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Tethered, or Untethered? On the interplay between stablecoins and major cryptoassets

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A B S T R A C T

Stablecoins and their leader Tether have been one of the controversial topics of cryptomarkets and their role in price rallies of the past few years has been questioned repeatedly. Using the generalized vector autoregressive framework and directed spillovers based on the forecast error variance decompositions, we find no evidence of stablecoins boosting the prices of other cryptoassets. On the contrary, the increased stablecoins issuances come in reaction to the other cryptoassets price changes, which suggests they rather reflect increasing demand in investing into the cryptomarkets that gets materialized in demand for the "digital fiat".

1. Introduction

Stablecoins, and most prominently Tether (USDT), have become an essential part of the cryptomarkets forming the "digital fiat" necessary for smooth and stable transfers between exchanges without risking abrupt changes in their prices in the time the transaction is being processed, which might be the case for other – "standard" – cryptoassets. However, stablecoins, and again mostly Tether, have also been the target of various scandalizing and disturbing claims, mostly with respect to their non-transparent backing by the actual fiat counterparts (mostly USD). Yet, a detailed global study of the interaction between stablecoins and other cryptoassets and how such dynamics connects to different market stages is missing. Even though Griffin and Shams (2020) argue that Tether played an important role in the 2017 cryptomarkets rally, Wei (2018) argues otherwise. A newer study of Ante et al. (2020) uncovers only a small effect of stablecoins issuances on the cryptoassets prices in 2019 and 2020.

Here, we markedly extend the existing literature and contribute to better understanding of the position stablecoins play in the cryptomarkets by examining the interaction between a set of stablecoins (rather than only USDT) and major cryptoassets (rather than only Bitcoin) covering the period between 2016 and 2021 (rather than only selected years) and investigating how such interconnections evolve in time (rather than providing only a global perspective). In the framework of directed spillovers (Diebold and Yilmaz, 2009; 2012) between the cryptoassets that is presented, we can identify a role the given asset plays in the system. Specifically for stablecoins, their possible boosting role would materialize in either a unidirectional effect coming from stablecoins to the other

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cryptoassets or a bidirectional effect between them implying a spiral-like dynamics. The opposite unidirectional spillover effect would suggest the rising cryptoassets prices leading to an increased demand for stablecoins. And the possible "keeping the bull run going" dynamics is expected to translate into the bidirectional spiral-like dynamics as well.

2. Methods

Diebold and Yilmaz (2009, 2012) propose a straightforward method of quantifying overall and directional spillovers in the generalized vector autoregressive (VAR) framework (Koop et al., 1996; Pesaran and Shin, 1998). For N variables, VAR(p) with p lags is defined as $x_t = \sum_{i=1}^{p}\phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon \sim (0,\Sigma)$ are i.i.d. disturbances. Such VAR(p) has a vector moving average (VMA) representation $x_t = \sum_{i=0}^{+\infty} A_i \varepsilon_{t-i}$, where the $N\times N$ coefficient matrices A_i follow the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_p A_{i-p}$, A_0 being an identity matrix, and $A_i = 0$ for $i < 0$. The VMA representation is crucial for constructing the popular impulse-response functions as well as the forecast error variance decompositions (FEVD). In this framework, the H-step-ahead forecast variance decomposition is defined as

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

where Σ is the variance matrix of the disturbances ε, σ_{jj} is the standard deviation of the jth disturbance, e_i is the selection vector with position i equal to one and zero otherwise, and A_h are the matrices from the VMA representation. This yields an $N \times N$ matrix representing self- (on-diagonal elements) and cross-variance (off-diagonal elements) shares, or spillovers. The spillovers are normalized so that $\widetilde{\theta}_{ij}^{g}(H) = \theta_{ij}^{g}(H)/\sum_{j=1}^{N}\theta_{ij}^{g}(H)$ to ensure $\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = N$. From this matrix, we can extract the following self-explanatory measures:

- The total spillovers: $S^g(H) = 100 \times \sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H)/N$
- Spillovers to i from all other j: $S_{i\cdot}^{g}(H) = 100 \times \sum_{j=1,j\neq i}^{N}\widetilde{\theta}_{ij}^{g}(H)/N$
- Spillovers from i to all other j: $S_{\cdot i}^{g}(H) = 100 \times \sum_{j=1,j\neq i}^{N}\widetilde{\theta}_{ji}^{g}(H)/N$
- Net spillovers from i to all other j: $S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$

The framework thus provides straightforward measures of total spillovers or connectedness of the whole system as well as the directed spillovers. In our analysis, we are mostly focused on the spillovers coming to and from stablecoins to describe their role in the other cryptoassets' dynamics. The well-established generalized VAR framework offers an ideal setting for such analysis.

3. Data

We are interested in an interaction and directional spillovers between major cryptoassets and stablecoins. As the representatives of the major cryptoassets, we use the historical big three – Bitcoin (BTC), Ethereum (ETH), and XRP[1]. Our stablecoins sample covers the free float supply of Tether (USDT) on all three blockchains (Omni, ETH, and TRX), Binance USD (BUSD), HUSD (HUSD), Paxos Standard (PAX), USD Coin (USDC) and current supply of Dai (DAI), Gemini Dollar (GUSD), Single Collateral DAI (SAI), TrueUSD (TUSD), and USDK (USDK)[2].

The beginning of 2016 is selected as the starting point for our analysis as even though Ethereum was proposed in 2013 and crowdfounded in 2014, the network was set up only in mid-2015. In addition, the variability of USDT as the dominant stablecoin before 2016 is rather low and thus not really interesting for a quantitative analysis. Fig. 1 graphically presents the time evolution of the total stablecoins supply and prices of the three major cryptoassets between 1 Jan 2016 and 12 Jan 2021 (the total of 1839 observations). We observe the bear market in 2016 followed by the hike of 2017, bear market of 2018 and 2019, getting us to 2020 and 2021 and the current price surges and new all-time-highs. Even though the global dynamics might seem similar, we see that these three cryptoassets all follow rather specific dynamics making the inclusion of all three rather than just the dominantly perceived Bitcoin worth it. What certainly strikes the eye is the overlapping dynamics (very profound in the graphics of Fig. 1) of Ethereum (which would be true for BTC as well as XRP in a different graphical representation or scale setting) and stablecoins during the 2017 price rallies hinting the relationship between the stablecoins and the other, standard, cryptoassets. Uncovering the leader in this joint dynamics is the main aim of this letter as it plays a crucial role in clarifying the role of stablecoins in the cryptoassets system.

[1] To avoid confusion, we stick to the XRP notation as Ripple is the issuing company name, not the coin's name. The prices for all three cryptoassets were obtained from coinmarketcap.com.

[2] The free float and current supplies were obtained from coinmetrics.io. For clarity, the free float supply is the best representation of the actual supply of a stablecoin in circulation. However, it is not easily obtainable for all stablecoins. Nevertheless, the free float supply part of our stablecoins sample forms a dominant majority of the overall stablecoins supply, i.e., the differences between the free float supply and the current supply for the smaller stablecoins are negligible.

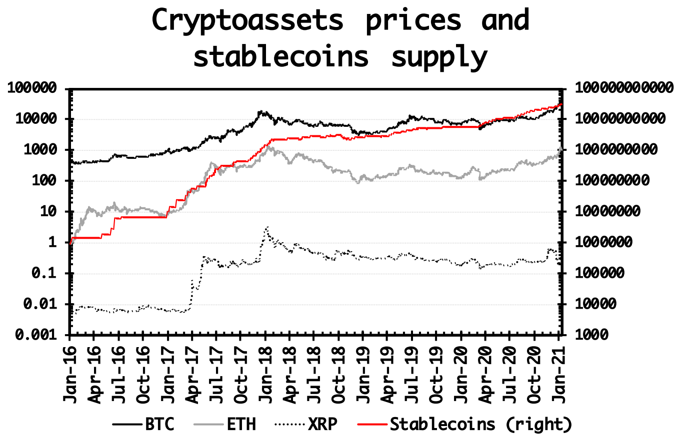

Fig. 1. Cryptoassets prices and stablecoins supply. Both prices (left y-axis) and supply (right y-axis) are presented in USD.

4. Results and discussion

4.1. Global connectedness and spillovers

Studying the relationship between stablecoins and other cryptoassets leads to identification of potential lead-lag (or impulse-response) relationship possibly in both short-term and long-term perspective. Therefore, we do not want to omit possible long-term effects here, especially due to a rather specific dynamics of the stablecoins supply which is quite jumpy, i.e., there are rather long periods of no change or tranquility followed by periods of abrupt influx of digital money into the system. The first step is thus verifying a possible cointegration relationship as the VAR framework described in the Methods section works for the vector error-correction models (VECM) as well as these can be represented in the VAR form. The standard Johansen testing procedures do not show clear cointegration relationship[3]. The need for possible long-term spillovers leads us to using price and supply series rather than their differences as most of the dynamics would be lost by differencing (we use the logarithmic transformations to control for different scaling of the series). As noted by Sims (1980) and Sims et al. (1990), the series for VAR do not need to be stationary as long as we are not interested in interpretation of the specific estimates, which we are not, and the VMA representation is justifiable even for non-stationary series. As the forecast variance decomposition in Eq. (1) is built on the VMA representation but also the variance matrix of disturbances, their stationarity is crucial for the whole procedure being feasible. We estimate the VAR system with lags selected based on the Akaike information criterion (AIC) with a maximum of 30 lags (a trading month for the cryptomarkets), leading to 3 lags. Unit root is rejected for residuals of all four equations of the system with p-values deep below any conventional level and stationarity is not rejected for either of the residual series with p-values safely above 0.10 (standard ADF and KPSS tests, respectively). We can thus confidently continue with the procedure.

The system of logarithmic prices of BTC, ETH, and XRP and logarithmic supply of stablecoins is estimated. The results for the forecasting horizon of $H = 100$[4] are summarized in Table 1. The table shows the spillovers for two specifications following Barunik and Krehlik (2018) – *(left)* for the standard Σ matrix in Eq. (1), and *(right)* for the diagonal Σ matrix in Eq. (1). Such separation is crucial for understanding the source of spillovers as these might be dominated by the contemporaneous correlations effect (series moving together) rather than the cross-correlation effect (one series leading another one). The total spillover index of the analyzed system of cryptoassets rounds up to 37 (maximum of 100) which makes it at par with levels reported by Diebold and Yilmaz (2009) in their original paper for the stock market indices. However, when we control for correlation between the assets, the overall index drops to 16, i.e., over half of the total connectedness is formed by contemporaneous correlations rather than cross-correlations. Looking at the diagonal of the table, we observe a high degree of auto-correlation in the assets, which is not surprising. We are much more interested in the off-diagonal elements representing the directional spillovers. As we are mostly interested in the interaction of stablecoins within the system, let us focus on the first row and first column of the table. The first row represents the spillovers coming from other assets towards stablecoins. Around 20% of the total spillovers coming towards stablecoins (70% is attributed to the auto-correlation) comes from Bitcoin, even after controlling for the contemporaneous correlation. The rest, around 10%, comes from Ethereum and XRP combined. The total spillovers coming from other assets get to around 8. From the other side, the first column represents the spillovers from stablecoins towards other cryptoassets. But here they are practically zero for either of the assets and the overall spillovers going to other assets total to practically zero. The way the price of major cryptoassets, but mostly Bitcoin, influence the total supply of stablecoins and thus their issuance is practically two orders of magnitude higher than the other way around.

[3] The testing procedure is available upon request. In short, Ethereum contains a unit root only with a time trend but the testing procedures do not find cointegration in the time trend specifications of the VECM models.

[4] We inspect the spillovers up to 100 trading days as we are interested in possible long-term effects and shocks transmission within the system.

Table 1

Overall spillovers of the system. The diagonal elements represent (self-)spillover due to the auto-correlation structure. The off-diagonal elements represent the (cross-)spillovers due to shocks in other respective assets. For an asset in the given row (column), the values in columns (rows) represent spillovers coming from (going towards) the asset in the specific column (row). The values are separated by the — character to separate the spillovers based on the standard forecast error variance decomposition in Eq. (1) (left) and the diagonal restriction of the Σ matrix in the same equation (right). The last row and last column represent the total spillovers going towards other assets and coming from other assets for the given asset, respectively. The values in the last row and column position represent the total spillover index of the system.

	Stablecoins	Bitcoin	Ethereum	XRP	FROM
Stablecoins	67.51|68.22	20.78|21.43	11.65|3.76	0.06|6.58	8.12|8.12
Bitcoin	0.11|0.69	67.96|89.42	27.62|3.58	4.32|6.31	8.01|2.65
Ethereum	0.26|0.17	30.70|8.90	57.23|90.76	11.81|0.18	10.69|2.31
XRP	0.07|0.01	14.00|0.47	26.12|13.80	59.81|85.72	10.05|3.57
TO	0.11|0.22	16.37|7.70	16.34|5.29	4.05|3.27	36.87|16.47

The global perspective of the spillovers within the system of major cryptoassets and stablecoins points directly and clearly towards evident spillovers coming from the major cryptoassets, mostly Bitcoin, towards stablecoins and not the other way around. This suggests that the increase in stablecoins supply, i.e., new allowances, come after the price increases in the cryptomarkets, pointing towards the demand hypothesis of the stablecoins issuances. There is no sign of stablecoins issuances boosting the prices of the other major cryptoassets. Even though this global perspective is very clear, the spillovers can be rather dynamic in their evolution (Diebold and Yilmaz, 2009; 2012; Barunik and Krehlik, 2018) so that a deeper look into possible changing market dynamics structure is at hand.

4.2. Evolution of stablecoins' role in the system

As the cryptomarkets are rather dynamic and they often experience abrupt changes in market capitalizations, it is natural to investigate whether the spillover structure reported in the previous section is stable in time. We reestimate the VAR, corresponding FEVDs and spillover statistics on a rolling window of 365 days (a trading year for cryproassets) with a step of 1 day. The optimal lags are still selected based on AIC, but now for each of the rolling estimations separately. The forecasting horizon remains at $H = 100$.

Overall spillovers, directional spillovers and net spillovers for stablecoins[5] and their evolution in time are depicted in Fig. 2. First, the results do not differ much for the spillovers calculated with the full or the diagonal variance matrix of the VAR residuals. The basic trends and movements are very similar. Second, the overall spillover index is higher than the global index estimated for the full sample. That is due to the fact that the moving window VARs can fit the shorter samples better, uncovering the correlation structures more precisely and also highlighting that the global estimation is not sufficient to properly understand the systemic interconnections. The spillover index mostly varies between 50 and 70 for the full variance matrix and it shows somewhat higher variability when the contemporaneous correlations are controlled for. However, we do not see any structural differences between these two types of overall spillover indices. And third, as the overall spillover index is rather stable in time, the directional spillovers are mostly asymmetrical. The global picture of the stablecoins supply being boosted by the other cryptoassets price increases is translated into the local dynamics as well. However, there are several exceptions when the spillovers to stablecoins drop very low while the spillovers towards them spike. The most prominent and also quite persistent one, which represents itself in rather high positive net spillover values, spans over the year 2019.

The end of 2018 and the beginning of 2019 had been the times when Bitcoin (and the market overall) reached its lowest point since the back-then all-time-highs of the late 2017, Bitcoin almost touching the $3,000 mark. To make a qualified interpretation of such dynamics, we look at all three spillover indices for stablecoins together. The profoundly positive net spillovers coming from stablecoins to the other cryptoassets is formed by the highest levels of the spillovers coming from stablecoins and the lowest levels going towards stablecoins in the whole examined period. It thus seems that the market participants understood and identified the low prices of the late 2018 and early 2019 as the bottom points of the cryptomarkets at that time and started buying for what they considered cheap prices. The increased demand for investment into cryptoassets materialized in increased purchases of stablecoins that were used to buy these major cryptoassets (as their supply is mostly fixed, at least in the short and medium term). We do not identify such spillover dynamics as a sign of the bubble-boosting mechanism induced by stablecoins (Griffin and Shams, 2020) as the spillovers towards stablecoins drop to practically zero during this period in 2019. In the bubble-boosting machine, we would expect the spillovers both from and towards stablecoins to increase as the increasing prices would lead to a higher number of participants entering the market, demanding digital cash that would further inflate the prices that would spiral further up. We do not observe even a hint of such dynamics.

5. Conclusions

We investigated the spillovers within the system of major cryptoassets and stablecoins. Using the spillover index and directional spillovers both from the global and the local perspective, we have found no evidence of stablecoins artificially boosting the prices of

[5] We are primarily interested in the role of stablecoins in the system. Results for other parts of the system, i.e., BTC, ETH, and XRP, as well as rolling pairwise spillovers are available upon request.

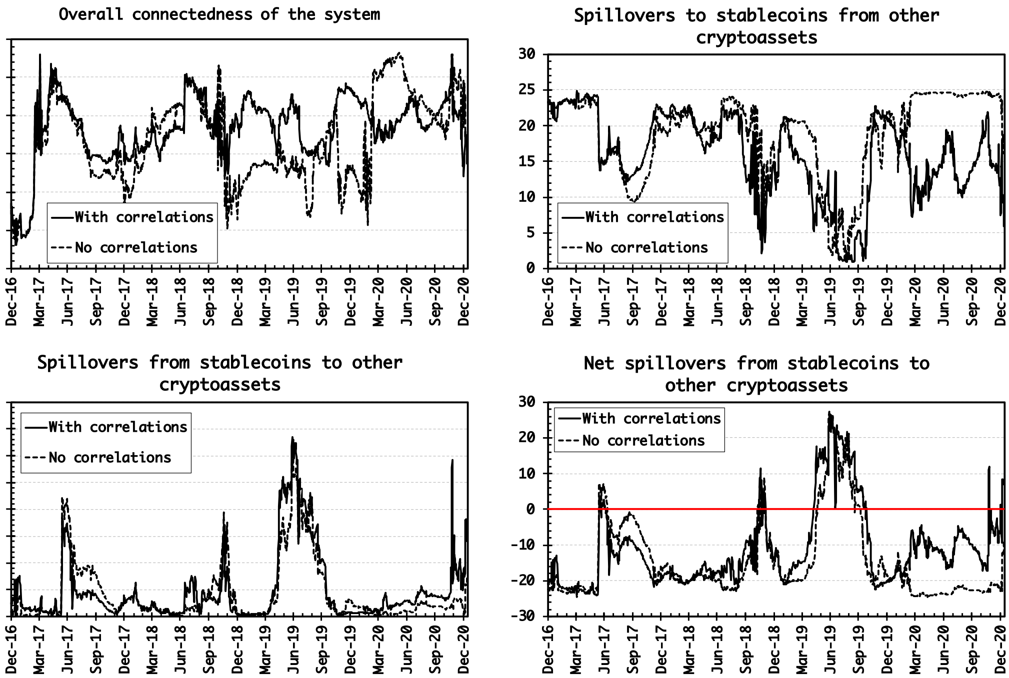

Fig. 2. Evolution of overall and directional spillovers in time. The spillover indices are based on the rolling VAR with a window of 365 days (a trading year) and a step of 1 day, optimal lags are selected based on AIC, and we use the forecasting horizon of $H = 100$ as for the global VAR.

other cryptoassets. On the contrary, the increased stablecoins issuances come as reaction to the other cryptoassets price hikes, thus rather reflecting increasing demand in investing into the cryptomarkets that gets materialized in demand for the "digital fiat". As there is only a limited amount of empirical topical literature, the presented results form a solid contribution towards understanding the role stablecoins play in the cryptomarkets.

CRediT authorship contribution statement

Ladislav Kristoufek: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing.

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