ORIGINAL ARTICLE

Cryptocurrencies and stablecoins: a high-frequency analysis

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Abstract

We analyze cryptoasset markets (cryptocurrencies and stablecoins) at high frequency. We investigate intraday patterns. We show that Tether plays a crucial role as a safe haven and/or store of value facilitating trading in cryptocurrencies without going through traditional currencies. Markets centered on cryptocurrencies and stablecoins play a primary role aggregating preference/technology shocks and heterogeneous opinions, instead markets centered on the US dollar play a marginal role on price formation.

Keywords Stablecoin · Cryptocurrency · Intraday · Time series

JEL Classification E41 · E50

1 Introduction

In this paper, we analyze cryptoasset markets at high frequency considering markets where fiat money is traded against cryptoassets as well as markets where cryptoassets are exchanged against each other. We consider cryptocurrencies, i.e., cryptoassets having their native blockchain, such as Bitcoin and Ether, and stablecoins, i.e., tokens pegged to a fiat money, in our case the US dollar.

For each market, we consider the following time series: return, number of trades, trading volume, volatility, quoted spread and order flow. Exploiting intraday data of

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cryptoassets, we shed light on two main topics: intraday patterns of financial time series, and relationships among markets.

Differently from many papers that concentrate on markets where cryptoassets/currencies are traded against the US dollar, see (Ante et al., 2020; Aste, 2019; Baumohl & Vyrost, 2020; Baur et al., 2018; Bistarelli et al., 2019; Griffin & Shams, 2020; Grobys, 2021; Hoang & Baur, 2021; Härdle et al., 2020; Paul & Agnes, 2017; Lyons & Viswanath-Natraj, 2020; Makarov & Schoar, 2020; Silantyev, 2019; Wang et al., 2020) or other currencies, see Pagnottoni & Dimp (2019), we also deal with markets where cryptoassets are traded between them. To limit the scope of our analysis, we deal with the two most important cryptocurrencies (Bitcoin and Ether) and the stablecoin Tether.

Our choice of concentrating on these cryptoassets is motivated by their relevance. Bitcoin and Ether are the two cryptocurrencies with the largest capitalization in US dollar from February 2016 (few months after the launch of Ethereum) to nowadays. Trading volume of markets where Tether is exchanged against major cryptocurrencies has steadily grown with Tether becoming the cryptocurrency with the largest trading volume since the second quarter of 2019. Also its market capitalization increased significantly: during the period covered in our analysis (one year and a half), Tether capitalization went from two billion dollars to sixteen billion, notice that the rise in capitalization is exclusively due to the increase in the number of tokens in circulation as the stablecoin is pegged to the US dollar.

Our analysis allows us to investigate the role of stablecoins, and in particular of Tether, in cryptoasset markets going beyond the investigation of manipulation of the Bitcoin market as discussed in Griffin and Shams (2020); Lyons and Viswanath-Natraj (2020). In nutshell, we show that Bitcoin, Ether and Tether constitute a domain which is separated from the markets where these cryptoassets are traded against the US dollar. We provide evidence showing that the first domain is the "real market", that is it is the market where prices are formed aggregating preference/technology shocks and heterogeneous opinions. These markets are strongly correlated along several dimensions (return, trading volume, volatility). The markets where cryptocurrencies are traded against US dollar play a secondary role. The connections between the two subsets of markets are rather limited.

The paper contributes to several strands of literature on cryptoassets.

First, we provide the first investigation of intraday patterns of cryptoassets. While there is an extensive literature on intraday patterns of stock markets, the topic is almost unexplored for cryptoassets. As far as the stock market is concerned, the evidence shows that trading volume, volatility and bid-ask spread follow a U-shaped pattern during a trading day, see e.g., Brock and Kleidon (1992); Foster and Viswanathan (1993); Goodhart and O'Hara (1997). These co-movements are difficult to explain through theoretical models: as a matter of fact, in a private information framework it is possible to reconcile the positive correlation between trading volume and volatility but not with bid-ask spread, see (Admati & Pfkeiderer, 2015; Foster & Viswanathan, 1990). The U-shaped pattern is traced back to the fact that market closures drive information clusterings that are associated with trading volume and volatility, see (Brock & Kleidon, 1992; Gerety & Harold Mulherin, 1992). Notice that stock markets are not open twenty four hours a day as cryptoassets ones. The

most relevant case of market open all day is provided by the exchange rate: in that market trading activity and volatility are associated with the arrival of news, see (Chang & Taylor, 2003; Martens, 2001). As far as we know, the only paper dealing with intraday patterns of cryptocurrencies is Wang et al. (2020). They show that the shape of trading volume for the Bitcoin-US Dollar exchange appears to be a V reverse, whereas the volatility does not follow any specific pattern through the day. The peaks on trading activity are associated with the opening of stock markets in Asia, Europe and United States. We do confirm that trading activity on cryptoassets is driven by financial activity around the globe with a peak in trading volume and volatility associated with opening of trading in stock markets in US and in Far East and Europe to a less extent.

As far as time series connections are concerned, we observe a significant difference considering markets where a cryptoasset is exchanged against the US dollar and markets where cryptoassets are exchanged against each other. Only for the second set of markets, we observe a significant positive correlation between trading volume and volatility highlighting that these are the markets where prices are formed aggregating opinions and preference/technology shocks. It seems that markets where cryptoassets are traded against the US dollar play a secondary role. Notice that no connection is established between bid-ask spread and volatility showing that trades and price movements are not motivated by private information.

We also contribute to the literature on the relationship between stablecoins and cryptocurrencies. Stablecoins (and in particular Tether) are strictly related to Bitcoin as their market movements are associated with volume and return in the cryptocurrency market. Two main hypotheses have been investigated empirically in the literature: manipulation of the Bitcoin market via stablecoin; stablecoin as a "safe haven" against Bitcoin.

As far as the first hypothesis is concerned, several papers investigated the possibility that Tether issuances (and therefore trades on the primary market) are associated with manipulation of Bitcoin. Griffin and Shams (2020) shows that issuances of Tether (Tether grants) are followed by a flow of Tethers to the Bitcoin market, Tether issuances follow market downturns of Bitcoin and are followed by an increase in Bitcoin prices. This pattern suggests that Tether issuance/conversion into Bitcoin are used to inflate/manipulate the latter market, the result has been confirmed for other stablecoins in Ante et al. (2021, 2020). Wang (2018) shows that Tether grants are timed to follow Bitcoin downturns and are followed by subsequent high Bitcoin/ Tether trading volume, however the impact of Tether grants on Bitcoin subsequent returns is not statistically significant. No manipulation effect of Tether grants has been detected in Lyons and Viswanath-Natraj (2020); Kristoufek (2020).

The evidence provided in Wang (2018) suggests that Tether could be a "safe haven" against Bitcoin variability. An hypothesis partially confirmed by Baur and Hoang (2021) considering the reaction of stablecoin returns to extreme negative return of Bitcoin: they show that Tether is really a safe haven with a negative coefficient associated with extreme negative return of Bitcoin. Lyons and Viswanath-Natraj (2020) shows that Tether and other stablecoins exhibit safe haven properties. Their interpretation is that, during risky periods, stablecoins play the role of store of value incurring minimal intermediation costs.
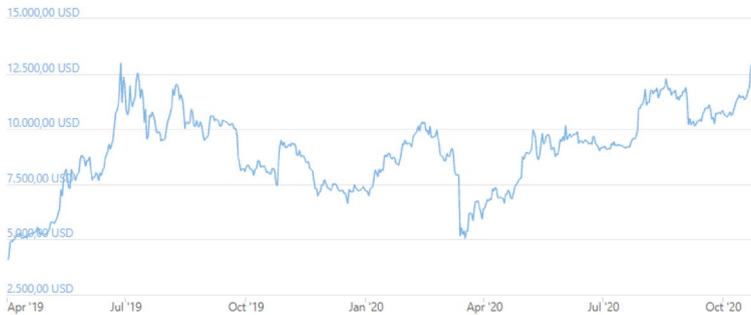
Fig. 1 Bitcoin value in USD on the period April 1, 2019–October 31, 2020

Independently of the rationale for the relation between Tether and Bitcoin, these papers suggest that Tether deserves a privileged position in cryptocurrency markets for trading reasons. We corroborate this interpretation showing that Tether introduced a structural change, separating the markets against Tether from the markets against US dollar. Our analysis suggests that it is the first group of markets that drives price formation, making the second group play a secondary role.

The paper is organized as follows. In Sect. 2, we describe the dataset of our analysis. In Sect. 3, we provide a descriptive analysis, while an intraday analysis of the main financial market quantities is presented in Sect. 4. In Section 5, we analyze market relationships including lead-lag effects.[1]

2 The dataset and the markets

We focus our analysis on the period April 1, 2019–October 31, 2020, see Fig. 1 for the US dollar price of Bitcoin during the period of the analysis. We refer to a pair for the market of the currency/assets involved, e.g., BTC-USD stands for the Bitcoin-US Dollar pair/market. The BTC-USD price represents the amount of USD necessary to buy/sell a BTC. Each pair of currency/assets is traded in several exchanges.

To better understand the nexus among standard currency, cryptocurrencies and stablecoins, we consider the following example. A person holding BTC on a wallet, sells them against USD in Exchange A, and uses USD to acquire Ether (ETH) in Exchange B. To deploy these trades, the steps could be as follows: the person

1. sends BTC to Exchange A, and sells them against USD. Then asks Exchange A to transfer the acquired USD to a bank account;
2. transfers USD to Exchange B (via bank transfer or credit card);
3. acquires ETH against USD and asks Exchange B to move ETH to a wallet.

[1] All codes are available on

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Quantlet.com

The bank transfer from Exchange A to the agent can take a significant time delay, and usually there are high fees. An alternative approach would be to leave a certain amount of USD deposited on different exchanges, to be used for trading, but this approach is inefficient as it requires a significant amount of USD to be allocated in the exchanges.

A shortcut is provided by stablecoins, tokens that have been introduced to capitalize the benefits of cryptocurrencies along with price stability. Exploiting stablecoins the transactions involved in the second example can be carried out as follows: the person

1. sends BTC to Exchange A, and sells them against a stablecoin. Then asks Exchange A to move the stablecoins to a wallet;
2. transfers stablecoins from the wallet to Exchange B;
3. acquires ETH against stablecoins and asks Exchange B to move ETH to the wallet.

In this case, no bank transfer is necessary. This example highlights the relevance of stablecoins in cryptoasset markets to facilitate transactions of cryptoassets when USD are not directly involved, i.e., when trades only occur in the cryptoassets domain. The relevance of stablecoins instead of the USD as a reserve asset operating in cryptoassets is also due to fees:[2] for example, the BTC-USD pair has a minimum (maximum) taker fee among all the exchanges considered in our analysis equal to 0.09% (0.20%), while the minimum (maximum) fee to exchange Bitcoin with the stablecoin Tether is 0.06% (0.10%). Lower fees explain why markets where cryptocurrencies are exchanged with a stablecoin have trading volume larger than markets where cryptocurrencies are exchanged against the USD, see Table 3.

In the above examples, the transfers of ETH or BTC are registered on the blockchains. A piece of information that has been used in several papers on cryptoassets, see (Ante et al., 2020, 2021; Griffin & Shams, 2020). However, we can not recover the complete information on the deals from the blockchain, e.g., the BTC-USD exchange rate associated with the transaction. For this reason we opted to deal with information (trades and order books) gathered directly from exchanges using market rather than blockchain data as in Brandvold et al. (2015); Lyons and Viswanath-Natraj (2020); Wang (2018); Wang (2018). The advantage is particularly significant in case of an intraday analysis for which synchronicity of price and trading volume is crucial. On the importance of the right choice of the data provider in cryptocurrency markets, we refer to Alexander and Dakos (2020); Manahov (2021).

We consider markets involving different types of assets/currencies: currencies, cryptocurrencies, stablecoins. As far as currency is concerned, we only deal with

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[2] Crypto exchanges adopt a maker-taker fee schedule based on the rolling 30-day cumulative trading volume. Fees decrease with the volume. Here we consider the current fees for the first level of the schedules of all exchanges trading the corresponding pair, that is the maximum fee. The maker fee is paid by the trader posting the quote to the order book while the taker fee is paid by the trader filling the quote and initiating the trade. The maker fee is equal or less than the taker fee to incentivize traders to provide liquidity.

Table 1 Market capitalization and trading volume of BTC, ETH and USDT according to http://coinmarketcap.com as at 2020-10-04

symbol	name	marketcap (millions USD)	24h daily volume (millions USD)
BTC	Bitcoin	197 687	71 251
ETH	Ether	39 907	10 696
USDT	Tether	16 391	30 365

the US dollar (USD). We consider the two most relevant cryptocurrencies by market capitalization: Bitcoin (BTC) and Ether (ETH). We started our analysis considering several stablecoins, then we restricted our attention to the stablecoin with the largest market capitalization: Tether (USDT), a stablecoin pegged to the US Dollar and collateralized by the US dollar itself (fiat-backed stablecoin). For more details on the design and classification of stablecoins, see Moin et al. (2019). Table 1 shows market capitalization and trading volume of the cryptoassets considered in our analysis. BTC, ETH, and USDT are the three cryptoassets with highest capitalization, covering 64% of the market capitalization of all the cryptoassets.

Our dataset includes six pairs and twenty-two exchanges, see Table 14 in the Supplementary material for the list of exchanges for each pair. The list of exchanges has been selected to cover at least 70% of each market according to coinmarketcap.com data regarding the trading volume in September 2020.[3] We consider three different sets of pairs: BTC and ETH against USDT (2 pairs), ETH against BTC (1 pair), BTC, ETH, USDT against USD (3 pairs). In our analysis, we aggregate observations from different exchanges for each market.

The dataset is made up of two different types of data: tick-by-tick trading information, and order book information. We emphasize that our dataset represents the registered trading activity occurring in the different exchanges with synchronous trading/price observations. As already discussed, the transfers of cryptoassets in their corresponding blockchains do not correspond to a synchronous market activity. Moreover, blockchain data suffer of another pitfall: even if the transfer of cryptoassets is done towards an address belonging to an exchange, the user of that address might or might not trade in the market. Our dataset captures actual trading activity.

Trading information is obtained from Kaiko.[4] For each transaction, trade information includes the following items: Exchange, Currency/asset pair, Date (timestamp in milliseconds), Price of the transaction in the reference currency, Amount (quantity of the asset in the reference currency), Sell (True or False, referring to the

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[3] Only exchanges with a CoinMarketCap Confidence Indicator equal to High were considered towards the total trading volume of the pair. CoinMarketCap exploits a machine learning model to estimate volumes of every single market pair that exchanges report. With estimated volumes, they detect outliers where exchanges report far higher volumes than the model predicts, allowing to flag them accordingly to their confidence indicator. A high confidence indicator corresponds to high level of confidence in the market's reported volume. https://coinmarketcap.com/.

[4] Kaiko has been collecting trading information about cryptocurrencies since 2014, it provides data for more than 100 exchanges and more than 70 000 currency pairs. https://www.kaiko.com/.

trade direction, a trade marked as 'true' means that a price taker placed a market sell order).

Information about the order book is obtained from Kaiko which queries the Application Programming Interface of the exchanges and takes snapshots of their order books at one minute frequency. In addition, for the USDT-USD pair, we used the provider CryptoTick to obtain trade and order book data from Bitfinex exchange.[5] Kaiko takes two order book snapshots per minute for all pairs and exchanges. The order book snapshots include all bid and ask prices placed within 10% of the mid-price at the time the snapshot is taken. The following information is obtained: Date (timestamp in milliseconds), Type (a=ask, b=bid), Price (price of the quote in the reference currency), Amount (quantity of asset to buy or sell in the reference currency). A snapshot of the limit book of CryptoTick represents the fifty best levels for each side of the book. Each level contains the price and cumulative size of resting orders on that level. The snapshot is recorded every second if the order book changed in at least one of the first fifty best levels. The order book snapshot includes the following pieces of information: Time_exchange (UTC timestamp of the book provided by the exchange), asks[0-50].price (ask prices incrementing from the spread), asks[0-50].size (total amount of volume resting on the corresponding ask price), bids[0-50].price: (bid prices decrementing from the spread), bids[0-50].size (total amount of volume resting on the corresponding bid price).

3 Descriptive statistics

In this section, we provide basic statistics for the cryptocurrency pairs in the dataset. We concentrate on price and return, number of trades and trading volume, volatility, quoted spread and order flow.

We deal with outliers applying a variation of the methodology proposed in Brownlees and Gallo (2006). For each point-observation of the raw high frequency time series, we consider the interval of sixty seconds centered on that point and exclude it if the price is more than three standard deviations away from the mean price computed for that interval. The observation is discarded for all time series. For all pairs except USDT-USD, less than 0.01% of the original sample was discarded, while for USDT-USD the fraction was around 5%.

Depending on the pair, it may be useful to concentrate our attention on price or return time series. In case of USDT-USD, it makes sense to look at the price (or parity deviation, i.e., price minus 1 USD) as USDT is backed by reserves with a parity at 1 US dollar. Instead, in case of BTC and ETH, it is more useful to consider the asset return as these cryptocurrencies are not pegged to a parity and therefore the return turns out to be the most interesting piece of information.

First, we analyze the USDT-USD price, concentrating on parity deviation. Prices are sampled at a one second frequency. For each one second interval, we compute

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[5] https://www.cryptotick.com/.

Fig. 2 Pairs considered in the analysis
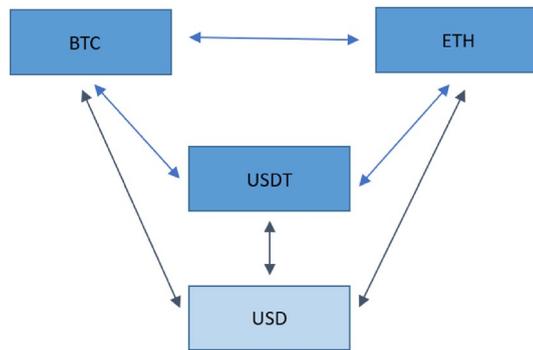
Table 2 Statistics for one minute log-returns. The coefficient of variation (cv) is the standard deviation divided by the mean

Symbol	Mean	stddev	skewness	kurtosis	min	max	cv
BTC-USDT	9.19×10^{-7}	0.0011	−0.16	188.26	−0.06	0.07	1167.89
ETH-USDT	1.93×10^{-6}	0.0013	0.05	215.49	−0.08	0.08	661.12
ETH-BTC	9.05×10^{-8}	0.0008	−0.53	160.18	−0.06	0.05	9125.92
BTC-USD	-5.54×10^{-5}	0.0049	−1.30	163.77	−0.42	0.14	−88.93
ETH-USD	-6.64×10^{-5}	0.0069	−0.03	56.24	−0.16	0.12	−104.17
USDT-USD	-2.14×10^{-6}	0.0028	1.02	331.21	−0.08	0.08	−1326.76

the price as the average price of trades executed during that second, the prices observed at that second are weighted by the volume of the corresponding trades. The parity deviation has mean value 0.001517, standard deviation 0.004631; the minimum deviation in the dataset is -0.032410, while the maximum is 0.079708.

In our preliminary analysis, we also considered other stablecoins: USD Coin (USDC), True USD (TUSD), Paxos (PAX), and Dai (DAI). It turns out that TUSD, USDC and USDT are the most "stable" coins, e.g., parity close to zero. We restricted our analysis to USDT because its market is the most active: considering the number of trades over a one minute interval, USDT is the most traded stablecoin both against cryptocurrencies (ETH and BTC) and USD. In particular, the BTC-USDT market is the only one with trades in every minute of the sample. We observe that all the stablecoins (with the exception of DAI) are actively traded against BTC and ETH.[6] Instead, with the the exception of USDT, they are rarely traded against the USD.[7] These features led us to restrict the analysis to USDT (Fig. 2).

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[6] The fraction of minutes with no trades is 88.19% for BTC-DAI, 32.37% for ETH-DAI, between 4% and 9% for ETH-PAX, ETH-TUSD, ETH-USDC, and between 1% and 4% for BTC-PAX, BTC-TUSD, BTC-USDC. Other results are provided in Table 3.

[7] The fraction of minutes with no trades is 99.37% for TUSD-USD, 95.92% for PAX-USD, 94.45% for USDC-USD, 79.98% for DAI-USD, and 45.94% for USDT-USD.

Table 3 Statistics for the number of trades at the one minute frequency. The coefficient of variation is the standard deviation divided by the mean

Symbol	Mean	stddev	skewness	kurtosis	min	max	zero_perc	cv
BTC-USDT	1221.80	1165.40	6.67	91.78	14	43828	0.0000	0.95
ETH-USDT	651.66	672.37	6.90	105.35	0	33991	0.0001	1.03
ETH-BTC	297.11	319.16	10.85	250.01	11	23626	0.0000	1.07
BTC-USD	145.12	205.49	9.92	180.85	0	10423	0.0000	1.42
ETH-USD	62.65	98.95	10.59	221.51	0	5334	0.0011	1.58
USDT-USD	7.50	18.27	13.32	457.71	0	1598	0.4594	2.44

Table 4 Statistics for daily trading volume in USD. The coefficient of variation is the standard deviation divided by the mean

Symbol	Mean	stddev	skewness	kurtosis	min	max	cv
BTC-USDT	1.87×10^9	8.79×10^8	1.78	5.30	6.18×10^8	6.96×10^9	0.47
ETH-USDT	4.79×10^8	3.13×10^8	2.27	7.92	6.84×10^7	2.48×10^9	0.65
ETH-BTC	2.58×10^8	1.55×10^8	1.57	3.44	3.82×10^7	1.11×10^9	0.60
BTC-USD	3.71×10^8	2.88×10^8	2.86	13.12	6.63×10^7	2.61×10^9	0.78
ETH-USD	9.57×10^7	8.58×10^7	2.52	9.01	7.07×10^6	6.14×10^8	0.90
USDT-USD	1.24×10^7	1.09×10^7	1.74	3.33	8.01×10^5	7.15×10^7	0.88

In Table 2, we provide basic statistics for log-returns sampled at the one minute frequency. Starting from the price sampled at a one second frequency, we compute the one minute log-return. For each minute t, where there is at least one executed trade, we identify the first second within that minute with a transaction. We denote the price of that transaction as p_t and the log-return r_t for minute t is computed as $r_t = \log(\frac{p_t}{p_{t-1}})$. If no trade is executed during minute t, then $r_t = 0$. Notice that the average log-return is positive if cryptoassets are exchanged against other cryptoassets and negative if they are exchanged against the USD. Notice that the standard deviation of returns in markets involving USD is much higher than the one observed in the three markets involving only cryptoassets.

As far as the number of trades is concerned, we consider a one minute time interval. Table 3 provides basic statistics for the number of trades. Trading activity displays a significant degree of variability. Considering the average number of trades, we observe that the most active markets are BTC-USDT, ETH-BTC and ETH-USDT. The USDT-USD market is by far the less active market, but also ETH-USD and BTC-USD show a limited average amount of trades. These results suggest the relevance of markets where BTC and ETH are exchanged against each other or against USDT. Market activity is much more limited for markets where cryptoassets are traded against USD, in particular in case of USDT.

Table 5 Statistics for annualized daily volatilities based on one minute log-returns. The coefficient of variation is the standard deviation divided by the mean

Symbol	Mean	stddev	skewness	kurtosis	min	max	cv
BTC-USDT	0.64	0.45	4.87	41.43	0.1583	5.71	0.70
ETH-USDT	0.78	0.50	5.39	48.60	0.2266	6.25	0.64
ETH-BTC	0.54	0.26	4.02	27.49	0.1797	3.00	0.49
BTC-USD	1.69	3.14	5.55	31.61	0.2835	23.37	1.86
ETH-USD	3.15	3.91	4.56	24.26	0.4635	29.13	1.24
USDT-USD	0.89	1.85	5.77	35.97	0.0545	16.20	2.09

Table 4 reports information on daily trading volume. Trading volume is computed considering transaction values converted in USD. As exchange rate, we apply the daily size-weighted average trading price of the appropriate pair. As an example, for BTC-USDT with volume denominated in BTC, we consider the average trading price of the pair BTC-USD considering all the transactions occurred in all the exchanges. No conversion is necessary for pairs having USD as quote currency. The results on the trading volume of the various pairs is similar to the one obtained for number of trades.

To analyze market volatility, we consider the one day realized volatility σ_t for day t:

$$\sigma_t := \sqrt{\sum_s \ln^2 \left(p_{s+1}/p_s\right)},$$

where the sum is performed across all the one minute intervals of the day. Table 5 shows basic statistics for annualized realized volatilities of cryptoassets. We notice a very low return volatility for ETH-BTC and that volatility is high in case of cryptocurrencies traded against USD. These results confirm those obtained for the standard deviation of logarithmic returns.

The order flow is computed at the one minute frequency. It is defined as the buyer-initiated volume minus the seller-initiated volume:

$$OF = \sum_{i=1}^{n} V_i \cdot S_i,$$

where V_i is the volume of the i-th trade and S_i denotes the market side initiating the trade: 1 if it is the buyer, -1 if it is the seller. Table 6 shows basic statistics for the order flow. Notice that on average, BTC-USDT and ETH-USDT are seller markets while BTC-USD is a demand driven market. These results suggest that there is a prevalence of traders going from BTC and ETH to USDT as a reserve asset to operate on cryptoassets and that traders in prevalence acquire BTC exchanging them for USD. Notice that the directionality of trading activity is not reflected on the mean return of the assets.

We also compute the quoted bid-ask spread gathering information from the order book. The quoted bid-ask spread is provided by the difference between the best ask price and the best bid price in the order book of all the exchanges. Notice that being

Table 6 Statistics for order flow based on one minute intervals. The coefficient of variation is the standard deviation divided by the mean. To facilitate the comparison order flow has been transformed to US dollars using average daily rates

Symbol	Mean	stddev	skewness	kurtosis	min	max	cv
BTC-USDT	−13829.53	636071.06	−2.18	202.35	-5.43×10^7	2.56×10^7	−45.99
ETH-USDT	−7316.94	199468.53	−2.66	315.80	-1.33×10^7	1.10×10^7	−27.26
ETH-BTC	728.89	116323.78	−0.99	94.39	-7.56×10^6	4.09×10^6	159.59
BTC-USD	8338.23	350093.51	−2.99	283.21	-2.48×10^7	1.86×10^7	41.99
ETH-USD	−573.26	102771.34	-6.57	646.60	-1.06×10^7	6.08×10^6	−179.27
USDT-USD	216.83	42372.78	−7.11	1574.08	-3.96×10^6	3.61×10^6	195.42

Table 7 Statistics for the bid-ask spread based on one minute intervals. The coefficient of variation is the standard deviation divided by the mean. The spread is expressed as basis points of midpoint of bid/ask prices

Symbol	Mean	stddev	skewness	kurtosis	min	max	cv
BTC-USDT	3.09	22.41	36.16	1409.47	−37.32	906.30	7.24
ETH-USDT	205.69	1018.55	6.87	50.92	−1404.57	10394.68	4.95
ETH-BTC	10.89	24.59	10.12	157.80	−56.40	1000.94	2.26
BTC-USD	4.01	10.73	11.79	241.16	−86.04	749.26	2.68
ETH-USD	14.13	37.57	2.41	87.20	−665.38	1001.52	2.66
USDT-USD	2.49	5.82	100.21	25665.48	0.00	1866.42	2.33

the assets traded in different exchanges it may occur that there is a negative bid-ask spread in case the order books of two different exchanges show an arbitrage opportunity with the best bid price lower than the best ask price, see (Makarov & Schoar, 2020). Table 7 provides basic statistics for this quantity based on one minute interval. We observe that spreads are relatively small with the exception of ETH-USDT.

4 Intraday analysis

In this section, we first of all investigate the intraday breakdowns for trading volume, return variance, number of trades, order flow, and bid-ask spread. The daily breakdown is performed as follows. For trading volume and number of trades, we aggregate the data on an hourly basis for each day, we normalize the datum with respect to the activity over the entire day, then we average the day-hour observations over the dataset. Trading volume is computed converting the value in USD using the average exchange rate of the corresponding day. As far as the variance (squared volatility) is concerned, we compute five minute logarithmic return, then we compute the realized variance over one hour, we normalize it with respect to the realized variance over the entire day and finally we average the day-hour observations over the sample. Regarding the order flow, the aggregation is performed over a one-hour interval and then we average day-hour observations over the sample without normalizing them over the day. The order flow is converted in USD using the average exchange rate of the day. As far as the quoted spread is concerned, the aggregation over a one-hour interval is performed as the average of the observations over the interval and then the value is averaged over the dataset. The spread is expressed in basis points of the mid-point of bid/ask prices without normalization with respect to the evolution over the day. We have also computed the effective spread as twice the absolute difference between the trade price and the mid-point, we opted not to consider it as it does not add too much to the analysis.

In Figures 4–8 of the Supplementary material, we report the intraday patterns for BTC-USDT, BTC-USD, ETH-USDT, ETH-USD and ETH-BTC. In Figure 9

(Supplementary material), we show the intraday pattern for USDT-USD, in this case, we also report the breakdown for the parity deviation, defined as the difference between the stablecoin price and the pegged value of 1 USD. The parity deviation has been computed as the average over a one-hour interval and then it is averaged across the days in the dataset. The time stamp in the figures is provided by Universal Time Coordinated (UTC).

To the best of our knowledge, the only paper discussing the intraday pattern of cryptocurrencies is Wang et al. (2020). They show that the shape of trading volume for the BTC-USD market appears to be a reverse V, whereas the volatility does not follow any specific pattern through the day. The peaks on trading activity are associated with the opening of stock markets in Asia, Europe and United States. It turns out that Bitcoin transactions are high when the European and US stock markets are open.

We remark that our dataset is much more recent: they consider the sample January 2015–December 2018. In our analysis, trading volume and number of trades show a similar intraday pattern with a two peaks shape. All the markets show a peak at 4.00 p.m. which corresponds to activity between 3.00 p.m and 4.00 p.m., a period of time immediately following the opening of stock markets in New York. Then all markets show a decrease in market activity with a small upsurge around 11 p.m. – midnight. which corresponds (with a little advance) to the opening of stock markets in Asia. Then trading activity decreases until 8.00 a.m. when stock markets open in Europe and then continue to raise until the stock markets open in US. From these pictures it emerges that the activity in US is predominant. The upsurge related to the opening of stock markets in Asia is less relevant but is significant. The only market which seems not to be affected significantly by the opening of markets in Asia is the BTC-USD market, confirming the analysis in Wang et al. (2020), the pattern of the trading activity in this market looks more like having a single peak.

A two peaks shape is observed for the realized variance of markets where cryptoassets are exchanged between them (BTC-USDT, ETH-BTC, ETH-USDT). No clear pattern is observed for USDT-USD, ETH-USD and, in part, for BTC-USD.

As far as the order flow is concerned, no clear pattern is observed. In agreement with the descriptive statistics reported in Sect. 3, on average the order flow in the BTC-USD market is positive, while the order flows in the ETH-BTC, ETH-USD, ETH-USDT markets are mostly negative, the same is observed for BTC-USDT with a significant positive peak at 5.00 p.m. No pattern can be observed for the order flow of the USDT-USD market. We can confirm that the BTC-USD market is a demand driven market and that all the markets involving ETH and USDT seem to be seller markets with the exclusion of the peak for the BTC-USDT market. The BTC-USD market being demand driven can be associated to the fact that investors tend to apply a buy BTC to enter the cryptoasset markets.

No clear pattern can be identified on the quoted spread.

These results suggest that although cryptoasset markets are open 24 hours a day with no closure period, trading activity and volatility are affected by closures of financial markets around the globe as stock exchanges, see Brock & Kleidon (1992),

Table 8 Correlations of financial time series at the 5 min level (upper triangle) and at the 1 hour level (lower triangle). Values in bold are not statistically significant at the 1% level

Symbol	Measure	Bid-ask spread	Logreturn	Trades	Order flow	Volume	Volatility
BTC-USD	Bid-ask spread	1.00	**0.02**	0.11	**−0.02**	0.11	**−0.02**
BTC-USD	Logreturn	0.01	1.00	0.03	0.13	**−0.00**	−0.42
BTC-USD	Trades	0.09	−0.01	1.00	−0.09	0.93	−0.03
BTC-USD	Order flow	−0.01	0.15	−0.13	1.00	−0.11	**0.01**
BTC-USD	Volume	0.08	−0.01	0.93	−0.12	1.00	0.03
BTC-USD	Volatility	−0.01	−0.14	**0.00**	**−0.00**	0.03	1.00
ETH-USD	Bid-ask spread	1.00	−0.03	0.09	−0.03	0.09	0.06
ETH-USD	Logreturn	−0.01	1.00	**0.00**	0.09	**−0.01**	−0.35
ETH-USD	Trades	0.07	−0.01	1.00	−0.17	0.92	−0.03
ETH-USD	Order flow	−0.01	0.10	−0.16	1.00	−0.25	**−0.00**
ETH-USD	Volume	0.07	−0.01	0.91	−0.23	1.00	**0.01**
ETH-USD	Volatility	0.04	−0.08	**−0.01**	**−0.01**	0.02	1.00
BTC-USDT	Bid-ask spread	1.00	0.03	**0.02**	**0.01**	0.05	0.03
BTC-USDT	Logreturn	0.01	1.00	−0.07	0.55	−0.05	−0.06
BTC-USDT	Trades	0.02	−0.06	1.00	−0.16	0.88	0.46
BTC-USDT	Order flow	**0.00**	0.49	−0.12	1.00	−0.10	−0.18
BTC-USDT	Volume	0.04	−0.06	0.89	−0.09	1.00	0.52
BTC-USDT	Volatility	0.03	**0.00**	0.40	−0.11	0.43	1.00
ETH-USDT	Bid-ask spread	1.00	**−0.00**	**−0.00**	**0.00**	0.02	**0.01**
ETH-USDT	Logreturn	**−0.00**	1.00	−0.09	0.58	−0.08	−0.14
ETH-USDT	Trades	0.01	−0.06	1.00	−0.20	0.89	0.46
ETH-USDT	Order flow	**-0.00**	0.52	-0.14	1.00	−0.16	−0.20
ETH-USDT	Volume	0.02	−0.06	0.91	−0.13	1.00	0.52
ETH-USDT	Volatility	0.01	−0.01	0.37	−0.11	0.39	1.00
ETH-BTC	Bid-ask spread	1.00	**0.00**	0.07	0.06	0.07	0.03
ETH-BTC	Logreturn	**−0.00**	1.00	**0.00**	0.25	**−0.00**	**−0.00**
ETH-BTC	Trades	0.06	−0.02	1.00	0.05	0.82	0.62
ETH-BTC	Order flow	0.02	0.29	−0.01	1.00	0.11	**−0.00**
ETH-BTC	Volume	0.05	−0.02	0.80	−0.01	1.00	0.49
ETH-BTC	Volatility	0.02	**−0.00**	0.46	−0.02	0.34	1.00
USDT-USD	Bid-ask spread	1.00	−0.05	0.15	−0.06	0.14	0.15
USDT-USD	Logreturn	**−0.00**	1.00	**−0.02**	**0.01**	**−0.02**	0.06
USDT-USD	Trades	0.09	**−0.00**	1.00	**−0.02**	0.82	**−0.01**
USDT-USD	Order flow	−0.01	**−0.00**	−0.03	1.00	−0.14	**−0.02**
USDT-USD	Volume	0.06	**−0.00**	0.64	−0.22	1.00	**0.01**
USDT-USD	Volatility	0.10	0.06	**−0.01**	**−0.01**	**0.01**	1.00

and not by the arrival of news as in the exchange rate markets, see (Martens, 2001; Chang & Taylor, 2003).

To further investigate the intraday patterns of the time series, we compute correlations between trading volume, number of trades, volatility, quoted bid-ask spread,

order flow and logarithmic return. We work at two different frequencies: five minute and one hour. In Table 8 we report the correlations between these time series for pairs BTC-USDT, BTC-USD, ETH-BTC, ETH-USD, ETH-USDT and USDT-USD. Correlation of financial time series at the five minute (one hour) frequency are reported in the upper (lower) triangle. We observe no significant differences changing the sampling frequency, correlations are slightly stronger at five minutes than hourly.

Markets show different regularities depending on the type of cryptoassets. The main differentiation concerns markets where an asset is exchanged against the USD (BTC-USD, ETH-USD, USDT-USD) and markets where cryptoassets are exchanged between them (BTC-USDT, ETH-BTC, ETH-USDT). We observe the following:

- there is little correlation between trading volume (number of trades) and volatility for the first set of markets, while correlations are positive, high and statistically significant for the second set of markets;
- logarithmic return and order flow are positively correlated for the second set of markets while correlation is very limited for markets involving USD (it is even statistically insignificant in case of USDT-USD);
- there is no correlation between the bid-ask spread and market activity, order flow and volatility in all the markets;
- there is negative correlation between trading volume and order flow for all the markets with the exception of ETH-BTC;
- BTC-USD and ETH-USD show a strong negative correlation at five minute interval (but not at one hour) between return and volatility.

The first result shows that the regularities observed in stock markets (positive correlation between trading activity and volatility) are encountered only in markets where cryptoassets are exchanged between them. Leveraging theoretical models in Admati and Pfleiderer (2015); Foster and Viswanathan (1990), we claim that these markets play a crucial role in aggregating technology/preference shocks and heterogeneous opinions. Instead markets where cryptoassets are traded against the USD don't play a significant role on price formation/discovery.

Notice that in cryptoasset markets, we do not have private information about the value of the asset. This may explain the fact that we do not observe a significant correlation between the quoted bid-ask spread and trading activity-volatility as in models with private information, see, e.g., Glosten and Milgrom (1985).

The positive correlation between return and order flow agrees with what is observed in stock markets, see Chordia et al. (2002). The magnitude of the correlation is significantly higher in case of the second set of markets. The result highlights that liquidity and price pressure mostly matter in markets where cryptoassets are exchanged between them. In these markets, the pressure from the buy (sell) side of the market leads to a positive (negative) return. This result shows that in these markets the order flow contributes to price discovery, that is these markets are central for price formation aggregating opinions and preference/technology shocks. The interesting point to remark is that these markets are less efficient than stock exchanges:

Table 9 Correlation of log-returns at the five minute level (upper triangle) and at the one-hour level (lower triangle) across all pairs

	BTC-USD	BTC-USDT	ETH-BTC	ETH-USD	ETH-USDT	USDT-USD
BTC-USD	1.00	0.20	−0.02	0.08	0.17	−0.01
BTC-USDT	0.17	1.00	−0.05	0.14	0.76	**0.00**
ETH-BTC	**−0.00**	−0.05	1.00	0.08	0.44	**0.00**
ETH-USD	0.24	0.12	0.06	1.00	0.17	**0.00**
ETH-USDT	0.15	0.77	0.42	0.14	1.00	**0.00**
USDT-USD	**−0.01**	**0.01**	**0.00**	**0.00**	**0.01**	1.00

Values in bold are not significant at the 1% level

correlation is high at the hour frequency while in stock exchanges the order flow does not affect market return at the hour frequency, see Chordia et al. (2005). It seems that price formation occurs in markets where cryptoassets are exchanged between them rather than in markets where they are exchanged against US dollar, the process takes more time than in the stock exchanges. This interpretation agrees with the first regularity discussed above.

Notice that in Chordia et al. (2002) order flow and trading volume/number of trades turn out be positively correlated, a result which is not confirmed in our setting. This result shows that large trading volume in cryptoasset markets is associated to "sell" periods.

With the exception of BTC-USD and ETH-USD, there is no relationship between return and volatility. For the markets where the two cryptocurrencies are traded against the USD, the negative correlation is strong at the five-minute frequency and low at the one-hour frequency, highlighting that cryptocurrency sell-offs may lead to (temporary) significant market movements.

In a nutshell, we can summarize that intraday patterns and the analysis of the correlation between the financial time series of each market suggest that cryptoasset markets are split in two subsets: markets where cryptoassets are exchanged between them and markets where cryptoassets are exchanged against the USD. The first set of markets plays a relevant role on price formation, the second set plays a secondary role. Moreover, as cryptoassets do not involve private information, the bid-ask spread does not react to market activity.

5 Market relationships

We now turn to investigate connections among markets.

Given the one second price time series, the correlation between asset returns is computed at the five minutes and hour frequency. In Table 9 we provide the correlations among returns of different markets.

The literature concentrates on markets where cryptoassets are traded against USD. Baur and Hoang (2021) shows high return correlations among "non-stable" coins at both the hourly and the daily frequency, weaker evidence is provided in

Table 10 Correlation of trading volume at the five minute level (upper triangle) and at the one-hour level (lower triangle) across all pairs. All values are significant at the 1% level

	BTC-USD	BTC-USDT	ETH-BTC	ETH-USD	ETH-USDT	USDT-USD
BTC-USD	1.00	0.84	0.62	0.74	0.72	0.38
BTC-USDT	0.87	1.00	0.57	0.65	0.77	0.30
ETH-BTC	0.68	0.60	1.00	0.69	0.70	0.29
ETH-USD	0.82	0.72	0.75	1.00	0.83	0.37
ETH-USDT	0.78	0.82	0.72	0.88	1.00	0.32
USDT-USD	0.51	0.41	0.38	0.54	0.47	1.00

Griffin and Shams (2020). In contrast, return correlations among stablecoins are low at the hourly level, but become relatively high at the daily level. The return correlations between stablecoins and "non-stable" coins are generally close to zero at both frequencies except for Tether with correlations around 0.2, see also Hoang & Baur (2021).

Our analysis provides different results. As far as correlation between BTC-USD and ETH-USD is concerned, we observe weak positive correlation. The correlation increases at the hour level as it is observed in Griffin and Shams (2020)[Table I, Panel B].[8] We observe the centrality of ETH-USDT, which is strongly correlated (above 40%) with BTC-USDT and ETH-BTC. We also observe a (small) negative correlation between BTC-USDT and ETH-BTC. These results show that when the value of ETH -in BTC- increases (decreases), there is a high probability that its value —in USDT— increases (decreases) and vice versa. A similar relation holds true between the value of BTC in ETH and in USDT. This evidence can be interpreted through the no-arbitrage lens: if the value of a cryptoasset increases with respect to another, then the most likely scenario is to observe a contemporaneous increase of its value with respect to a third cryptoasset, ruling out arbitrage opportunities. Notice that the market for the conversion of Tether in USD is uncorrelated with the other markets. Differently from Hoang and Baur (2021), the correlations among minor stablecoins and Bitcoin are rather small, see Table 15 in the appendix.

These results confirm the centrality of USDT to trade BTC and ETH with strong correlations among these markets, while markets where cryptocurrencies are exchanged against the USD play a less significant role.

In Table 10, we provide the correlation between trading volume in different markets. As observed in Hoang and Baur (2021), trading volumes in different markets are strongly correlated, however, we observe lower correlation (than other markets) in trading volume between the USDT-USD market and the other markets. In Table 11, we provide the correlations of the realized volatility in different markets. It is interesting that we confirm the segmentation of markets observed above: strong positive correlations are observed between volatilities of markets where a cryptocurrency is exchanged

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[8] For an analysis, with daily data, of the relation between BTC-USD and ETH-USD, the reader can also refer to Ciaian et al. (2018).

Table 11 Correlation of volatility at the five-minute level (upper triangle) and at the one-hour level (lower triangle) across all pairs. Values in bold are not significant at the 1% level

	BTC-USD	BTC-USDT	ETH-BTC	ETH-USD	ETH-USDT	USDT-USD
BTC-USD	1.00	0.05	0.02	0.55	0.05	0.50
BTC-USDT	0.05	1.00	0.41	0.04	0.81	0.01
ETH-BTC	0.03	0.65	1.00	0.04	0.70	**0.01**
ETH-USD	0.90	0.03	0.03	1.00	0.05	0.49
ETH-USDT	0.04	0.92	0.83	0.04	1.00	**0.01**
USDT-USD	0.75	**0.02**	**0.01**	0.75	**0.01**	1.00

against USD (BTC-USD, ETH-USD, USDT-USD) and strong correlations are detected between volatilities for markets where cryptoassets are exchanged against each other (BTC-USDT, ETH-BTC, ETH-USDT). Notice that the correlations between markets belonging to the two blocks of markets are almost insignificant. This evidence suggests that markets belong to different domains and that volatility is driven by different sources: aggregation of preference/technology shocks and heterogeneous opinions in one case and exogenous demand changes in case of markets with the USD due to investors entering or exiting the cryptoassets domain.

The strong correlation between stablecoins and BTC daily volatility detected in Hoang and Baur (2021) is confirmed, the highest level is observed for USDT, see Table 16 in the Supplementary material for other stablecoins.

Confirming the literature on intraday analysis of stock exchanges, there is no correlation among bid-ask spreads of different markets, see Table 12.

To further investigate the BTC, ETH, USDT and USD nexus, we analyze the lead–lag relationships among the markets. As in de Jong and Nijman (1997), lead–lag relationship is established through a linear regression. For example, the lead–lag relationship between BTC-USD and BTC-USDT is evaluated performing the linear regression on the log-return of the exchange rates:

$$\log\left(\frac{\text{BTC-USDT}_t}{\text{BTC-USDT}_{t-\Delta}}\right) = \alpha_i + \beta_i \times \log\left(\frac{\text{BTC-USD}_{t-i\Delta}}{\text{BTC-USD}_{t-(i+1)\Delta}}\right) + \varepsilon_i, \quad i = 1, \dots, 5.$$

where Δ is set to be one hour. We assess that BTC-USD leads BTC-USDT if the p-value of β_1 is smaller than 0.05 (or 0.01). For the sake of brevity, in Table 13 we only report the regressions and the β coefficients that are statistically significant at 5% level.[9]

Figure 3 summarizes the results confirming the existence of two blocks of markets: the one of cryptoassets against other cryptoassets, and the one of cryptoassets against USD. The two blocks are connected with few weak relationships (p-value smaller than 0.05, but larger than 0.01).

The lead–lag analysis provides information about the time evolution of exchange rates in the cryptoasset markets. Starting from the block at the top in Fig. 3, i.e.,

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[9] All the results are available upon request.

Table 12 Correlation of bid-ask spread at the five-minute level (upper triangle) and at the one-hour level (lower triangle) across all pairs. Values in bold are not significant at the 1% level

	BTC-USD	BTC-USDT	ETH-BTC	ETH-USD	ETH-USDT	USDT-USD
BTC-USD	1.00	0.03	0.03	0.06	0.02	0.07
BTC-USDT	0.04	1.00	**0.00**	0.03	**0.00**	0.04
ETH-BTC	0.04	**0.00**	1.00	0.03	-0.01	0.02
ETH-USD	0.08	0.03	0.03	1.00	0.02	0.05
ETH-USDT	0.02	**0.00**	**-0.01**	0.02	1.00	0.05
USDT-USD	0.09	0.05	0.04	0.07	0.06	1.00

Table 13 Lead-lag effect: regression coefficients β_i for regression $Y = \alpha_i + \beta_i X_i + \varepsilon_i$, $i = 1, \cdots, 5$. Only coefficients from a regression with p value smaller than 0.05 are reported, * corresponds to a p value smaller than 0.01. If a pair does not appear in the table (as dependent or independent variable), it means that there is no regression with p value smaller than 0.05

$Y =$	ETH-USD_t	ETH-USDT_t	BTC-USDT_t		BTC-USD_t	USDT-USD_t
$X_1 = \text{BTC-USD}_{t-\Delta}$	0.2013*	-0.0159	-0.0144	$\text{ETH-USD}_{t-\Delta}$ 0.2160*	0.0296*	
$X_2 = \text{BTC-USD}_{t-2\Delta}$	0.1429*	–	–	$\text{ETH-USD}_{t-2\Delta}$ 0.2220*	0.0201*	
$X_3 = \text{BTC-USD}_{t-3\Delta}$	0.1672*	–	–	$\text{ETH-USD}_{t-3\Delta}$ 0.1782*	-0.0241*	
$X_4 = \text{BTC-USD}_{t-4\Delta}$	0.1940*	–	–	$\text{ETH-USD}_{t-4\Delta}$ 0.2293*	-0.0353*	
$X_5 = \text{BTC-USD}_{t-5\Delta}$	0.1891*	–	–	$\text{ETH-USD}_{t-5\Delta}$ 0.1905*	-0.0195*	

$Y =$	ETH-BTC_t	ETH-USDT_t	USDT-USD_t		BTC-USD_t	ETH-USD_t
$X_1 = \text{BTC-USDT}_{t-\Delta}$	-0.0234*	-0.0312*	0.0183	$\text{USDT-USD}_{t-\Delta}$ 0.0474*	-0.0368*	
$X_2 = \text{BTC-USDT}_{t-2\Delta}$	–	-0.0274*	–	$\text{USDT-USD}_{t-2\Delta}$ -0.0927*	-0.1107*	
$X_3 = \text{BTC-USDT}_{t-3\Delta}$	–	-	–	$\text{USDT-USD}_{t-3\Delta}$ –	–	
$X_4 = \text{BTC-USDT}_{t-4\Delta}$	–	-	–	$\text{USDT-USD}_{t-4\Delta}$ –	–	
$X_5 = \text{BTC-USDT}_{t-5\Delta}$	–	-	–	$\text{USDT-USD}_{t-5\Delta}$ –	–	

$Y =$	ETH-BTC_t	USDT-USD_t		BTC-USDT_t
$X_1 = \text{ETH-USDT}_{t-\Delta}$ 0.0437*	0.0175		$\text{ETH-BTC}_{t-\Delta}$ 0.0398*	
$X_2 = \text{ETH-USDT}_{t-2\Delta}$		-	$\text{ETH-BTC}_{t-2\Delta}$ 0.0218*	
$X_3 = \text{ETH-USDT}_{t-3\Delta}$		-	$\text{ETH-BTC}_{t-3\Delta}$ 0.0189*	
$X_4 = \text{ETH-USDT}_{t-4\Delta}$		-	$\text{ETH-BTC}_{t-4\Delta}$ –	
$X_5 = \text{ETH-USDT}_{t-5\Delta}$		-	$\text{ETH-BTC}_{t-5\Delta}$ –	

cryptoassets against USD, we observe a strong (positive) connection between BTC-USD and ETH-USD. If the value of Bitcoin (in USD) increases or decreases, the same is likely to happen to the value of ETH (in USD) and vice versa, showing the strong interconnection between the two cryptocurrencies.

Fig. 3 Lead–lag: arrows show the lead–lag relation with a *p* value smaller than 0.05. If close to an arrow there is a star, it means that the p value is also smaller than 0.01. The red sign (+ or -) is the sign of the first coefficient, β_1, see Table 13
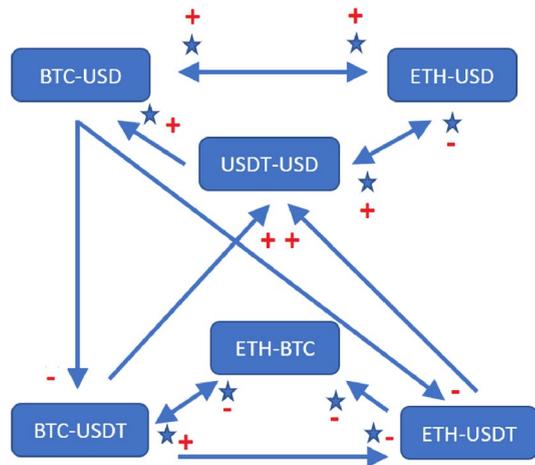
The relations between USDT-USD and both BTC-USD and ETH-USD appear to be more complex with different signs: positive in the first case and negative in the second case. Notice that the relation for a two hour interval turns out to be negative in both cases. Notice that even the lead–lag relation between ETH-USD and USDT-USD changes sign after the second hour.[10] The presence of negative coefficients in lead–lag coefficients when USDT-USD is involved is driven by its features: being pegged to the dollar, USDT cannot diverge from 1 USD for a long time. Because of the nature of USDT, we cannot observe a bull (or bear) market loop among the three pairs, e.g., an increase (decrease) of BTC-USD leading to an increase (decrease) of ETH-USD, leading to the increase (decrease) of USDT-USD, and so on. Changes of exchange rates in USD of BTC and ETH positively affect the price of USDT in USD but the feedback effect goes in the opposite direction because of the stabilization mechanism of USDT-USD (aiming at ruling out no arbitrage opportunities) which insulates this market with respect to the other two.

Let us consider now the block at the bottom in Fig. 3, i.e., the one of cryptoassets against other cryptoassets. We notice the negative relation between BTC-USDT and ETH-USDT, i.e., if the amount of USDT necessary to acquire BTC increases, then the amount of USDT to acquire ETH is likely to decrease. We observe a negative lead–lag relation between ETH-USDT and ETH-BTC, corresponding to a negative relation between USDT-ETH and BTC-ETH, i.e., if the amount of ETH necessary to acquire USDT increases, then the amount of ETH necessary to acquire BTC is likely to decrease. Finally, we observe a negative relation between ETH-BTC and USDT-BTC (corresponding to the positive lead–lag relation between ETH-BTC and BTC-USDT in Table 13), i.e., if the amount of BTC necessary to acquire ETH increases, then the amount of BTC necessary to acquire USDT is likely to decrease.

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[10] The lead–lag relation between BTC-USD and USDT-USD is negative but is rather small and is not statistically significant.

These negative lead–lag relationships highlight a "substitution" circle among the two cryptocurrencies and the stablecoin: if investors move their interests from a cryptoasset to another one then the price of the first cryptoasset is likely to decrease. The substitution effect confirms that markets where cryptoassets are traded between them reflect preference and opinion shocks among traders. This interpretation is not corroborated by the negative relation between BTC-USDT and ETH-BTC, corresponding to a positive relation between USDT-BTC and ETH-BTC. The positive relation may be traced back to the predominance of BTC as a gate to enter the cryptoasset environment.

Finally, even if with weak significativity, the leading relation of BTC-USD with both BTC-USDT and ETH-USDT, confirms the centrality of the BTC-USD market to enter the cryptoasset domain.

The lead–lag analysis confirms the differences between the two blocks of markets. The one centered on exchange with the US dollar is strictly interconnected with similar market movements balanced by a feedback in the opposite direction from the USDT-USD market. The dynamics inside the block of cryptoassets markets is more complex with a substitution between BTC and ETH capturing change in preferences/technology perceptions and opinions among traders.

6 Conclusion

Cryptoassets represent interesting markets for several reasons: they are fully decentralized, open all day, fully anonymous, no best price execution obligations are at work, their fundamental value is difficult to catch. These features render the analysis of these markets at high frequency very interesting to investigate price formation dynamics.

We have shown that it is not really interesting to look at markets where cryptocurrencies are exchanged against traditional currencies. These markets are uninformative about preferences and opinions of investors and technology shocks. They are mostly driven by exogenous changes in demand of cryptocurrencies. The real markets — those where prices are formed aggregating preference shocks and agents opinions — are those where Bitcoin and Ether are exchanged against Tether. Tether turns out to be a crucial asset to facilitate trades in cryptoassets.

The markets where Bitcoin and Ether are exchanged against Tether are more liquid with respect to the markets where cryptocurrencies are exchanged against the USD. Moreover, in the former markets, fees are lower. Preliminary results shows that in the former markets, there are more frequent arbitrage opportunities, most of them becoming negligible if the fees, even if low, are applied, while in the markets against USD there are less (but usually larger) arbitrage opportunities, with positive net profits. This topic is currently under investigation.

The relevance of stablecoin markets in the cryptoassets domain calls for a reinforcement of their regulation to guarantee that price formation, liquidity and best execution requirements comply with standards of traditional financial markets as put forward in some recent policy papers, see (Arner et al., 2020; European Central Bank, 2020; Bank for International Settlements and IOSCO, 2021).

Declarations

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