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On the role of stablecoins in cryptoasset pricing dynamics

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Abstract

We examine the interactions between stablecoins, Bitcoin, and a basket of altcoins to uncover whether stablecoins represent the investors' demand for trading and investing into cryptoassets or rather play a role as boosting mechanisms during cryptomarkets price rallies. Using a set of instruments covering the standard cointegration framework as well as quantile-specific and non-linear causality tests, we argue that stablecoins mostly reflect an increasing demand for investing in cryptoassets rather than serve as a boosting mechanism for periods of extreme appreciation. We further discuss some specificities of 2017, even though the dynamic patterns remain very similar to the general behavior. Overall, we do not find support for claims about stablecoins being bubble boosters in the cryptoassets ecosystem.

Keywords: Cryptocurrencies, Cryptoassets, Bitcoin, Stablecoins, Tether

Introduction

Cryptoassets[1] have come a long way since the introduction of Bitcoin in 2008 (Nakamoto 2008) and the now-legendary pizza purchase in May 2010, which is considered the first transaction between Bitcoin (and thus cryptoassets in general) and the standard economy. The 10,000 bitcoins paid for two pizzas provide a nice perspective of the progress that Bitcoin and the cryptomarkets have made since then. Although the last few years have been dominated by the events of 2017, when we experienced the cryptoassets boom (and the later bust), blockchain development and possible applications have seemingly evolved in the background, at least for those watching the process from outside of the field. As 2017 and part of 2018 can be seen as the years of ICOs (initial coin offerings, i.e., counterparts to the standard initial public offerings, IPOs) and 2019–2021 have thus far been the years of DeFi (decentralized finance, i.e., a notion to replace traditional financial instruments in the decentralized blockchain architecture), the system of stablecoins has, rather quietly, been evolving as well. Stablecoins are (usually) token-based

[1] To avoid confusion between various divisions and structures, we refer to all cryptocurrencies/coins, smart-contract bearing coins, and tokens as "cryptoassets" and thus follow, e.g., the Bank of England nomenclature (https://www.bankofengland.co.uk/knowledgebank/what-are-cryptocurrencies).

cryptoassets pegged mostly to fiat currencies (predominantly the US dollar), but there are also commodity-backed (such as Digix gold tokens), cryptocurrency-backed (such as Havven and Dai), and algorithmic (such as Empty Set Dollar and Frax) stablecoins. Their main objective is to enable easy transactions between different cryptoasset exchanges with a stable exchange rate, thereby bypassing the inherent large volatility of other cryptoassets (Bullmann et al. 2019) as without stablecoins, many (even large) exchanges listed cryptoassets pairs only with another cryptoasset (mostly Bitcoin and Ethereum) rather than providing exchange pairs with fiat currencies. Although, their role in the decentralized finance protocols has likely overcome their "easy transfer" perception in the last few years.

? FIND IT!

Research into cryptoassets flourished during and after the crypto-boom of 2017, when not only Bitcoin appreciated approximately 20 times from $1000 at the beginning of 2017 to its all-time-high of around $20,000 but also altcoins (as alternative cryptocurrencies/coins to Bitcoin) and token-based ICOs surpassed almost imaginary levels of price surges (with Ethereum, as the second most popular cryptoasset, surging from $8 at the beginning of 2017 to more than $700 by the year's end and reaching its all-time-high of $1370 in mid-January 2018 and ICOs raising more than $5.3B by the end of 2017 (Adhami et al. 2018)). However, this research has focused mostly on the rather standard financial aspects such as profitability, predictability, efficiency and trading strategies (Kristoufek 2013; Baur et al. 2018; Kosc et al. 2019; Wheatley et al. 2019; Wen et al. 2019; Grobys et al. 2020; Gerritsen et al. 2020; Sebastiao and Godinho 2021; Kou et al. 2021), portfolio diversification, risk management, connectedness (Kondor et al. 2014; Bouri et al. 2017; Klein et al. 2018; Yi et al. 2018; Corbet et al. 2018; Mensi et al. 2019; Kajtazi and Moro 2019; Katsiampa et al. 2019a; Platanakis and Urquhart 2020; Akyildirim et al. 2020; Li et al. 2021), and price formation (Kristoufek 2015, 2019; Ciaian et al. 2016; Ciaian and Rajcaniova 2018; Mai et al. 2018; Phillips and Gorse 2018; Katsiampa et al. 2019b; Zhang and Li 2020; Zha et al. 2020). A comprehensive review is given in Corbet et al. (2019). In contrast, research into stablecoins has attracted only little attention even though their market capitalization, which can be seen as a money supply in the standard economics terms, increased approximately 200 times in 2017 and they play an essential role in trading[2]. Legitimity of stablecoins is thus a crucial factor when discussing the overal cryptomarkets structure, dynamics, and future development.

TRAIDING PAIR ?

Bullmann et al. (2019) categorize stablecoins with respect to three key dimensions—issuer accountability, decentralization of responsibilities, and what underpins the asset value. They argue that there is a trade-off between the novelty of the stabilization mechanism and the capacity to maintain a stable market value. Some of the stablecoins (not all) are then labeled as actual cryptoassets with crypto-related governance and regulatory issues. Once a clear governance framework for such is set, the authors believe that these can be subject to warranted regulatory scrutiny and recognition. The stability of stablecoins is examined by Wang et al. (2020), Baur

[2] Even though Bitcoin is a clear market leader, when one checks pairs with the highest volumes for the second largest cryptoasset Ethereum (ETH), the three highest volumes are reported for stablecoins pairs, specifically with USDT on Binance, USDT on Huobi Global, and BUSD on Binance (as of June 2021). There is only one BTC pair (on Binance) in the Top 10 with respect to the trading volume.

and Hoang (2020) and Lyons and Viswanath-Natraj (2020), and they all identify stablecoins as safe havens during standard market conditions, with premiums during critical events. Bullmann et al. (2019), Han et al. (2020) and Nabilou (2020) explore stablecoin suitability as a central bank digital currency (CBDC). Han et al. (2020) propose a three-layer structure, including a supervisory layer, a network layer and a user layer. Nabilou (2020) examines a possible CBDC issued by the European Central Bank and lists a set of legal challenges that would need to be resolved before such an issuance.

Apart from the utility and stabilization the stablecoins might provide to the cryptoassets markets, there has been an ongoing discussion of their bubble-boosting effect and role in the 2017 cryptoassets price surges. As Tether (USDT) has long been the most important and voluminous of the stablecoins, the literature focuses primarily on its role in cryptomarkets. Wei (2018) studies the effect of Tether issuances on Bitcoin prices and argues that there is no causal relation between Tether grants and increasing Bitcoin prices. However, the grants lead to an increased trading volume of Bitcoin. Griffin and Shams (2020) provide a very detailed network analysis and find that purchases in Tether played an important role in the 2017 price upheaval, usually coming after the market downturns to further boost the upward price trend. These manipulations are traced back to a single market player on the Bitfinex exchange who purchased large amounts of Bitcoin when the prices were falling and after the printing of Tether. These findings are somewhat supported by the newer study of Ante et al. (2020), who present the case study of 565 stablecoins issuance events of \$1 M and more between April 2019 and March 2020. They find statistically significant abnormal returns both before (up to 12 h before) and after (up to 24 h after) the issuance. However, the cumulative abnormal returns over the full event window reach only around 1%. The main motivation of the current research is to provide a point of view of the global cryptomarkets dynamics with respect to the interaction between stablecoins and the rest of the market with the main focus on the possible bubble-boosting role of newly issued stablecoins on the overall market value.

Herein, we expand on the previous findings in various dimensions, providing a broad insight into the interaction between stablecoins issuances and other cryptoassets valuation. First, we extend the covered period and study the relationships between March 2015 and July 2020. Second, we focus on a large pool of stablecoins to see their overall effect. Third, we focus on both Bitcoin as a dominant cryptoasset and a basket of altcoins as their dynamics had been quite diverse historically and mostly during the bull run of 2017. Combining these extensions, we concentrate on the stablecoins role in the cryptomarkets value formation. Specifically, we tackle the question whether the amount of stablecoins in circulation (in USD) reflects the demand factors in the market and/or whether we can find evidence of suspicious bubble-boosting or even bubble-igniting dynamics. Based on the results, we argue that stablecoins mostly reflect an increasing demand for investing in cryptoassets rather than serve as a boosting mechanism for periods of extreme appreciation. We further discuss some specifics of 2017, even though the dynamic patterns remain very similar to the general behavior. We provide several robustness checks and we also discuss possible sources of differences with respect to other topical results in the literature, mainly the Griffin and Shams (2020) paper that has set the tone of the stablecoins discussion that followed and is widely referred to outside the academic research [e.g. (Bloomberg 2021, 2019) and The Wall Street Journal (WSJ 2021)] despite its methodological limitations that we discuss in a separate section. Overall, we do not find evidence of stablecoins as bubble boosters, quite the opposite, our results suggest their inflow due to increased investment demand.

Dataset description and initial analysis

We study the interactions between stablecoins and the rest of the cryptoassets. We cover all stablecoins with a market capitalization of at least $1 M as of 12 July 2020. This criterion provides us with 28 stablecoins[3]. 24 of the stablecoins are pegged to the US dollar (USD), 2 are pegged to the euro (EUR), and there are single cases of anchoring to the Swiss franc (CHF) and the Chinese renminbi (CNY). Currently, approximately 80% of the stablecoin capitalization is formed by Tether (USDT), and the existence and data availability of this dominant stablecoin sets the examination period starting on 6 March 2015. With an end date of 11 July 2020, we obtain 1955 daily observations[4].

For the set of cryptoassets (cryptocurrencies/coins and tokens), we use the top 10 with respect to market capitalization (not including USDT, which is now in the top 5) as of 12 July 2020, and we add several "old-timers" that have been historically popular and are usually also in the top 10 but recently fell off the list. These criteria provide us with 14 cryptoassets[5]. Similarly, although in a weaker manner, the market is dominated by Bitcoin, with the so-called BTC dominance currently at approximately 60%.

With a dominant asset in each group, we focus on the interaction between three variables—Bitcoin as the dominant cryptocurrency, the rest of cryptocurrencies and tokens put into a single basket (altcoins), and the basket of all stablecoins. Figure 1 shows the reasonability of this split. Apart from the very beginning of the analyzed period, stablecoin capitalization is strongly dominated by USDT. However, the dynamics of altcoins is much more interesting, with a rally in 2017. Altcoins are thus worth a separate deeper investigation rather than only the examination of either Bitcoin alone or the cryptomarket as a whole. As we want to study both Bitcoin and altcoins, the prices alone become insufficient; thus, we need to adhere to an index of value for the basket of assets. The most straightforward one is market

[3] With respect to the market capitalizations, in the descending order: Tether (USDT), USD Coin (USDC), Paxos Standard (PAX), Dai (DAI), Binance USD (BUSD), TrueUSD (TUSD), HUSD (HUSD), STASIS EURO (EURS), QCash (QC), USDK (USDK), sUSD (SUSD), Neutrino Dollar (USDN), JUST (JST), Gemini Dollar (GUSD), 1SG (1SG), Anchor (ANCT), USDQ (USDQ), CryptoFrank (XCHF), VNDC (VNDC), USDJ (USDJ), bitCNY (BITCNY), EURBASE (EBASE), EOSDT (EOSDT), Constant (CONST), USDx stablecoin (USDx), bitUSD (BITUSD), NuBits (USNBT), Egoras Dollar (EUSD).

[4] The basic information about stablecoins was taken from https://cryptoslate.com/cryptos/stablecoin/ and the time series were downloaded from https://coinmarketcap.com/, both on 12 July 2020.

[5] With respect to the market capitalizations, in descending order: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), Bitcoin SV (BSV), Cardano (ADA), Litecoin (LTC), Chainlink (LINK), Binance Coin (BNB), Crypto.com Coin (CRO), EOS (EOS), DASH (DASH), Stellar (XLM), Monero (XMR). These selected cryptoassets cover approximately 90% of the overall cryptomarket capitalization (not including stablecoins), and their price history is reliable. Obtaining reliable time series for the overall cryptomarket capitalization has proven problematic with unreasonable capitalization jumps.

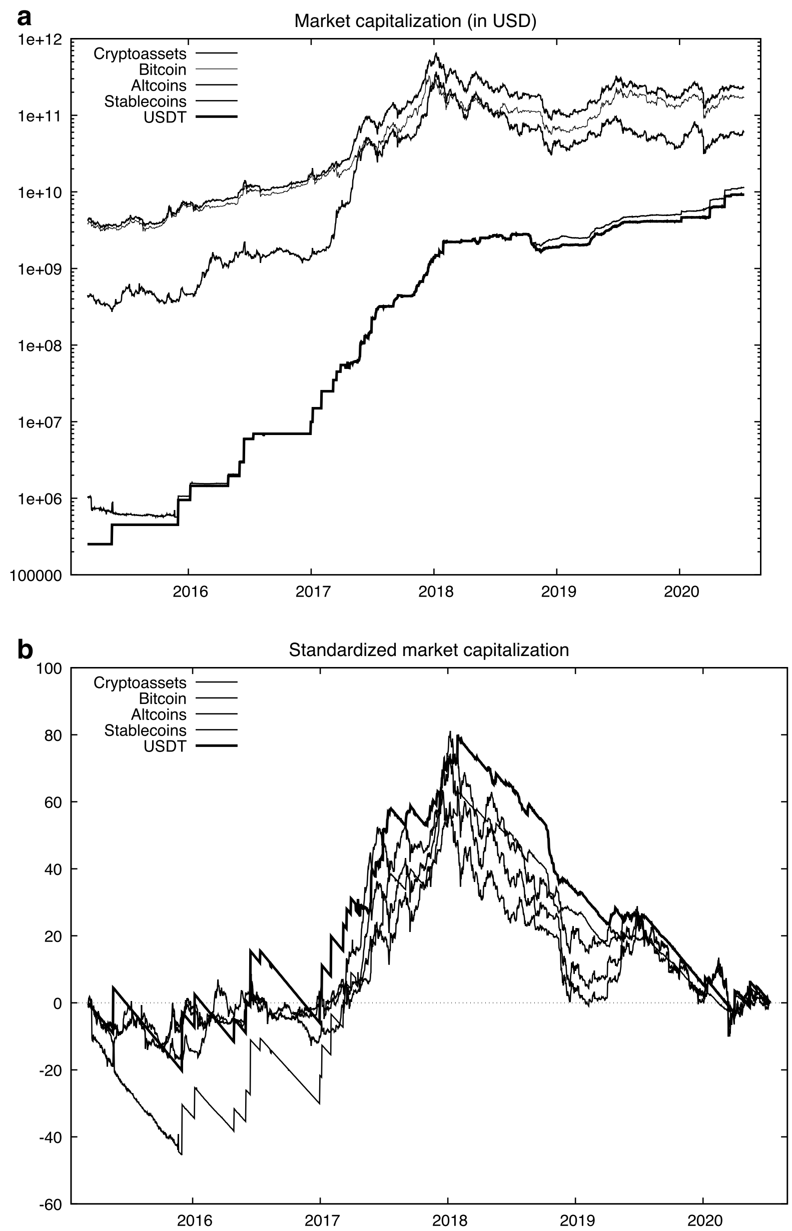

Fig. 1 Time evolution of market capitalization. (Left) Market capitalization of the variables of interest in USD. (Right) Integrated demeaned and standardized logarithmic first differences of the variables of interest. All series are shown between 6 March 2015 and 11 July 2020, giving 1955 observations.

capitalization, which can be seen as a circulating-supply-weighted price index. In addition, utilizing market capitalization instead of simple prices has another advantage in incorporating changing circulating supply of the coins and tokens, which can be seen as a parallel to the adjusted (for splits, dividends and distributions) prices for the standard financial assets. Utility of market capitalization in the cryptoassets markets has been recently put forward by Li et al. (2019) and Liu et al. (2019). Maybe even more importantly, even if we focused on only Bitcoin, a single altcoin and a single stablecoin, prices would still not be an ideal candidate for the analysis. This is due to a practically constant price of most of the stablecoins.

Table 1 Descriptive statistics

	Cryptoassets	Bitcoin	Altcoins	Stablecoins	USDT
Mean	0.0020	0.0019	0.0025	0.0048	0.0054
SD	0.0392	0.0390	0.0506	0.0416	0.0427
SD/mean	19.1275	20.0483	20.1057	8.7357	7.9474
Minimum	− 0.4759	− 0.4646	− 0.5079	− 0.3469	− 0.1102
Maximum	0.1765	0.2252	0.3206	0.6842	0.7453
Skewness	− 1.3226	− 0.9595	− 0.5057	7.7569	10.5810
Excess kurtosis	14.8840	14.2680	9.1247	104.9000	136.1300
$q_{0.05}$	− 0.0606	− 0.0619	− 0.0754	− 0.0157	− 0.0079
$q_{0.95}$	0.0621	0.0610	0.0835	0.0238	0.0191

The statistics are presented for the logarithmic differences of market capitalizations. Cryptoassets represent the total market capitalization of the highly capitalized cryptocurrencies and tokens (listed in the text), not including the stablecoins. Stablecoins represent the total market capitalization of the 23 stablecoins listed in the text

Comparing the variance of Bitcoin and Tether as the most dominant of their type, there is a difference of two orders of magnitude for our sample. Prices and returns of stablecoins thus carry very limited, if any, information. In contrast, market capitalization of a stablecoin, connected with its practically constant price, provides information about circulating money supply of its type. We thus adhere to market capitalizations moving forward. The pronounced sawtooth patterns in Fig. 1 then represent large stablecoins issuances that are characteristic for their dynamics and would remain hidden if the price or returns series were used. Figure 1 also presents the increasing importance of stablecoins in the whole system. Starting at less than 0.0001% of the whole market capitalization, their importance and utility has rocketed since then, mostly between 2017 and 2018, when their capitalization grew from less than \$10M to around \$2B. Currently, the overall stablecoin capitalization stands at above \$11B, i.e., approximately 4% of the total cryptomarket capitalization. The right panel of Fig. 1 shows the integrated demeaned and standardized logarithmic differences of the baseline series. Visually, all the series follow rather similar dynamics, which is true not only for Bitcoin and altcoins but also for stablecoins, which seem to closely mimic the other cryptoassets. However, the actual correlation between the (logarithmic differences of) stablecoins and either Bitcoin or altcoins is very low at − 0.0261 and − 0.0006, respectively, while the correlation between Bitcoin and altcoins is high at 0.6111. Putting together the low correlation between the stablecoin and nonstablecoin cryptoassets with a graphical representation of the series suggesting the interconnection of the integrated series makes it necessary to focus not only on the possible short-term comovements but also on the potential long-term relationships.

Table 1 summarizes the basic descriptive statistics of the logarithmic differences of the baseline series. We see that all have a positive mean, i.e., a positive trend in time for the original series. Unexpectedly, the standard deviations are of a similar order of magnitude, with the highest uncertainty associated with altcoins. When the standard deviation is scaled by the mean value, i.e., when we check the variation coefficient, we see that the nonstablecoin cryptoassets are much more unstable compared to the stablecoins. The extreme value statistics are rather interesting. The minima, i.e., the

Table 2 Results of the unit root tests

	Original			Standardized		
	ADF stat	*p* value	lags	ADF stat	*p* value	lags
Cryptoassets	− 1.2659	0.6474	0	− 1.0846	0.7240	0
Bitcoin	− 1.1708	0.6891	0	− 1.3491	0.6085	0
Altcoins	− 1.3426	0.6116	0	− 0.9150	0.7839	0
Stablecoins	− 0.6740	0.8512	0	− 0.7533	0.8312	0
USDT	− 1.7611	0.4003	0	− 0.8301	0.8099	0

The augmented (Dickey and Fuller 1979) test is performed on the original (logarithmic) series (left panel) and the standardized ones (integrated demeaned and standardized logarithmic differences of the original series, right panel). The optimal number of lags for the test is based on BIC (also shown in the table)

maximum losses for the cryptoassets, reach approximately 50%, with the highest loss connected to altcoins. However, altcoins also possess the highest gains, i.e., the maxima, at 32%, whereas Bitcoin reaches only 22% and the overall cryptoasset capitalization is only 17%, which suggests that altcoins and Bitcoin do not co-move so strongly during extreme positive events, or at least they do so less at these times than they do during the most extreme negative events. While the minima and maxima of the nonstablecoin cryptoassets are direct reflections of the price changes and, to much a lesser extent, of the circulating supply increases (as these are mostly given by an algorithm and/or a well-specified procedure/formula), the extreme movements of stablecoins are mostly driven by their supply, as the prices are pegged to their fiat counterparts and remain mostly stable (for those that are USD pegged) or copy the exchange rates of the USD and their underlying currency (for the others). Their dynamics are evidently highly asymmetric, with a maxima of approximately 70% for both USDT and all stablecoins, which is further reflected in a profoundly positive skewness. The nonstablecoin cryptoassets are negatively skewed, signaling more extreme negative events. The difference between the two groups is further reflected in the extreme leptokurtosis of the stablecoins. The fifth and ninety-fifth quantiles show that stablecoins are in fact more stable in the bulk of their distributions, yet still apparently asymmetric; however, the extreme events of substantial issuances/emissions/creation override the overall dynamics. These distributional properties are illustrated in the histograms in Fig. 4 and they suggest that the inspection of the relationships in extreme events, i.e., in specific quantiles of the distributions should take place to provide a more informed insight into the overall dynamics.

The appropriate model selection usually builds on some basic statistical and dynamic properties of the analyzed processes as well as the target of the examination. As we are interested in studying interactions and possible causal relationships between the processes and our baseline statistical hypotheses are “value of stablecoins in the system does not (Granger-)cause valuation of cryptoassets/Bitcoin/altcoins” and vice versa, we opt for a general framework of vector autoregressive (VAR) models in the baseline setting. As the unit root dynamics cannot be rejected for any of the series (as shown in Table 2), this outcome directs us towards either the standard VAR on the first differences of the series or the vector error-correction model if the series are cointegrated.

Methods

We aim to quantify the relationship between stablecoins and other cryptoassets by focusing on interactions and causality and ideally splitting the difference between the short-run and long-run dynamics. The general VAR framework is a standard environment for such examination as it provides enough flexibility and intuitive tools to answer the questions at hand.

Let us have a data matrix $x = (t \times k)$ where t is the time series length (number of observations) and k is the number of variables. In our specific case, we have $t = 1955$ and $k = 3$ (the logarithmic market capitalizations of stablecoins, Bitcoin, and altcoins). The cointegrated VAR in its rather general form is written as follows:

$$\Delta x_t = \sum_{i=1}^{p} \Phi_i \Delta x_{t-i} + \alpha\beta' x_{t-1} + \pi + \delta t + \varepsilon_t \tag{1}$$

where p is the number of lags considered in the VAR parametrization, Φ_i is a vector of parameters of the autoregressive part of the model for lag $i = 1, \ldots, p$, $\alpha\beta' \equiv -\Pi$ is a cointegration matrix Π where α is a matrix of adjustment vectors, β is a matrix of cointegration vectors, π is a constant, and δ is the time trend parameter. The rank of Π specifies what kind of relationship/model we are working with. When $\Pi = 0$, the system reduces to a standard VAR. However, when $Rank(\Pi) = k$, i.e., it has a full rank, then processes in x are not unit roots but are instead stationary such that an appropriate approach is to apply VAR on the original processes rather than on the first differences. The interesting configuration emerges when $0 < Rank(\Pi) < k$, which leads to the so-called cointegration (Banerjee and Hendry 1992; Hendry and Juselius 2000, 2001; Juselius 2006). ?

The notion of cointegration goes back to Granger (1981) and Engle and Granger (1987) and suggests that even though two (or more) series are nonstationary, a linear combination might exist that is stationary and can be consistently estimated. The product $\beta' x_{t-1}$ in Eq. 1 is then interpreted as a long-run equilibrium of the system. Cointegration implies that deviations from such equilibrium (usually referred to as the error-corrections term or terms, depending on the number of cointegrated vectors) are stationary and with finite variance, i.e., the system tends back to its long-run equilibrium. When the series are nonstationary but not cointegrated, i.e., when $\Pi = 0$, there is no long-run equilibrium, and one needs to focus mostly on the short-run dynamics and interactions via the standard VAR framework.

Even though the bivariate cointegration can be tested through the Engle and Granger (1987) approach via a combination of the augmented Dickey-Fuller tests (Dickey and Fuller 1979), in the multivariate setting, one needs to stick to the pair of Johansen tests (Johansen 1991, 1995)—the trace test and the maximum eigenvalue test. As the labels suggest, the former is based on the trace of the Π matrix, and the latter looks at the maximum eigenvalue of the Π matrix. These two tests, combined with testing stationarity of the error-correction terms, usually give a clear answer to whether the series are cointegrated or not.

As Eq. 1 can take various parametrizations, there are several possible ideal model specifications. An interested reader is directed to the theoretical foundation works of Ericsson et al. (1998) and Hoover et al. (2008), in addition to the previously mentioned ones. For transparency and replicability, we adhere to the following steps:

1. Run the augmented Dickey-Fuller tests (Dickey and Fuller 1979) on the original series with lags based on BIC (Schwarz 1978), with a maximum lag of 30 days (i.e., a trading month, as cryptocurrencies trade on a 24/7 basis). Check whether the time trend is needed to achieve nonstationarity.
2. Estimate Eq. 1 with the optimal number of lags based on BIC (a maximum lag of 30 days). Check the significance of the time trend. Heteroskedasticity and autocorrelation consistent (HAC) standard errors are used.
3. Find the number of cointegrated vectors via the Johansen tests (Johansen 1991, 1995) (both trace and L_{max}) using the number of lags and trend specifications based on the previous steps.
4. If the cointegrated vectors are identified, estimate the cointegrated VAR (error-correction model) through the Johansen procedure (Johansen 1995). If the cointegrated vectors are not identified, estimate the standard VAR on the differenced series.
5. Check the unit roots of the error-corrections terms (for the cointegrated VAR) or the residuals (for the standard VAR) the same way as explained in Step 1.

Once the model specification is selected, we can proceed to the analysis of interactions and causality. For the former, we will present the impulse-response functions as a representation of how shocks propagate in the system (Koop et al. 1996; Lütkepohl 2007). For the latter, we will study the Granger causality between the pairs of variables both in the short term (through the joint hypothesis testing of the cross-correlation components in Eq. 1) and in the long term [through the VAR on the level variables, following (Toda and Yamamoto 1995)]. All tests are performed with either heteroskedasticity consistent (HC, Davidson and MacKinnon 2003) or heteroskedasticity and autocorrelation consistent (HAC, Newey and West 1987) standard errors, as necessary.

Results

Basic model specification

We analyze the interconnections between Bitcoin, altcoins, and stablecoins in the VAR framework. As already shown in Table 2, their logarithmic market capitalizations contain unit roots; thus, they are good candidates for either VAR on the first differences or the cointegration relationship. As cointegration dynamics is a generalization of the standard VAR model, we start with testing the cointegration vectors via the Johansen tests. Table 3 summarizes the results of both tests and clearly shows that there is one cointegration relationship identified in the system of three variables. As the cointegrated VAR representation of the cointegration relationship confirms a statistically significant time trend, we present the results only for specifications with a restricted trend and an unrestricted trend that are well in hand. According to Hendry and Juselius (2001), the selection between the restricted and unrestricted version of the cointegration model is usually made based on a possible quadratic time trend in the original integrated series. Inspecting the series dynamics (in Fig. 1), we see (and estimation confirms) that the market capitalizations are better described by a nonlinear time trend. We thus adhere to

Table 3 Results of the Johansen cointegration tests

# of Cointegrated vectors	Eigenvalue	Trace test	*p* value	L_{max} test	*p* value
Cointegration with restricted trend					
0	0.0167	46.9930	0.0169	32.8380	0.0033
1	0.0063	14.1550	0.6504	12.3170	0.3987
2	0.0009	1.8386	0.9644	1.8386	0.9652
Cointegration with unrestricted trend					
0	0.0166	44.9150	0.0029	32.6020	0.0021
1	0.0062	12.3140	0.2916	12.1780	0.2319
2	0.0001	0.1360	0.7123	0.1360	0.7122

Both Johansen tests (Johansen 1991, 1995)—trace and maximum eigenvalue—are presented here. As the VAR representation of VECM given in Eq. 1 shows a significant time trend in the relationship, we restrict the testing to the cases of the restricted and unrestricted trend. More details are given in Hendry and Juselius (2001)

Table 4 Granger causality on market capitalizations

Hypothesis (H_0)	Short-term		Long-term	
	(df = [2, 1941])		(df = [4, 1938])	
	F-stat	*p* value	*F*-stat	*p* value
Bitcoin *does not* G-cause stablecoins	1.7818	0.1686	2.7213	0.0282
Altcoins *do not* G-cause stablecoins	2.1937	0.1118	1.0928	0.3584
Stablecoins *do not* G-cause Bitcoin	3.0146	0.0493	1.5559	0.1835
Altcoins *do not* G-cause Bitcoin	4.5221	0.0110	2.6620	0.0311
Stablecoins *do not* G-cause altcoins	3.6879	0.0252	2.2342	0.0631
Bitcoin *does not* G-cause altcoins	1.2256	0.2938	1.1036	0.3532

The short-term Granger causality testing statistic is based on the joint significance of the VAR components in the VECM model. The long-term causality testing statistic is based on the joint significance of the VAR components in the nonstationary VAR on the system of original (logarithmic) series, according to Toda and Yamamoto (1995)

the unrestricted trend specification of the cointegration model[6]. The estimated model in the VAR representation (Eq. 1) is summarized in Table 6. The unit root dynamics of the error-correction term are safely rejected by the ADF test with a testing statistic of $\tau = -4.1672$ and a p value of 0.0050 (with lags selected with respect to BIC and after the time trend inclusion). The model specification is thus confirmed as valid, and we can proceed to further analysis.

Granger causality and impulse-response functions

Granger causality testing is a standard way of inspecting whether movement in one variable is preceded by movement in another variable. These movements can be examined from either a short-term perspective or a long-term perspective. In practice, the former is a joint significance test of the VAR components in Eq. 1, while the latter is a joint significance test of the VAR components of the integrated (not the differenced) processes with the proper lag selection, as given in Toda and Yamamoto (1995), which is mostly as long as the residuals are not autocorrelated. Both can be used in the standard VAR

[6] The results, implications, and discussion that follow do not differ qualitatively when considering the restricted trend specification instead of the unrestricted one.

and the cointegrated VAR settings. The results of the tests are summarized in Table 4. In the short term, the changes in the Bitcoin market capitalization are Granger-caused by both altcoins and stablecoins market capitalization changes, while stablecoins are not Granger-caused by either Bitcoin or altcoins. Conversely, stablecoins Granger-cause changes in altcoins. In the long term, the causations are quite different. Bitcoin Granger-causes stablecoins, stablecoins Granger-cause altcoins (even though only at the 90% significance level rather than at the 95% level that we adhere to throughout the text), and altcoins Granger-cause Bitcoin. These dynamics create a characteristic triangle/circle in the long-term dynamics of the whole system. However, it needs to be noted that even though the Granger causality testing does undercover the flow of the effects (from one variable to another), it does not show the direction of the effects (positive or negative). One can either inspect the estimates of the VAR representation or illustrate the effects using the impulse-response functions.

The impulse-response function (IRF) represents a propagation of a standard deviation shock from one variable to another, again measured in standard deviations, and its decay over time. Technically, the functions are the moving average representations of the estimated VAR model. As the shocks into the system are assumed to be exogenous, which is hardly ever true for economic and financial systems, one needs to specify an ordering of the system variables and how the shock is expected to propagate, usually based on an understanding of the underlying system. Here, we tried all possible permutations of ordering, and the results do not differ on a qualitative basis; they all tell the same story. Eventually, we present the impulse-response functions with the ordering based on the results of the long-term Granger causality—Bitcoin → stablecoins → altcoins.

We present the impulse-response functions in Fig. 2. The effects of shocks are shown up to 180 days after the shock to see potential long-run effects and whether and how they diminish over time. The black curves represent the size of the effects, and the shaded areas show the 90% confidence bands based on bootstrapping. As we have three variables of interest, the figure shows nine charts. On the diagonal, we have the autocorrelation effects, which are the least interesting ones as they merely present that the three variables are highly persistent, as reflected in not rejecting the unit root dynamics by the ADF tests earlier. The rows (columns) represent the effects on (of) Bitcoin, altcoins, and stablecoins market capitalizations. We see that in the long run, Bitcoin is not significantly affected by either altcoins or stablecoins. Altcoins are strongly positively affected by Bitcoin, and the effect is very persistent, with a coefficient (which is parallel to a cross-correlation) of 0.6. Even though the effect persists, the confidence band widens markedly; however, even after the 180 days shown in the chart, the effect is still safely significantly different from zero. Stablecoins do not affect altcoins in the long run. However, they are highly affected by both Bitcoin and altcoins, with an almost perfect transmission (the effect close to 1) of the Bitcoin shocks into the stablecoins capitalization; in addition, even though the effect is lower for altcoins, their effect on the stablecoins is still very prominent (with the effect of approximately 0.5 after 180 days).

As some of these outcomes are slightly different from the long-run Granger causality results, we can also focus on the first 30 days of the IRFs in Fig. 5. Some short-run dynamics emerge, and these dynamics likely translate into long-run tests. Interestingly, we see that the Granger causality from altcoins to Bitcoin is identified here as well, but

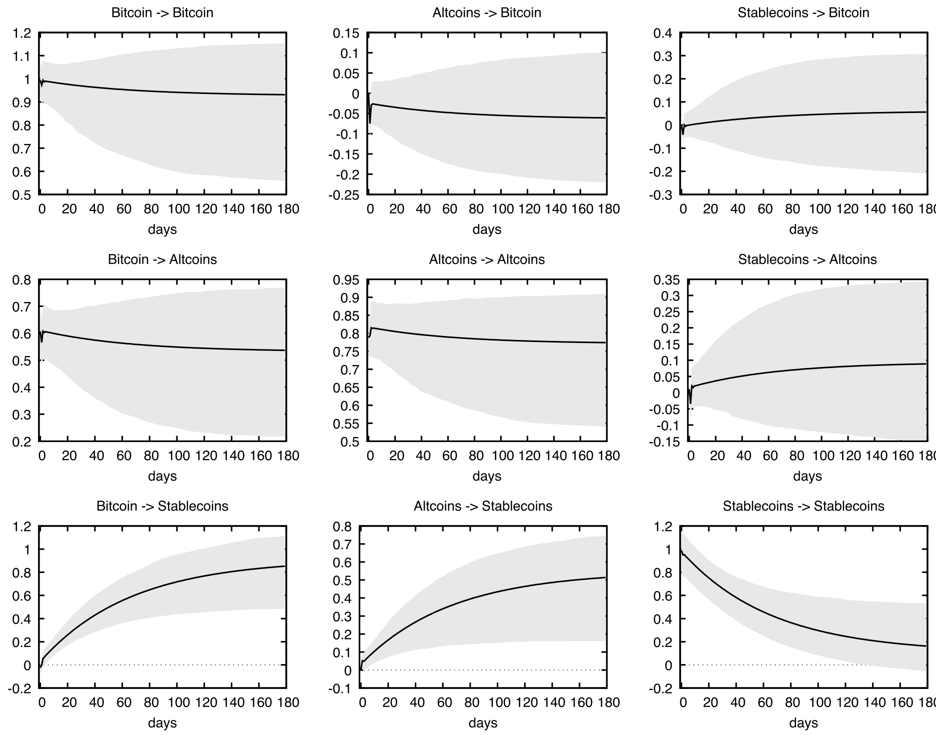

Fig. 2 Impulse-response functions of market capitalizations (long run). Impulse response functions based on the cointegrated VAR with 2 lags and an unrestricted trend are shown for the time horizon of 180 days (*x*-axes) with a standard deviation of the given series as a unit of measurement. The effect of a unit standard deviation shock is shown on the *y*-axes. The black curves show the estimated effects, and the shaded areas represent the 90% bootstrapped confidence bands

the effect is negative. Similarly, we see a significant bump in the flow from stablecoins to Bitcoin, but it is again negative. The results of the impulse response functions are thus consistent with the results of the Granger causality tests for market capitalizations of the three cryptoassetasset classes.

Interpretation, discussion and robustness checks

In this section, we provide a more detailed interpretation of the results presented above followed by an analysis of the bull-run year 2017 to see whether the dynamics and connections differ or not. As the analyzed series posses rather heavy tails and some recent studies suggest non-linear dynamics in the cryptomarkets, we provide additional evidence of the relationship between stablecoins and other cryptoassets through the lens of quantile-specific Granger-causality and causality based on the Rényi transfer entropy. The results are further checked against different sample specifications.

General interpretation

Currently the most complex study focusing on the role of stablecoins, specifically Tether (USDT), in the cryptoassets markets is certainly (Griffin and Shams 2020). They analyze the role of USDT in the Bitcoin price dynamics during the 2017 hikes within a network framework focusing on the Tether and Bitcoin flows between different exchanges. Their interpretation is built on (mostly) competing hypotheses of “demand pull” and "supply push". The former implies that the Tether inflows/issuances reflect an increasing demand in investing into Bitcoin. The latter asserts that USDT boosts the price inflation or at least keeps it going through smoothing out the negative price corrections. Even though the frameworks of their analysis and the one presented here are quite different (a network analysis focusing on a single stablecoin and a single cryptoasset in a system of many exchanges compared to a causality study focusing on a set of stablecoins and a set of cryptoassets from a macroscopic perspective), the drivers behind the connection between stablecoins and cryptoassets remain the same and within the standard economics logic—supply and demand. In our analysis, the demand drive of stablecoins inflows into the market would materialize into cryptoassets prices (and thus capitalizations) leading gains in stablecoins stock while the supply side hypothesis would be represented by inflating stablecoins stock preceding price rallies in the other cryptoassets. We keep the discussion and interpretation within the known issues connected to stablecoins and add them to the mix.

We have examined the interactions and possible causal relationships between market capitalizations of stablecoins, Bitcoin, and altcoins to see whether stablecoins can be identified as a spark or a mover in relation to the other cryptoassets gains. In the examined period between 2015 and 2020, the results suggest that the stablecoin issuances come after both Bitcoin and altcoin gains. Moreover, this effect is rather strong, with transmissions of approximately 80% and 50% of the Bitcoin and altcoin shocks, respectively, with a long-run equilibrium being achieved rather slowly, i.e., approximately after six trading months. The effect in the opposite direction, i.e., from stablecoins to Bitcoin and altcoins, is rather short-lived and barely statistically significant at approximately negative 4% transmission for both Bitcoin and altcoins. The interpretation of such results is conditional on the status and validity of stablecoins. Looking at Tether as the most dominant stablecoin, its history has been quite controversial. Originally claimed to be fully backed by fiat USD deposits, Tether has never been properly audited, and its backing now also includes loans to affiliated companies (Kaminska 2017; Coppola 2019; Vigna 2019). Nevertheless, the proportion of USDT being backed by USD is not clear, even though a rather recent claim (April 2019) stated that approximately 75% of USDT is backed by cash and cash equivalents[7] and the Tether Ltd. webpage still claims[8] that "All tethers are pegged 1-to-1 with a matching fiat currency ...and are backed 100% by Tether's reserves. As a fully transparent company, we publish a daily record of our bank balances and the value of our reserves." The reality of being backed by fiat (or any other valuable assets) is crucial for further inference, as it leads to diametrically different outcomes and implications.

If Tether and other smaller stablecoins are mostly (but not necessarily fully) backed by other valuable assets, the uncovered dynamics would suggest that the growing prices of Bitcoin and altcoins lead to an increased demand for cryptoassets, which is consequently projected into the purchasing and thus the issuance of new USDT. The effect of Bitcoin growth has played a more important role here compared to

[7] According to a coindesk.com article available at https://bit.ly/39PkDZv; the shortened address is provided for brevity and graphical purposes, while full address is provided here.

[8] In its FAQ section: https://tether.to/faqs/.

that of altcoins. However, if stablecoins are issued out of thin air, i.e., with only minimal or no backing, the results of the presented analysis would imply that the stablecoins are being created falsely simply to inflate the prices and support the bull run with "newly printed money ." Either way, stablecoins issuance is not an ignition point of bull runs or cryptoassets' appreciation in general. This is well in hand with the results of Wei (2018) who finds no evidence for Tether inflating Bitcoin prices, only the traded volumes, which further supports the demand-based interpretation of the stablecoins growing capitalization. However, the results of Griffin and Shams (2020) and partly also of Ante et al. (2020) suggest that Tether is being used to smooth out the corrections in the cryptoassets appreciation; specifically, it is being issued and pumped into the system after the prices stop growing and start correcting downwards. The monetary injections then start a new growth period as the market has been persuaded that there has been only a mild correction that does not signal any coming trend reversal. As our results do not suggest this interpretation under either condition, we focus on the specific time periods of these two studies.

Bull run of 2017

Griffin and Shams (2020) study the 2017 bull run, also referred to as the Year of Altcoins, as some of these gains actually surpassed the Bitcoin gains by an order of magnitude; thus, we focus on this year separately as well. We restrict the original dataset to the range between 1 Jan 2017 and 31 Dec 2017 and repeat the same procedure as for the original dataset. Table 7 summarizes the results for the Granger causality for this period. Note that the optimal number of lags for the cointegrated VAR is only one; thus, for the short-term causality, we see t-statistics instead of F-statistics, which, however, allow us to see the direction of the effect. We find the results rather similar to those for the whole period (Table 4), i.e., short-term causality from stablecoins and altcoins towards Bitcoin and stablecoins causing changes in altcoins, while in the long term, we again find a triangle of Bitcoin boosting stablecoins, stablecoins causing altcoins, and changes in altcoins preceding changes in Bitcoin. In addition, we also see that altcoins Granger-cause Bitcoin in the long term, which is different compared to the overall dynamics. Putting these interactions together, Fig. 6 presents the impulse-response functions based on the Granger causality found with the order of stablecoins $\rightarrow$ altcoins $\rightarrow$ Bitcoin. As the time series length is decreased to a single year, i.e., 365 days, we present the functions only up to the 30th time lag. We observe that the functional shape for the pairs of interest is quite similar to that for the dynamics of the whole examined period. However, there are two important differences. First, the shorter time series is reflected in much broader confidence intervals; thus, even though the transmission from Bitcoin and altcoins to stablecoins is of a rather similar shape and level as that for the whole period, the effect is not statistically significant. Second, the negative dip in the temporal surface of the shock effect coming from stablecoins to both Bitcoin and altcoins, which has been observed for the whole period, is much more pronounced here than in the overall period. In fact, the bounce-back towards equilibrium from this initial reaction is much slower. In light of the evidence presented by Griffin and Shams (2020), such an IRF shape allows for the following interpretation: stablecoins issuances in 2017 were followed by further corrections of the other cryptoassets (both Bitcoin and altcoins) before returning back to a growing trend. Our results thus do not directly contradict the interpretation of Griffin and Shams (2020), who state that Tether issuances were used to smooth out the corrections in the price inflation of the other cryptoassets. However, we must admit that such an interpretation is quite a stretch from the impulse-response dynamics that we show emerging in 2017. It is one thing to not contradict; however, validating is quite another one. Either way, our results do not suggest any kind of self-boosting mechanism or spiral between stablecoins and the other cryptoassets, and they also do not suggest that stablecoins would be the initiators of the 2017 appreciation.

Year 2018 onwards

Ante et al. (2020) study a more recent period between April 2019 and March 2020, focusing on the stablecoin issuances above $1M, and they find that these issuances mostly come in approximately a week after negative returns in the cryptomarkets and that such injections boost the consequent dynamics. Interestingly, they do not find a connection between the size of the issuance and the size of the return effect. It is thus not clear whether these bounce-backs are caused by stablecoins issuances or the inherent serial correlation structure of the cryptoassets (in our dataset, the overall market capitalization, as well as Bitcoin itself and altcoins, have a negative first-order autocorrelation, even though these are barely statistically significant). Either way, the overall interpretation still largely depends on the stablecoins backing, as the issuances might easily be caused by investors buying into the market to make profit on the late correction of the market. Focusing our analytical apparatus on the newer period from 1 Jan 2018 onwards, we find no cointegration relationship between the stablecoin and nonstablecoin cryptoassets, which directs us towards the standard vector autoregressive model without error correction for the long-run equilibrium. Even more interestingly, we find no evidence of Granger causality between the cryptoassets, as summarized in Table 8, even when we consider the 90% confidence level. However, there are several relationships that are at the edge of this level; thus, we still present the impulse-response functions, even though now, these are based on the Toda and Yamamoto (1995) long-term VAR to see the possible long-run dynamics between the series. In Fig. 7, we see a similar story as the one for the whole analyzed period, albeit the effects are much weaker here. There is no palpable shock transmission from stablecoins to the other cryptoassets, and the increases in the stablecoin capitalization preceded by Bitcoin and altcoin appreciation are rather weak but still statistically significant.

Non-linear causality

As recently reported by Corbet et al. (2020), studying dependence among cryptoassets and also between cryptoassets and standard financial assets only with respect to the bulk of their distributions could leave important information about their connections hidden. We have shown in the Dataset description and initial analysis section that all analyzed series are far from the Gaussian distribution so that studying their behavior in the tails might bear some fruits. To check whether this is the case for the dynamics between the stablecoins and the remaining cryptoassets, we utilize the quantile-specific Granger causality test of Jeong et al. (2012) which builds on ideas (Zheng 1998) and (Li 1999) and delivers an asymptotically normally distributed testing statistic. Keeping the number of

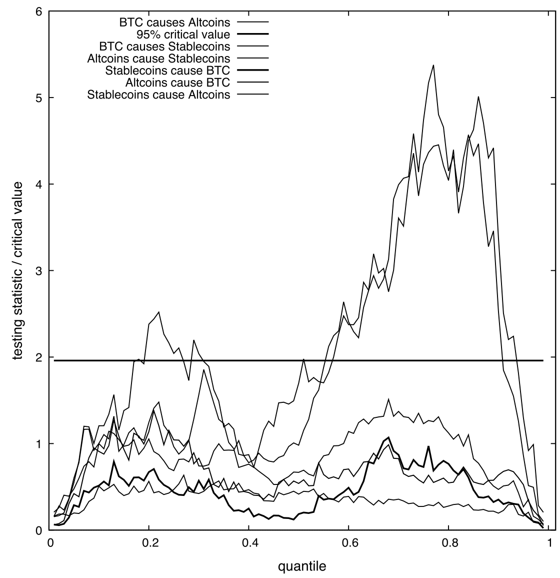

Fig. 3 Quantile-dependent Granger causality on market capitalizations. Testing statistics for all pairs are showed with a critical value for the null hypothesis of no causality from the first variable to the second one, with quantile specifics connected to the former. As the testing statistic is asymptotically normally distributed, the critical value is simply the 95th percentile of the standard Gaussian distribution, i.e., approximately 1.96 (Jeong et al. 2012). If the testing statistic exceeds the critical value, causality for the given quantile is identified. The testing statistics are calculated for the range of quantiles between 0.01 and 0.99 with a step of 0.01

lags the same as for the case of the linear Granger causality of the VECM model, i.e., 2 lags, Fig. 3 illustrates the testing statistics for all pairs of analyzed assets and the critical value for the 95% significance level (as the testing statistic is asymptotically normally distributed under the null hypothesis, the testing statistic is the same for all pairs, in this case it is equal to the 95th quantile of the standard Gaussian distribution). In the pair, the first named variable is the impulse/leading variable that also specifies the distribution quantile and the second named variable is the response/lagging variable. The testing statistics are calculated for the quantile range between 0.01 and 0.99 with a step of 0.01, i.e., we have 99 quantiles. The outcome is very straightforward. There are only two directed pairs that show statistically significant results. For the higher quantiles between approximately 0.55 and 0.95, Bitcoin leads the changes in stablecoins and altcoins lead the changes in stablecoins. For the Bitcoin-to-stablecoins pair, the testing statistics are significant also between quantiles 0.2 and 0.3. The evidence thus clearly shows that when Bitcoin and altcoins are growing or even booming, the stablecoins clearly follow. There is no evidence of such dynamics in the opposite direction, no evidence of stablecoins leading Bitcoin or altcoins, not for a single quantile of the given test. This further supports the demand-driven stablecoins emissions. The much weaker bump in the lower quantiles for the Bitcoin-stablecoins pair might reflect the dynamics asserted by Griffin and Shams (2020) who found stablecoins minting as a reaction to the Bitcoin downward correction, even though the test only shows causality but not whether the effect is positive or negative. Nevertheless, this corresponds to our discussion of this phenomenon within the baseline VECM/VAR framework, both in the direction and the magnitude.

Table 5 Rényi transfer entropy on market capitalizations

Hypothesis (H_0)	$q = 0.1$		$q = 0.2$		$q = 0.5$		$q = 0.8$	
	RTE	*p* value	RTE	*p* value	RTE	*p* value	RTE	*p* value
Bitcoin *does not* lead stablecoins	0.6485	0.0567	0.5524	0.0433	0.2626	0.0233	0.0725	0.0700
Altcoins *do not* lead stablecoins	0.6432	0.0700	0.5479	0.0500	0.2641	0.0267	0.0787	0.0400
Stablecoins *do not* lead Bitcoin	0.4948	0.7967	0.4281	0.7333	0.2185	0.3967	0.0724	0.1333
Altcoins *do not* lead Bitcoin	0.4711	0.8700	0.3951	0.8533	0.1709	0.8900	0.0463	0.8900
Stablecoins *do not* lead altcoins	0.5198	0.5567	0.4355	0.5567	0.1977	0.5567	0.0588	0.4033
Bitcoin *does not* lead altcoins	0.5475	0.3833	0.4551	0.3967	0.1903	0.5700	0.0449	0.8233

Rényi transfer entropy is estimated following Dimpfl and Peter (2013, 2014) with 2 lags following the short-term Granger causality specification in Table 4. $q < 1$emphasize the least likely, i.e. more unique or extreme, events so that $q \rightarrow 0$ is dominated by the most extreme events

Even though the test of Jeong et al. (2012) is non-parametric, we examine possible non-linear causality between the studied variables while still controlling for the extreme events dominance with an additional tool, specifically the transfer entropy. Following Dimpfl and Peter (2013, 2014), we deliver deeper insight into the relationship between stablecoins and other cryptoassets. Building on the concept of Rényi entropy (Rényi 1961), the procedure captures the information flow between series while possibly putting emphasis on rare/extreme events via its parameter q (sometimes α). For $q < 1$, the less likely (rarer) events are amplified, and for $q \rightarrow 0$, the statistic is dominated by the most extreme events. For $q = 1$, the standard Shannon entropy is retrieved, whereas for $q > 1$, frequent events, i.e., in the bulk of the distribution, are put more weight on. In Table 5, we summarize the results for all pairs under study for $q = 0.1, 0.2, 0.5, 0.8$, i.e., covering situations close to the causality almost around the distribution mean as well as emphasizing the extreme events. In the same logic as for the standard Granger causality, we present the testing statistics (Rényi transfer entropy) and respective p values for the null hypothesis that the first variable does not cause changes in the second one. Again, the evidence is rather straightforward. The only directed pairs that show statistically significant results are the ones where the information flows towards stablecoins and drives their dynamics and not the other way around. This is true for the cases of less likely events, copying the implications of the quantile-specific Grange causality test presented above. Such results go towards the demand-driven explanation of the stablecoins dynamics.

Sample construction robustness checks

As a robustness check, we have rerun the baseline VECM/VAR procedure for various alternative subsamples[9]. For altcoins, we have constructed the total market capitalization of the top 5 most capitalized non-Bitcoin non-stablecoin cryptoassets, giving us the

[9] These alternative datasets are attached to this article together with the series used in the original analysis.

set of Ethereum, XRP, Bitcoin Cash, Cardano, and Litecoin. For stablecoins, we consider two additional alternatives—Tether solely and stablecoins with the market capitalization above \$100 M (instead of \$1 M), which has given seven stablecoins. Combining the alternatives, we obtain four additional model settings—Bitcoin with original altcoins set and either USDT or stablecoins above \$100 M, and Bitcoin with the top 5 altcoins and either USDT or stablecoins above \$100 M. We do not include the original stablecoins set (above \$1 M market capitalization) to the mix to keep the number of combinations bearable. In addition, the difference between the original stablecoins series and the new one with stablecoins with the market capitalization above \$100 M is rather small.

The whole cointegration/VAR procedure has been performed for the four alternative scenarios and the following Granger-causality tests and impulse-response have been run. The results remain qualitatively the same as for the original setting. The only visible difference lays in a slightly weaker, yet still statistically significant, effect of the smaller set of altcoins on stablecoins which can be attributed to the importance of altcoins outside of the five most capitalized assets for the whole system dynamics. As the results are very similar to the original ones and also for the sake of brevity and text clarity, we do not present the tables and figures for the alternative scenarios here and these remain available upon request.

"Demand pull" versus "supply push"

Comparisons to the study of Griffin and Shams (2020), being the most prominent and comprehensive topical study, are at hand as the results, from the big picture perspective, are quite the opposite. There are at least two explanations. First, the covered time periods differ. As already stressed, the mentioned study focuses on the year of 2017 whereas we cover a much longer period. In addition, our results for 2017 do not contradict the "supply push" hypothesis the former study puts forward, even though our empirical results do not provide much support for it either. Second, and likely more importantly, we believe both hypotheses are not given equal treatment by the authors. For the "demand pull", there are two testable hypotheses, whereas for the "supply push", there are five. By itself, this is not necessarily problematic. However, there, for one of the two demand-side hypotheses, the specification is both quite speculative and methodologically questionable. For the former, one might argue that the USDT/USD exchange rate may well represent the excess demand for Tether but one might also say that the price above \$1 is rather a risk premium for holding deposits not in fiat compensating for the risk an investor will not be able to convert back to fiat. Then, the original interpretation does not necessarily hold. And for the latter, this hypothesis is then tested on a rather simple regression of the Tether and Bitcoin flows from and to the Bitfinex exchange on the lagged Tether and Bitcoin returns (Table VIII in Griffin and Shams 2020). The "demand pull" would then be claimed to exist if the lagged Tether returns were statistically significant. However, the Tether returns have practically no variability, i.e., very low variance, which makes them, in a way, another constant term in the regression. It is then not surprising that these are not statistically significant. This does not discredit the results for the "supply push" presented there but it suggests that the setting might not have been an ideal one for testing the "demand pull". We believe that our approach treats both hypotheses the same as there are clear, qualitatively and methodologically comparable features of all our tests—(quantile-specific) Granger causality, impulse-response functions, and more general non-linear causality—that would manifest for either of the hypotheses being true.

Conclusions

Putting all the results and findings of the previous research together, we can make several inferences. First and foremost, we find no evidence that stablecoins start price rallies for the other cryptoassets or that stablecoins boost the cryptomarket appreciation. Second and quite opposite, we see that stablecoins issuances come after, not before, the other cryptoassets' gains. The interpretation of this phenomenon is highly dependent on stablecoin backing. If the backing is valid and existent (but not necessarily a full backing), then the stablecoin influx signals an increased demand in investment in cryptoassets. If this does not occur and the stablecoins are created out of thin air, then it suggests that new stablecoins are being sent to the market to further inflate the other cryptoassets' prices. Even though it might seem difficult to identify which one of these two alternatives is more likely to occur without a proper audit into stablecoins backing on the one side or without a leap of faith on the other, the latter alternative suggests there would be a spiral-like boosting mechanism between stablecoins and the other cryptoassets. However, our results imply that this relationship is only one-sided, flowing from the other cryptoassets to stablecoins and not the other way around. Therefore, the former explanation, i.e., the growing cryptoasset prices attracting more investors who invest through stablecoins, emerges as the more realistic one. Third, 2017, seen as the year of massive cryptoasset gains, is characterized by stablecoin issuances preceding other cryptoasset losses, which is partially in sync with some previous research suggesting that stablecoin issuances are used to smooth out cryptoasset price corrections and move them back to the booming trend. Based on our results, such claims seem to be rather far-fetched, as we do not find any spiralling dynamics between stablecoins and the other cryptoassets, even for this particular year. In addition, these can simply be investors "buying the dip." The results are robust across various sample settings, time periods, and methodological approaches. Overall, the results suggest that both stablecoins and the growth in their issuances are mostly the reflection of an increasing demand for investment in cryptoassets rather than a boosting instrument for pricing rallies.

RESULTS

Appendices

See Figs. 4, 5, 6, 7 and Tables 6, 7, 8.

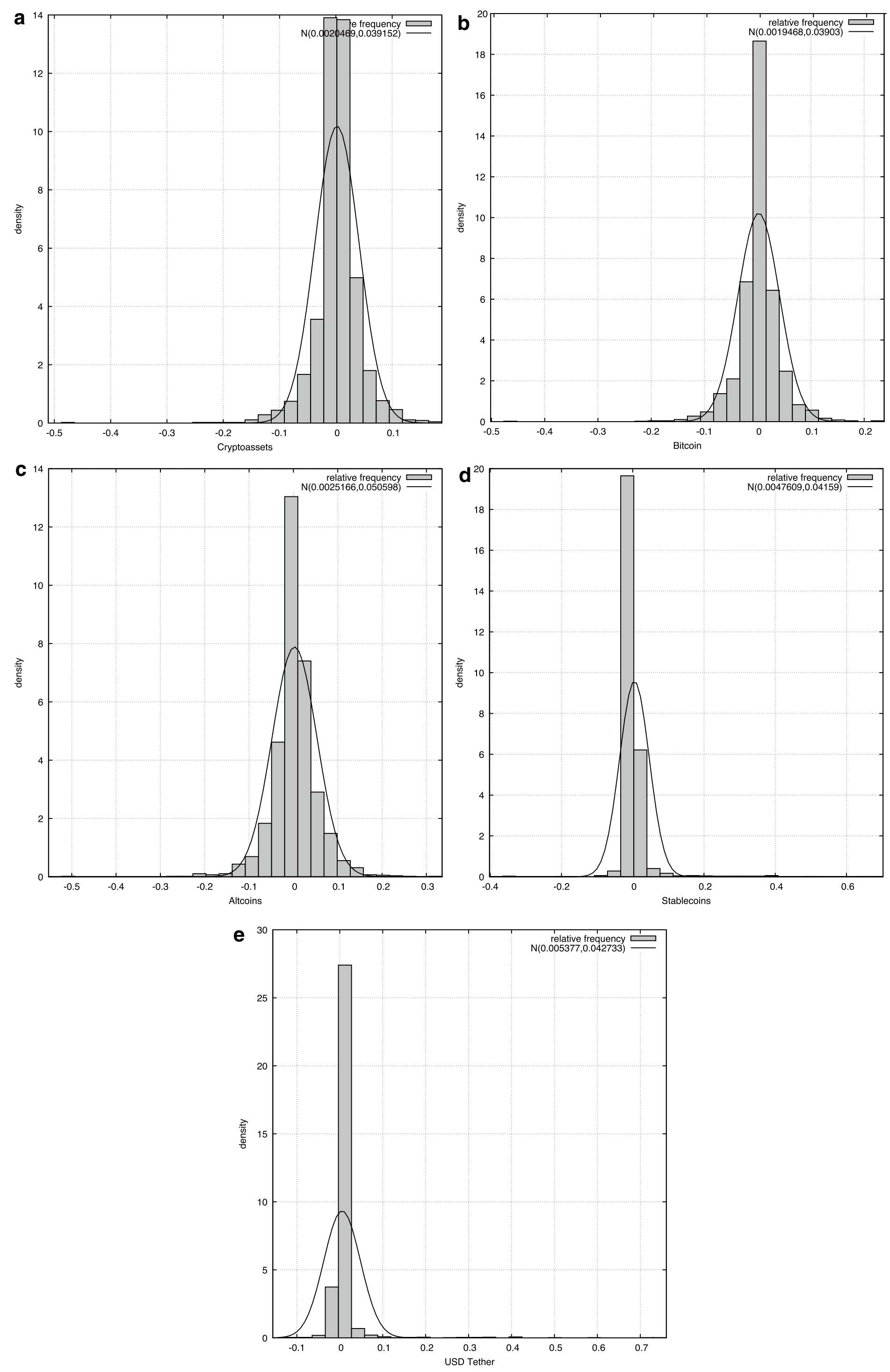

Fig. 4 Histograms for logarithmic differences of market capitalizations. Fits for the Gaussian distribution are shown as well representing the variables cannot be described as Gaussian as each variable has a set of extreme observations and their bulk is more concentrated around the mean value than what would be expected for Gaussian variables, i.e., behavior closer to the stable distributions, all in hand with Table 1

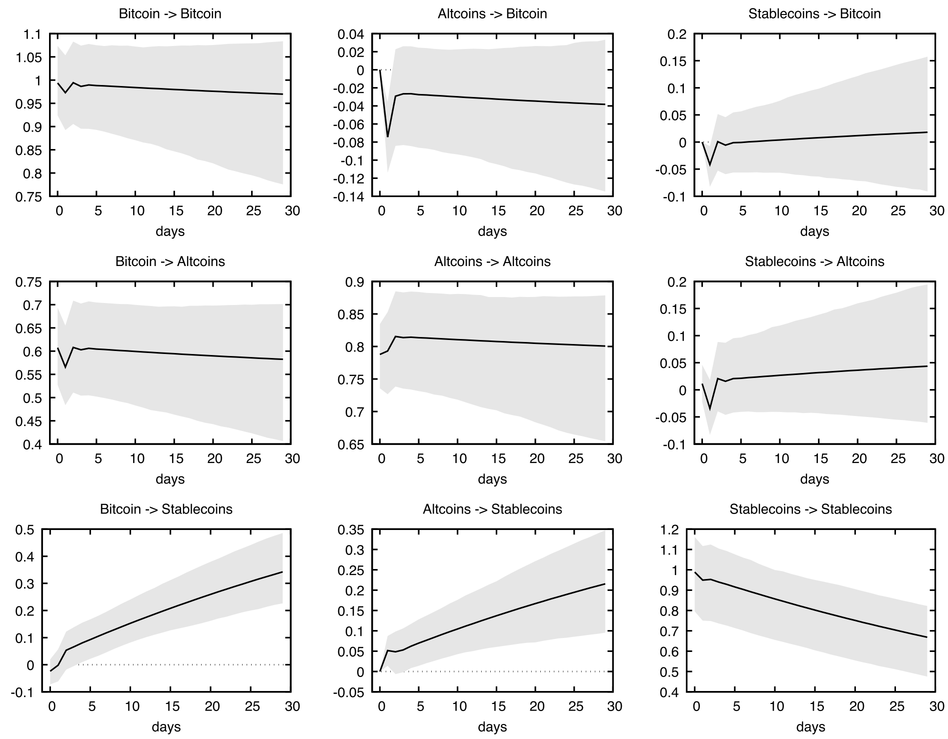

Fig. 5 Impulse-response functions of market capitalizations (short run). Impulse response functions based on the cointegrated VAR with 2 lags and an unrestricted trend are shown for the time horizon of 30 days (*x*-axes), with a standard deviation of the given series as a unit of measurement. The rest of the notation holds from Fig. 2

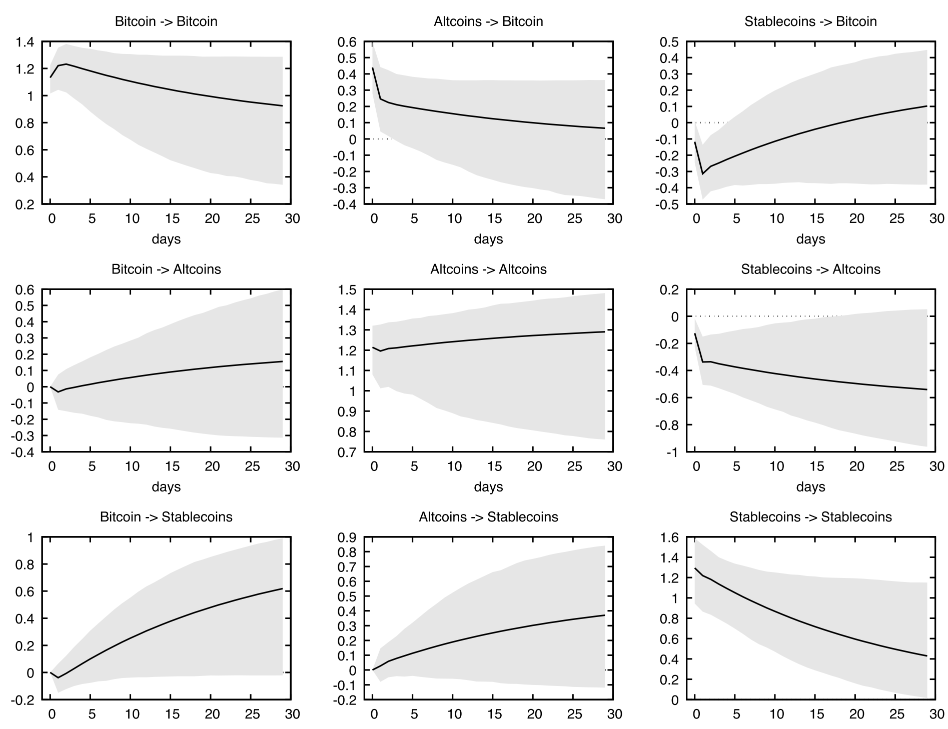

Fig. 6 Impulse-response functions of market capitalizations for 2017. Impulse response functions based on the cointegrated VAR with 1 lag and a restricted trend are shown for the time horizon of 30 days (*x*-axes), with a standard deviation of the given series as a unit of measurement. The rest of the notation holds from Fig. 2

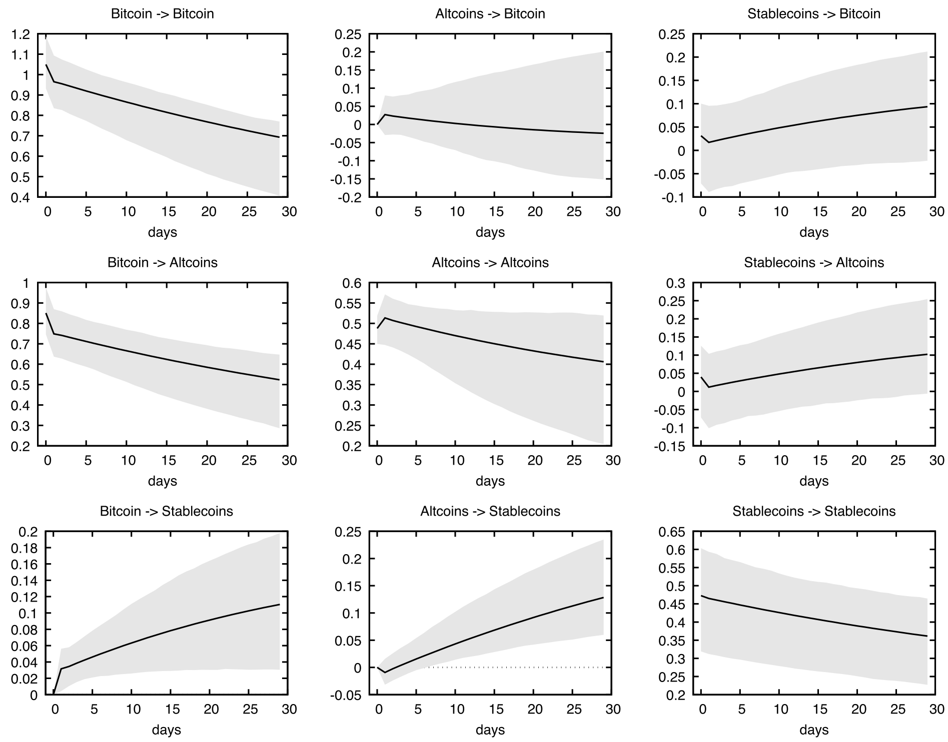

Fig. 7 Impulse-response functions of market capitalizations for 2018–2020. Impulse response functions based on the Toda and Yamamoto (1995) specification VAR with 2 lags without a time trend are shown for the time horizon of 30 days (*x*-axes), with a standard deviation of the given series as a unit of measurement. The rest of the notation holds from Fig. 2

Table 6 Estimated vector error-correction model in the VAR representation (on logarithmic market capitalizations)

	estimate	SE	*t*-stat	*p* value
Bitcoin equation				
intercept	0.1042	0.0772	1.3490	0.1775
ΔBTC_{t-1}	0.0397	0.0406	0.9782	0.3281
ΔBTC_{t-2}	− 0.0143	0.0371	− 0.3838	0.7011
$\Delta Alts_{t-1}$	− 0.0745	0.0285	− 2.6150	0.0090
$\Delta Alts_{t-2}$	0.0474	0.0255	1.8600	0.0631
$\Delta Stable_{t-1}$	− 0.0375	0.0232	− 1.6170	0.1059
$\Delta Stable_{t-2}$	0.0357	0.0216	1.6510	0.1059
BTC_{t-1}	− 0.0077	0.0053	− 1.4620	0.1440
$Alts_{t-1}$	0.0037	0.0027	1.3750	0.1693
$Stable_{t-1}$	− 0.0004	0.0024	− 0.1844	0.8537
t	< 0.0001	< 0.0001	0.8117	0.4171
	R^2	0.0145	F(10,1941)	2.7592
	$\bar{R}^2$	0.0094	*p* value	0.0022
	$\hat{\rho}$	− 0.0008	D-W stat	2.0007
Altcoins equation				
intercept	− 0.0281	0.1073	− 0.2622	0.7932
ΔBTC_{t-1}	− 0.0619	0.0462	− 1.3390	0.1808
ΔBTC_{t-2}	0.0343	0.0386	0.8887	0.3743

Table 6 (Continue)

	estimate	SE	*t*-stat	*p* value
$\Delta Alts_{t-1}$	0.0083	0.0421	0.1971	0.8438
$\Delta Alts_{t-2}$	0.0293	0.0285	1.0290	0.3038
$\Delta Stable_{t-1}$	− 0.0583	0.0261	− 2.2360	0.0254
$\Delta Stable_{t-2}$	0.0608	0.0297	2.0450	0.0410
BTC_{t-1}	0.0041	0.0076	0.5436	0.5868
$Alts_{t-1}$	− 0.0044	0.0045	− 0.9704	0.3320
$Stable_{t-1}$	0.0023	0.0037	0.6210	0.5347
t	> − 0.0001	< 0.0001	− 0.8494	0.3957
	R^2	0.0109	F(10,1941)	1.6235
	$\bar{R}^2$	0.0058	*p* value	0.0940
	$\hat{\rho}$	− 0.0010	D-W stat	2.0014
Stablecoins equation				
intercept	− 0.1698	0.0545	− 3.1150	0.0019
ΔBTC_{t-1}	− 0.0279	0.0291	− 0.9581	0.3382
ΔBTC_{t-2}	0.0566	0.0351	1.6110	0.1073
$\Delta Alts_{t-1}$	0.0451	0.0286	1.5760	0.1151
$\Delta Alts_{t-2}$	− 0.0112	0.0256	− 0.4384	0.6612
$\Delta Stable_{t-1}$	− 0.0271	0.0198	− 1.3680	0.1714
$\Delta Stable_{t-2}$	0.0178	0.0117	1.5250	0.1274
BTC_{t-1}	0.0085	0.0048	1.7780	0.0755
$Alts_{t-1}$	0.0082	0.0041	2.0020	0.0454
$Stable_{t-1}$	− 0.0137	0.0036	− 3.8250	0.0001
t	< 0.0001	< 0.0001	2.8400	0.0046
	R^2	0.0223	F(10,1941)	4.2237
	$\bar{R}^2$	0.0173	*p* value	0.0001
	$\hat{\rho}$	0.0001	D-W stat	1.9997

The cointegrated VAR is estimated with 2 lags and an unrestricted trend as described in the main text. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (SE) are reported

Table 7 Granger causality on market capitalizations for year 2017

Hypothesis (H_0)	**Short-term**		**Long-term**	
	(df = 340)		**(df = [3, 1355])**	
	***t*-stat**	***p* value**	***F*-stat**	***p* value**
Bitcoin *does not* G-cause stablecoins	− 0.0642	0.2753	2.7373	0.0434
Altcoins *do not* G-cause stablecoins	0.0240	0.6907	1.4331	0.2328
Stablecoins *do not* G-cause Bitcoin	− 0.1694	0.0006	3.6654	0.0126
Altcoins *do not* G-cause Bitcoin	− 0.1851	0.0012	2.5493	0.0556
Stablecoins *do not* G-cause altcoins	− 0.1560	0.0016	2.9457	0.0329
Bitcoin *does not* G-cause altcoins	− 0.0407	0.4634	1.0314	0.3787

Notation holds from Table 4

Table 8 Granger causality on market capitalizations for years 2018–2020

Hypothesis (H_0)	Short-term (df = 911)		Long-term (df = [2, 916])	
	t-stat	*p* value	*F*-stat	*p* value
Bitcoin *does not* G-cause stablecoins	0.0498	0.1978	0.8602	0.4234
Altcoins *do not* G-cause stablecoins	− 0.0189	0.4694	0.3720	0.6895
Stablecoins *do not* G-cause Bitcoin	− 0.0341	0.5596	2.2459	0.1064
Altcoins *do not* G-cause Bitcoin	0.0470	0.4818	0.5272	0.5905
Stablecoins *do not* G-cause altcoins	− 0.0806	0.1482	1.7684	0.1712
Bitcoin *does not* G-cause altcoins	− 0.1778	0.1003	2.0154	0.1339

Notation holds from Table 4

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40854-022-00343-8.

Additional file 1. Dataset.

Authors' contributions
This is a sole-authored article. The author read and approved the final manuscript.

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Availability of data and materials
Dataset is attached as "Additional file 1–Dataset."

Declarations

Competing interests
The author declares that he has no competing interests.

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