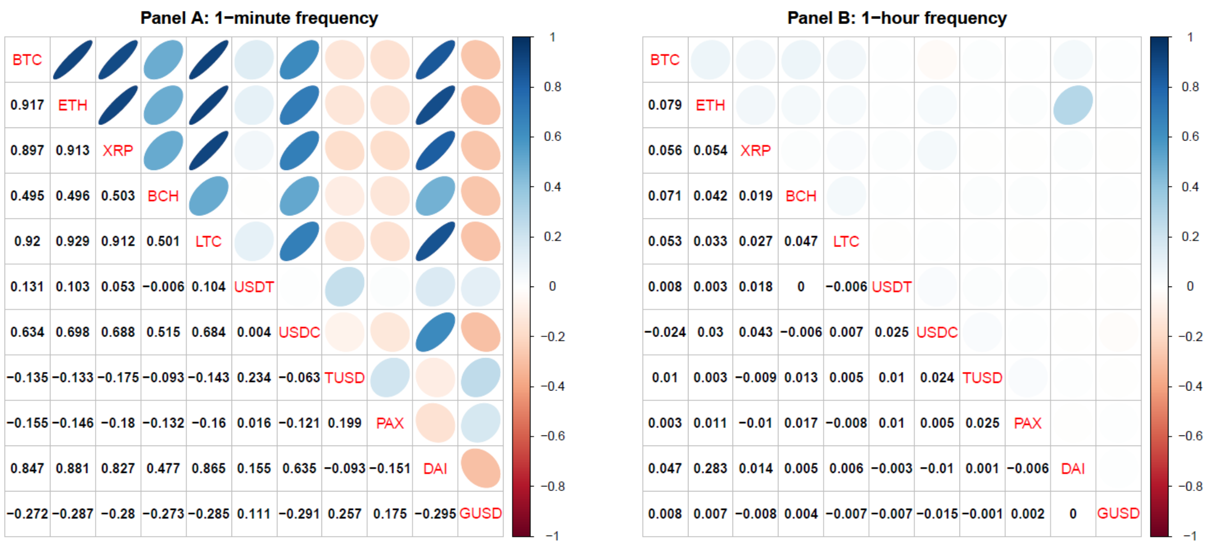

Figure 2: Extreme negative comovement (5^{th}-to-5^{th} quantile dependence)

3.2 Safe haven properties and stable-times dependence

We now turn to a different situation when nonstable coins report extreme negative returns while stablecoins have extreme positive returns (i.e., the 5^{th}-to-95^{th} quantile dependence, see Figure 3). Our previous results are confirmed – the 95^{th} quantiles of DAI and USDC are negatively correlated with the 5^{th} quantiles of nonstable coins, but TUSD, PAX, and GUSD react positively to extreme negative returns of nonstable coins.

[3] We do not present the daily results to preserve space (all figures are very similar to those of 1-minute frequency), but all the details are available upon request.

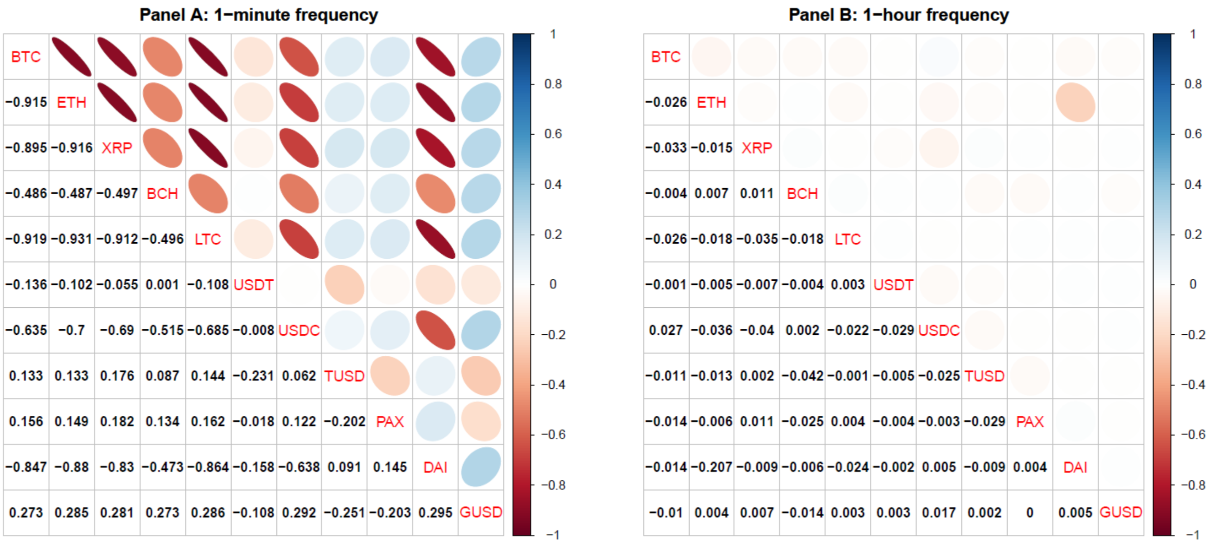

Figure 3: Safe haven properties (5th-to-95th quantile dependence)

In the median case (50th-to-50th quantile dependence, see Figure 4), even USDC and DAI are not strongly related to nonstable coins. The results at a 1-minute frequency among the nonstable coins are mixed, but at a 1-hour frequency, some unified modest coherencies are observed, confirming the generally accepted view that all cryptocurrencies are closely related. Our study shows that this is not always the case; the relation depends on the time frequency and the specific part of the joint return distribution.

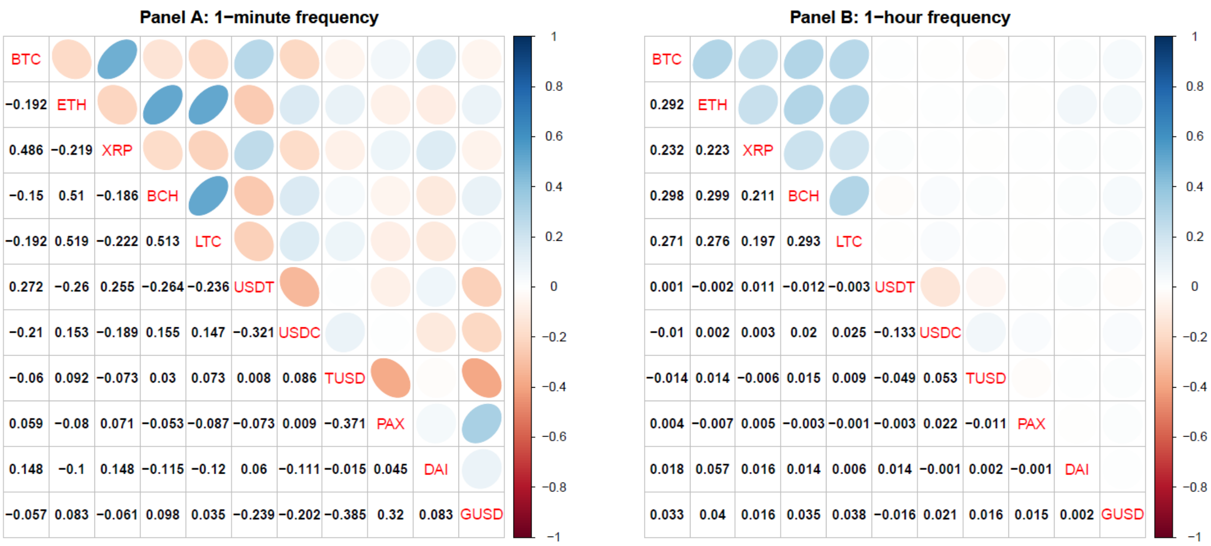

Figure 4: Stable time comovement (50th-to-50th quantile dependence)

3.3 Extreme positive comovement

To obtain the full picture, Figure 5 captures the coherencies during extreme positive times, i.e., the 95th-to-95th quantile dependence. When the returns are extremely positive, all nonstable coins are closely related, as are our two usual suspects – USDC and DAI. Other stablecoins' extreme positive returns (TUSD, PAX, GUSD) appear in different times as extreme positive returns on nonstable coins (hence, the coherency is negative among them).

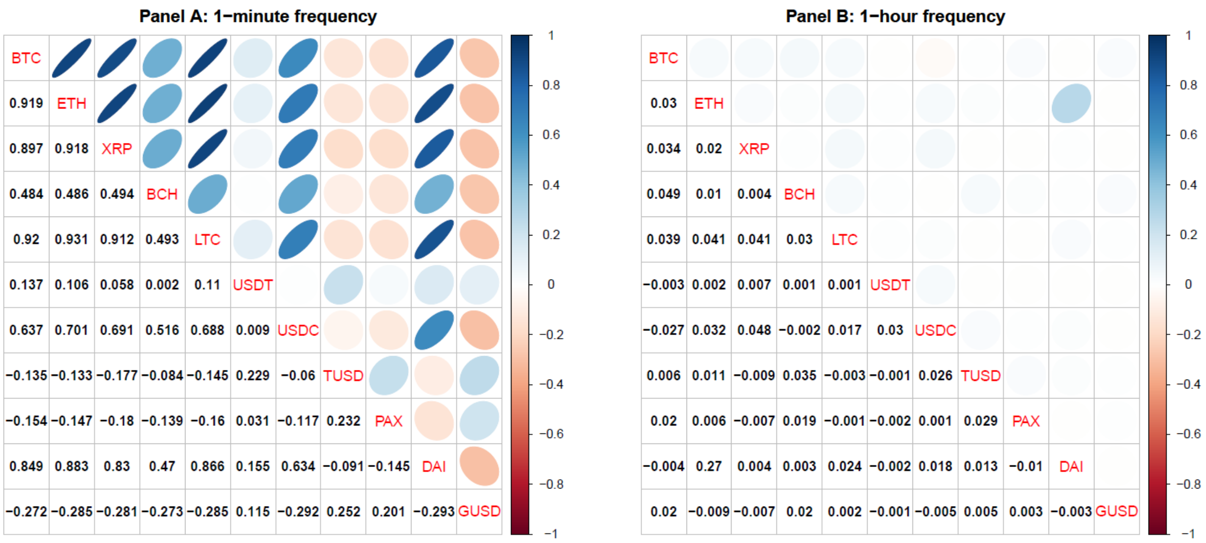

Figure 5: Extreme positive comovement (95^{th}-to-95^{th} quantile dependence)

Conclusions

In this paper, we test the safe haven properties of stablecoins against nonstable cryptocurrencies. One of the main advantages of our high-frequency dataset is that it provides full information about cryptocurrency price movements across 18 different exchanges. Using a quantile coherency measure, we were able to identify which stablecoins have good safe haven properties, which means they are not very stable, especially at the extreme quantiles of the joint return distribution.

Our results are in line with the general findings of Baur and Hoang (2020) – stablecoin returns illustrate that stablecoins are not consistently and reliably stable at all times. However, even if stablecoins do not live up to their name, the instability offers significant diversification benefits for cryptocurrency traders. We have found that three of six stablecoins in our sample (TUSD, PAX, and GUSD) have negative dependence on nonstable coins, even in the time of market distress: these three stablecoins appear to have very good safe haven properties.

Recall Figure 1, which captures the standard Pearson's correlations among 1-minute returns. All the correlations are essentially zero. We highlight this fact, as the quantile coherency results are significantly different and uncover various dependencies that remain hidden in the world of averages and linearity.

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