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Bitcoin unchained: Determinants of cryptocurrency exchange liquidity[☆]

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ABSTRACT

We study bitcoin to US dollar (BTCUSD) liquidity and liquidity determinants using order book data from three large cryptocurrency exchanges. The BTCUSD market is more liquid than US equity markets with bid–ask spreads often below 1 basis point. We find that BTCUSD liquidity is largely explained by same-exchange past liquidity, past cryptocurrency market-wide liquidity and volatility, and fees charged on the blockchain for bitcoin transfers. Surprisingly, we find that BTCUSD liquidity is unrelated to broader financial markets and financial market liquidity.

1. Introduction

Hundreds of thousands of bitcoins worth billions of dollars change hands every day. Potential investors and speculators purchase and often hold bitcoin using cryptocurrency exchanges. Today, only about 5% of bitcoin transfers occur on the blockchain and the remaining bitcoin transfers occur on a large number of cryptocurrency exchanges all over the world. This means that for every bitcoin transferred via the much touted blockchain roughly 19 are transferred via cryptocurrency exchanges. Exchanges have become so important that most of the largest bitcoin wallets are managed by exchanges, with the largest exchange holding more than 1% of available bitcoin currently valued at more than USD 3 billion.[1]

While the literature on price behavior of bitcoin is numerous, liquidity has gained less attention. However, understanding the liquidity of these cryptocurrency exchanges is important for a number of reasons. *First*, the liquidity on these exchanges is an important determinant of the success of bitcoin as the ability to readily convert bitcoin into cash and vice versa is an important determinant of its value (Biais et al., 2019). *Second*, investments in cryptocurrencies have experienced tremendous

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[1] See https://bitinfocharts.com/top-100-richest-bitcoin-addresses.html

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growth, leading to the introduction of ETFs, futures and options, and investment products that require frequent buying and selling of BTC on cryptocurrency exchanges. The liquidity of BTC exchanges is an important determinant of the attractiveness of these investments (Biais et al., 2019). *Third*, other cryptocurrencies and tokens are "priced" using BTC prices. *Fourth*, understanding how liquidity forms and what drives liquidity in the BTC market is tantamount to understanding how well a decentralized financial system can organize the supply and demand for liquidity, the original reason for the establishment of the Bitcoin Blockchain.

We study trading and liquidity on three of the largest cryptocurrency exchanges (Bitfinex, Bitstamp, and Coinbase Pro) for trades of fiat currency (USD) against cryptocurrency (bitcoin; BTC). The three trading venues account for roughly 47% of the total BTCUSD exchange trading volume (according to http://bitcoinity.org) during the sample period. We describe liquidity and the determinants of liquidity on these exchanges with a high-frequency data set covering the two-year period between December 15, 2017 and December 15, 2019. We consider four measures of liquidity, the percentage quoted bid–ask spread, effective bid–ask spread, price impact, and the cost of a roundtrip trade.

The literature on the liquidity of cryptocurrencies is nascent. Several papers describe liquidity using transactions data and/or low frequency data (Brauneis and Mestel, 2018; Dimpfl, 2017; Eross et al., 2019; Fink and Johann, 2014; Leirvik, 2022; Scharnowski, 2021; Shi, 2018; Wei, 2018). These papers study liquidity commonality and comparability of liquidity across exchanges. Few have used high frequency quote data (Brauneis et al., 2021; Dimpfl and Maeckle, 2020; Dyhrberg et al., 2018; Hautsch et al., 2021; Makarov and Schoar, 2020 and Marshall et al., 2019). Of these papers, only Dimpfl and Maeckle (2020) and Marshall et al. (2019) focus on liquidity directly. Our paper complements the previous studies by describing liquidity using high frequency measures across three large exchanges for a time period after cryptocurrencies became mainstream.

Moving past a simple description of liquidity levels we analyze the determinants of liquidity on each exchange using consolidated data across exchanges. These data are then used to answer a series of questions motivated by previous studies (e.g. Karnaukh et al. (2015) in FX markets and Liu and Tsyvinski (2021) for cryptocurrency risk and returns). We identify four categories of variables that may be related to bitcoin market liquidity: (1) general financial market variables, (2) global cryptocurrency variables, (3) blockchain-related variables and (4) local (exchange-specific) variables. The concrete questions are: are local (exchange specific) factors more important than global factors? Do financial markets, or financial market liquidity, affect cryptocurrency liquidity? Do blockchain variables such as mining fees or measures of blockchain congestion affect liquidity?

Following Karnaukh et al. (2015) we perform our analysis separately for subsets of explanatory variables and together in a full model that includes statistically significant variables from each subset. By isolating a set of candidate variables before testing them in a joint model, we reduce over-fitting and multicollinearity.

If bitcoin were like other financial instruments such as equity or foreign exchange (FX), an in-depth analysis of bitcoin would add little insight. However, there are important differences between cryptocurrencies in general and bitcoin in particular with respect to other financial instruments. It is plausible that these differences affect the determinants of bitcoin liquidity. Unlike FX and many equity markets, cryptocurrency markets are often populated by small and potentially unsophisticated investors. These markets are mostly unregulated. In particular, there is no regulation (such as the no trading through-rule in the US equity markets) that guarantees best execution of investor orders or guarantees that orders with the best price execute before order with worse prices at different exchanges. As a consequence, liquidity differences between different venues may be larger and more persistent in cryptocurrency than in equity markets. There are no trading halts because cryptocurrency exchanges are open 24 h a day, seven days a week. Relative tick sizes for bitcoin are lower by orders of magnitude than those in equity markets.[2] All traders can access the market directly rather than submitting their orders through a broker.

Another difference is that for most assets, market participants cannot view the ledger. For instance, in equity markets, we do not know how many investors, or accounts, hold an asset, how often those assets are transferred between owners, and how long it takes for a transaction to clear. Redditers devote massive amounts of time trying to estimate short positions, fails-to-deliver, and other ledger statistics. Clearly ledger statistics are relevant in all asset markets, but in cryptocurrency markets the central ledger is transparent. We generate economically relevant ledger (blockchain) statistics (unavailable in equity and FX markets) and test if and how they relate to the liquidity on exchanges.

Cryptocurrency exchanges generally settle transactions between buyers and sellers using their own wallets (rather than settling them through a centralized institution such as the DTCC) and thus do not use the blockchain. However, the speed with which bitcoins can be transferred on the blockchain and the cost of the transfer are still important. A simple example is with respect to cross-exchange arbitrage and liquidity provision. A trader wishing to trade on several venues needs to establish a relation with each venue she wants to trade at. Additionally, she needs to either maintain inventories of fiat currency and/or cryptocurrency at each venue, or she needs to transfer funds between venues. However, even the fastest blockchain transaction can take 10 min to clear, making arbitrage and liquidity provision opportunities more costly to exploit than in traditional markets (on this see Hautsch et al., 2021). This, in turn, may result in liquidity depending more on "local" (i.e., venue-specific) than on global factors.

Our analysis yields important and sometimes surprising findings. Relative quoted spreads on Coinbase Pro and Bitfinex are lower than those in highly liquid and well established equity markets, partly because of the existence of the minimum tick size. A 1-cent tick size on a $10 stock implies that the smallest admissible bid–ask spread is 10 basis points (bp), higher than the average BTCUSD spread on all three cryptocurrency exchanges during our sample period. While spreads are low, we find large differences across exchanges. Average quoted spreads (effective spreads) range from 0.52 (1.33) bp at Coinbase Pro to 7.11 (7.76) bp at Bitstamp. We

[2] In equity markets the spread is constrained by the 1-cent tick size (Rindi and Werner, 2017). The minimum tick size in the bitcoin exchanges under investigation is USD 0.01 (Bitstamp and Coinbase Pro) and USD 0.1 (Bitfinex), respectively. Because the BTC price is much higher than the price of a typical stock the tick size in relative terms is much smaller than it is on US equity exchanges and, consequently, it is much less of a constraint.

further find that the effective spread is larger than the quoted spread. This suggests that cryptocurrency market participants either do not time their trades with liquidity, or that they regularly submit orders that are larger than the available liquidity at the best prices. This is in contrast to equity markets where the quoted spread is often higher than the effective spread (e.g. Huang and Stoll, 1996; Hendershott and Moulton, 2011; Riordan and Storkenmaier, 2012, or Chung and Chuwonganant, 2014). Unlike for spreads, the average price impact[3] is roughly the same across the three exchanges, ranging from 0.70 to 1.03 bp.

When analyzing the determinants of liquidity we find that blockchain variables such as mining fees and local (trading venue-specific) variables such as past turnover determine bitcoin liquidity. Bitcoin liquidity decreases with higher volatility, a result which is consistent with standard theories of liquidity provision in financial markets. The relation between current and lagged cryptocurrency liquidity is negative, implying negative serial correlation in liquidity. Interestingly, it appears that bitcoin liquidity is detached from the conditions on other financial markets. Equity market returns, volatility, or liquidity do not significantly affect bitcoin liquidity. Variables relating to FX market activity are significant when considered in isolation but are insignificant once the full set of explanatory variables is included. The result that general financial market variables do not appear to affect bitcoin liquidity stands in contrast to the findings of Karnaukh et al. (2015) for the FX market.[4]

How should we interpret the finding that bitcoin liquidity is unrelated to general financial market variables? Does it imply that standard microstructure theory is not applicable to cryptocurrencies in general or bitcoin in particular? We find that this conclusion is not supported by the data. Market microstructure theory has presented numerous predictions on the source of the bid–ask spread. For instance, Garman (1976), Stoll (1978), Amihud and Mendelson (1980) and Grossman and Miller (1988) show that the spread arises due to the inventory holding costs of intermediaries. Our finding that bitcoin liquidity is negatively related to mining fees is consistent with these inventory models because higher mining fees make it more expensive to shift inventories between trading venues. Glosten and Milgrom (1985) and Kyle (1985) highlight losses associated with trading with more informed investors as the main driver of the bid–ask spread. As noted above we compute price impacts and show that they are non-negligible and a large component of the bid–ask spread. This suggests that adverse selection costs play an important role in liquidity provision on cryptocurrency exchanges. Thus, it appears that established microstructure theory is applicable to cryptocurrency markets. However, it also appears that the variables driving inventory holding costs and informational asymmetries in cryptocurrency markets are independent of those variables that drive inventory holding and adverse selection costs in equity and FX markets.

The remainder of the paper is organized as follows. Section 2 presents institutional details. Section 3 describes the data and descriptive statistics and Section 4 our results. We conclude and discuss future work in Section 5.

2. Institutional details

The idea of the Bitcoin protocol is that transfers of BTC occur via a public blockchain. In contrast, exchanges transfer bitcoin ownership without reporting it on the blockchain because all transactions are settled by the exchange. We refer to these transactions as *off-chain* transactions (as opposed to *on-chain* transactions which are reported on the blockchain). The total volume of BTC transactions is the sum of off-chain and on-chain volume. While data on aggregated exchange volume (i.e., off-chain volume) is readily available (e.g. on coinmarketcap.com), the on-chain volume may only be estimated.[5] We obtain volume estimates from blockchain.info. Fig. 1 shows that the proportion of off-chain volume fluctuated considerably at around 30% from 2014 until early 2017. With the start of the bitcoin bull market in 2017 off-chain volume has taken the leading part. By the end of our sample period (mid-December 2019) the total exchange volume amounts to a meanwhile stable proportion of almost 95% of total volume. This means that for every blockchain-reported transfer of one bitcoin there are exchange transfers of approximately 19 bitcoins at the same time, highlighting the tremendously increasing importance of exchanges.[6]

We collect data from three of the largest cryptocurrency spot trading platforms that trade bitcoin against the US dollar (BTCUSD): Bitfinex,[7] Bitstamp and Coinbase Pro. Note that we use fiat instead of tokenized USD. Our investigation extends over the period

[3] The price impact measures the change in the quote midpoint from immediately prior to a trade until a specified time after the trade and is a measure of adverse selection costs borne by the submitter of limit orders. See Section 3.2 for details of the calculation.

[4] It is consistent, though, with the results of Liu and Tsyvinski (2021) who report that the exposures of cryptocurrency returns to traditional asset classes (currencies, commodities, stocks) is low.

[5] This is due to the fact that the protocol of the Bitcoin Blockchain requires users to fully use their funds in every transaction, a mechanism called unspent transaction output (UTXO). If, for example, a user's balance amounts to 10 BTC, a transaction of 1 BTC to another address in the network consists of one transaction with a value of 10 BTC and another transaction with a value of 9 BTC, returned to the sender (but possibly to a different wallet of the sender; the returned amount is referred to as change). The gross volume thus is 10 BTC, effectively, only 1 BTC changes hands. See Cole et al. (2022) for an empirical analysis of the consequences of the UTXO mechanism in the Bitcoin Blockchain on transaction volume, transactions costs and unique user counts.

[6] This number should be treated with some caution. As some authors (e.g. Hougan et al., 2019; Cong et al., 2021) report, several exchanges artificially inflate trading activities by charting fake or non-economic trading volume to attract investors and increase their revenues. According to Hougan et al. (2019), however, the three exchanges analyzed in our study are among the most reliable platforms for reporting real volumes.

[7] In early October 2018 and coinciding with the decision of the platform to cut banking partnership with Caribbean-based banking partner Noble Bank International, rumors circulated in the markets that Bitfinex was in financial distress. Clients reported that they were no longer able to withdraw their fiat money from the platform. Bitfinex rejected this accusation in a notice to investors. However, in the following months customers on Bitfinex had to pay a substantial higher BTC price compared to other cryptocurrency exchanges. Market participants attributed this risk premium to the fact that the majority of BTC trading on Bitfinex has been against Tether, a so-called stablecoin which is supposed to be backed by an equivalent amount of traditional fiat currencies (e.g. Tether tokens backed by USD trade under the symbol USDT). Persistent rumors about possible market manipulations with Tether kept the BTC price on Bitfinex above average spiking at the end of April/beginning of May 2019 when Bitfinex and Tether Limited (the issuer of Tether) were accused by the New York Attorney General for not having publicly disclosed the loss of funds totaling USD 851 million. The price deviation subsided mid-May 2019 when the court determined the preliminary injunction to be reworded in order not to restrain Bitfinex's ordinary business.

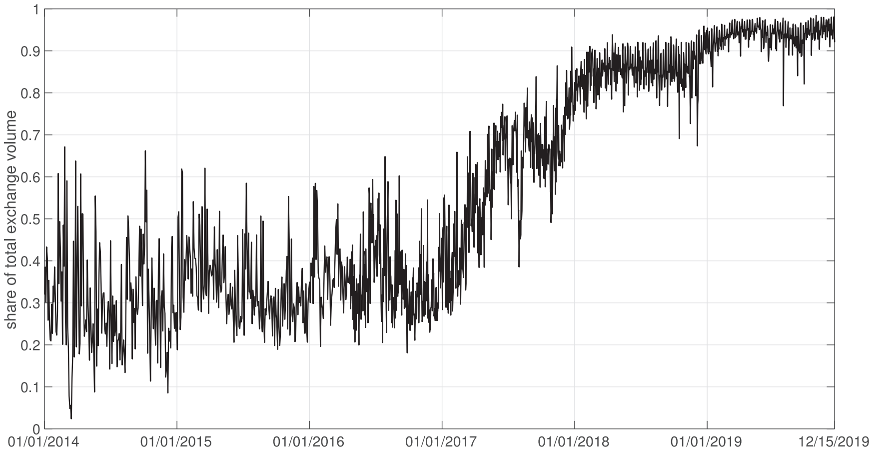

Fig. 1. Share of exchange transferred bitcoins to total bitcoin volume defined as exchange volume plus blockchain volume. Aggregate exchange volume stems from coinmarketcap.com, (estimates of) on-chain volume is taken from blockchain.info. Investigation period: 01/01/2014 to 12/15/2019.

December 15, 2017, to December 15, 2019. In the following we describe the institutional setting in place during our sample period. All platforms operate a fully electronic central limit order book with orders being matched based on price–time priority. They all specify a minimum order size and a rule for the smallest admissible price increment (the minimum tick size).

All three exchanges charge fees for executed orders, and they all have schedules in place where the fee is a decreasing function of the cumulative volume a customer executed during the previous 30 days. Bitfinex and Coinbase Pro operate maker/taker fee schedules where the fee for executed limit orders is lower (on Coinbase Pro in fact zero until March 2019) than the fee for executed market orders. Bitstamp, in contrast, operates a unified fee that is equal for executed limit and market orders. All three exchanges have revised their fee schedules during our sample period. These changes usually implied increasing fees for small customers and decreasing fees for large customers.[8] Towards the end of our sample period traders with USD equivalent trading volume below USD 10K during the previous 30 days were charged 0.5% on Bitstamp and Coinbase Pro. In contrast, the fee for executed limit orders submitted by high-volume customers approaches zero on all three exchanges. Bitstamp charges no fee at all, neither from liquidity providers nor from liquidity takers, in the largest volume bracket (cumulative volume above USD 10 billion a month), probably based on the belief that these traders attract sufficient trading interest from lower-volume customers to compensate for the lost fee revenue.

Contrary to popular belief that cryptocurrency exchanges are completely unregulated the exchanges we survey are regulated to a certain extent (not comparable, however, to the degree of regulation of traditional exchanges). Hougan et al. (2019) report that the three exchanges have registered in the US as Money Services Businesses (MSBs) with the Financial Crimes Enforcement Network (FinCEN) of the US Treasury Department. Among other things, FinCEN requires all MSBs to develop and implement a formal program to comply with anti-money-laundering regulations on the one hand and to report suspicious transactions or pattern of transactions in a separate activity report on the other hand. The exchanges under consideration also implemented formal market surveillance tools in 2018 that help detect market manipulations (like spoofing or wash trading). Moreover, Coinbase Pro was one of the first cryptocurrency exchanges to obtain a BitLicense from New York State Department of Financial Services.[9] The exchange also received an E-Money License from the UK Financial Conduct Authority in March 2018. Europe-based Bitstamp holds a license by the Luxembourg authorities to act as a payment institution allowing it to do business in all EU member states. The high reliability of trading activities on Coinbase Pro and Bitstamp is also reflected in the fact that these two exchanges have been among the constituent exchanges contributing data to the bitcoin reference rate underlying the CME bitcoin futures contract since it was listed in December 2017.[10]

3. Data and methodology

We compiled a high-frequency data set that covers the period from 12/15/2017 06:00 UTC to 12/15/2019 06:00 UTC, a total of $T = 1,051,200$ minutes. Over this period we used Matlab to continuously access the public and freely accessible REST API of

[8] Brauneis et al. (2022) investigate the introduction of maker fees and the simultaneous reduction in taker fees on Coinbase Pro in March 2019. This fee change increased total fees in cases where liquidity providers are low-volume traders while total fees decreased in cases where liquidity providers are high-volume traders. The authors find that quoted spreads increased (reflecting the increased maker fees), but this increase was overcompensated by the reduction in taker fees. Thus, while the visible execution costs increased, the total (cum-fee) execution costs decreased. Moreover, quoted depth and the number of transactions decreased post-change.

[9] Introduced in 2015, this regulatory framework governs digital-asset businesses acting as financial intermediaries in the state of New York and imposes higher regulatory requirements on regulated entities than the MSB license (e.g. concerning compliance, capital requirements or reports and financial disclosures). Bitstamp received its BitLicense in April 2019.

[10] Besides Bitstamp and Coinbase Pro, Kraken is the only cryptocurrency exchange continuously serving as a pricing source for the calculation of the reference rate since the introduction of the bitcoin futures contracts. See https://docs-cfbenchmarks.s3.amazonaws.com/CME+CF+Constituent+Exchanges.pdf; retrieved Jul. 30, 2022.

Table 1
Description of transactions and order book data for each exchange. The upper part reports the total number of transactions (numTx), the average time between two transactions (avg interim time; seconds), and the percentage of total transactions which are buyer initiated according to the trade indicator variable provided by the respective exchange (trade indicator Buy) as well as the average daily US dollar trading volume (avg daily US dollar volume). The lower part shows the number of order book snapshots (numOB snapshots) and the average time between two order book snapshots (avg interim time; seconds). Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

	Bitfinex	Bitstamp	Coinbase Pro	Overall
numTx	37,294,875	15,370,056	38,326,499	90,991,430
avg interim time (seconds)	1.6945	4.1116	1.6489	
trade indicator Buy	48.25%	56.45%	60.08%	
avg daily US dollar volume	196 m	90 m	111 m	
numOB snapshots	7,286,485	6,927,923	8,201,285	22,415,693
avg interim time (seconds)	8.6730	9.1219	7.7056	

Bitfinex, Bitstamp and Coinbase Pro. They provide live information on transactions and the current state of the order book. All public endpoints at each of these exchanges use GET requests for different types of information. We basically request records on ‘Trades’ / ‘Transactions’ and the ‘Orderbook’. Depending on the exchange, request parameters vary. For instance, Bitstamp only provides the full order book (with usually thousands of entries) whereas order book requests at Bitfinex and Coinbase Pro may be limited to the 50 best price levels on each side of the market. We performed a brief test of server response times (the time elapsed between the API call, the server’s response and saving the data locally). For a sample of 1,000 requests (in May 2018) Bitfinex on average responds within 0.34 s (0.33 s) on a transactions (order book) request. The corresponding values for Bitstamp (Coinbase Pro) are 0.22 s and 0.49 s (0.88 s and 0.91 s) for transaction and order book requests, respectively.[11]

As mentioned in Section 2 (see footnote 7) bitcoin prices on Bitfinex deviated from those on other trading venues between autumn 2018 and spring 2019 due to concerns about Bitfinex‘ solvency and rumors about market manipulation by the platform and Tether Limited. We therefore created a second data set by cutting the period from September 15, 2018, to May 31, 2019. We re-ran our entire analysis for this shortened time period. We obtained results that are qualitatively similar to those for the entire sample period. Therefore, we only report results for the latter.[12]

3.1. Transaction and order book data

We record an overall number of transactions during our sample period of over 90.99 million. For each transaction the data set includes the price and the corresponding trading volume, a UNIX time stamp, a unique exchange-specific ID and a trade indicator which indicates whether a transaction was buyer-initiated or seller-initiated. The upper part of Table 1 provides a short description of this data. The total number of transactions ranges from 15.37 million (corresponding to one transaction every 4.11 s) on Bitstamp over 37.29 million transactions (one transaction every 1.69 s) for Bitfinex to 38.33 million transactions (one transaction every 1.65 s) for Coinbase Pro. The fraction of buyer-initiated trades is less than 50% (at 48.25%) on Bitfinex and is above 50% (at 56.45% and 60.08%, respectively) on Bitstamp and Coinbase Pro. The average daily dollar trading volume ranges from USD 90 million (Bitstamp) to USD 196 million (Bitfinex). We observe several time intervals with gaps in the data. These may be due to actually missing trading activity, technical problems (failure of the internet connection, no response from the server etc.), or exchange-specific trading halts (e.g. due to maintenance, updates or hacker attacks). We identify between 6,329 (Coinbase Pro) and 54,911 (Bitstamp) intervals exceeding 1 min, between 2,825 and 3,126 intervals exceeding 10 min and between 1,724 and 2,027 intervals exceeding 30 min without transaction data.

Besides transactions we retrieve order book data from the three trading platforms. Specifically, we collect the 50 best bid and best ask prices with corresponding volumes. As for transaction data the frequency at which this information is available depends on server response times and the speed of the internet connection. As can be seen from the lower panel of Table 1 we collect between 6.93 million (Bitstamp) and 8.20 million (Coinbase Pro) UNIX time-stamped order book snapshots. On average, across the three exchanges, order book data is obtained every 8.5 s.

The 50 price levels that each snapshot contains represent considerable volume. For Bitfinex the mean total bid (ask) dollar volume amounts to USD 0.85 million (USD 0.85 million), for Bitstamp the 50 best bid orders (ask orders) on average sum up to USD 1.16 million (USD 1.12 million) and for Coinbase Pro the mean total dollar volume in bid (ask) orders amounts to USD 0.58 million (USD 0.61 million).

We sort the irregularly spaced raw data into one-minute intervals. We use the following notation. $P^b_{t,i}$ ($P^a_{t,i}$) refers to the best bid (best ask) of order book snapshot i in interval t, and $m_{t,i}$ denotes the quote midpoint. For each one-minute interval $t \in \{1, \dots, T\}$ we compute liquidity measures based on the first order book snapshot observed in that interval (i.e. we set i equal to 1). Since some of our liquidity measures (such as the price impact) also require data on subsequent transactions, the first order book of the interval is the best choice. $P_{t,j}$ denotes the price of transaction j in interval t.

[11] The data is timestamped by the respective exchange, i.e. we still get correct timestamps for transactions and order book snapshot even if the API call may take some seconds to complete.

[12] The results for the shortened sample period for the encompassing model (see Section 4.3) are available in the online appendix.

We include in our analysis only intervals for which we observe at least one sequence consisting of a first order book snapshot, followed by at least one transaction and a second order book snapshot thereafter. Applying this filter rule to the total number of 1,051,200 one-minute intervals results in 792,388/775,733/809,119 one-minute intervals for Bitfinex/Bitstamp/Coinbase Pro. The reduction in the sample size is due to cases in which there is either no transaction recorded during the one-minute interval, or in which one (or several) transactions are not preceded and/or followed by an order book snapshot within the one-minute interval. We refer to this data set as the exchange-specific data set because it contains, for each exchange, all one-minute intervals with complete information for that exchange. We further compile a synchronized, or synced, data set that only contains those one-minute intervals for which complete information is available for all three exchanges. This data set contains 702,788 one-minute intervals.

3.2. Liquidity measures

We provide an extensive analysis of the liquidity on the three bitcoin exchanges under investigation. Based on the one-minute interval data, we calculate the following standard measures of liquidity:

1. Percentage Quoted Spread QS. For interval t, this measure is defined as $QS_t = \frac{P^a_{t,1} - P^b_{t,1}}{m_{t,1}}$
2. Percentage Effective Spread ES. For interval t, the effective spread is defined as $ES_t = 2 \cdot Q_{t,j'} \cdot \frac{P_{t,j'} - m_{t,1}}{m_{t,1}}$, where j' refers to the first transaction after the order book snapshot was recorded and $Q_{t,j'}$ is a trade indicator variable ($Q_{t,j'} = 1$ for a buyer-initiated trade, $Q_{t,j'} = -1$ for a seller-initiated trade).[13]
3. Percentage Price Impact PI. We consider the first transaction that occurs after the order book snapshot and record the sign of the transaction. We then consider the quote midpoint $m_{t,i+1}$ from the next order book snapshot. The price impact for interval t is then calculated as $PI_t = \frac{Q_{t,j'} \cdot (m_{t,i+1} - m_{t,i})}{m_{t,i}}$. As a robustness check we also calculate one-minute price impacts using the first order book snapshots of two consecutive one-minute intervals with similar results (although mean and median price impacts are slightly higher).
4. Average BBO Depth $AvgD$. Depth for interval t is defined as $AvgD_t = \left(P^a_{t,1} \cdot V^a_{t,1} + P^b_{t,1} \cdot V^b_{t,1} \right)/2$, where $V^{a(b)}_{t,1}$ denotes the volume associated with the best ask and bid price, respectively.
5. US dollar Volume DV. For interval t, volume is defined as $DV_t = \sum_j P_{t,j} \cdot V_{t,j}$, where $V_{t,j}$ is the amount of bitcoins traded in transaction j.
6. Number of transactions $numTx$. This measure is defined as the total number of individual transactions observed in interval t.
7. Order Imbalance OI. For interval t, order imbalance is defined as
$OI_t = \frac{\sum_{j,Q_{t,j}=1} Q_{t,j} - \sum_{j,Q_{t,j}=-1} |Q_{t,j}|}{\sum_j |Q_{t,j}|}$.
8. Order Imbalance Volume OIV. For interval t, this measure is defined as
$OIV_t = \frac{\sum_{j,Q_{t,j}=1} P_{t,j} \cdot V_{t,j} - \sum_{j,Q_{t,j}=-1} P_{t,j} \cdot V_{t,j}}{\sum_j P_{t,j} \cdot V_{t,j}}$.

The quoted bid–ask spread is a valid measure of execution costs only for small trades, i.e. trades the size of which does not exceed the depth available at the best quotes. Larger market orders will walk up or down the book and will thus partly execute at worse prices. To assess the liquidity of the bitcoin markets for larger trades we use the order book data to calculate the weighted average price WAP at which a buy and a sell order of a given size USD Y would execute. Given the current order book for interval t, WAP_t is defined as $\frac{\sum_{j=1}^{J} A_j \cdot V_j}{\sum_{j=1}^{J} V_j}$ subject to $\sum_{j=1}^{J} A_j \cdot V_j = Y$ where A_j denotes the jth order in the order book, and A_j, V_j are the price and volume of the jth order, respectively. Note that the Jth order may be subject to partial execution, depending on the outstanding US dollar volume required to entirely fill the transaction volume Y. We calculate WAP for different order sizes. Specifically, we set Y equal to USD 500, USD 2,000, USD 40,000, and USD 100,000. These values roughly correspond to the median, the third quartile, the 99% and the 99.8% quantiles of the (aggregated) trade size distribution. We then calculate, separately for each trade size category, the difference between the weighted average prices of a buy and a sell order of the same size and express it as a percentage of the midpoint between these two prices. We refer to this measure as the percentage cost of a roundtrip trade (CRT, Irvine et al., 2000).[14]

9. Percentage cost of a roundtrip trade CRT. Given the weighted average prices (denoted WAP^b_t and WAP^a_t) in interval t for a buy and sell market order with given volume, the CRT_t in that interval is defined as:
$CRT_t = \frac{WAP^a_t - WAP^b_t}{0.5 \cdot (WAP^a_t + WAP^b_t)}$

4. Results

We present our results in three steps. We first provide evidence on the trading activity on the bitcoin exchanges and document its intra-day patterns. This is important because the exchanges operate 24 h a day. Thus, in contrast to equity markets, there are no

[13] The median delay between the first order book snapshot and the first transaction thereafter is 2s for Bitfinex, 2.8s for Coinbase Pro and 3s for Bitstamp.

[14] Following van Kervel (2015) we calculated another measure of the liquidity beyond the best quotes by aggregating the value (in USD) of bitcoins tradable at prices within the midpoint plus (minus) X basis points on the ask (bid) side. For X we choose 25, 50, and 100 basis points, respectively. When using this cumulative depth measure in our regression analysis (see Section 4.3) we obtain results which are very similar to those obtained using the CRT measure. These results are presented in the online appendix.

Table 2
Descriptive statistics for one-minute intervals for number of transactions (numTx), US dollar volume (DV), average trade size (based on the full record of transactions), order imbalance (OI), order imbalance volume (OIV) and volatility. Vola [prices/midpoints] refers to the standard deviation of the percentage change of transaction prices and quote midpoints, normalized to 60 s, respectively. The upper panel reports results for exchanges' individual data with a varying number of intervals with full data availability. The lower panel reports results for the synced data set with full availability of data for all three exchanges. Numbers refer to the mean except for total number of intervals, the median is reported in parentheses. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

	Bitfinex	Bitstamp	Coinbase Pro
Individual exchange data, numbers report mean (median)			
Total num intervals	792,388	775,733	809,119
numTx	45.75 (22)	19.64 (11)	46.66 (32)
DV [USD 1,000]	136.32 (28.85)	62.45 (16.76)	76.99 (22.34)
average trade size [USD]	2,928 (500)	3,088 (354)	1,623 (140)
Vola [prices; bp]	13.23	14.41	12.46
Vola [midpoints; bp]	13.69	12.46	13.19
OI	−0.02 (0.00)	0.18 (0.20)	0.28 (0.36)
OIV	−0.00 (−0.00)	0.13 (0.20)	0.13 (0.18)
Synced data $N = 702,788$ intervals, numbers report mean (median)			
numTx	48.61 (24)	20.49 (12)	48.85 (33)
DV [USD 1,000]	145.85 (33.26)	65.25 (18.29)	83.28 (25.57)
Vola [prices; bp]	13.70	14.54	12.92
Vola [midpoints; bp]	14.12	12.61	13.17
OI	−0.02 (0.00)	0.17 (0.20)	0.27 (0.34)
OIV	−0.00 (−0.01)	0.12 (0.18)	0.12 (0.17)

trading halts overnight. The second subsection provides a descriptive analysis of the levels and time-series patterns of liquidity. While liquidity is usually considered to be an important determinant of market quality, little is known on the liquidity of bitcoin exchanges. In the final subsection we analyze the determinants of liquidity in a regression framework. The results will reveal whether, and to which extent, liquidity in bitcoin markets is related to prices and liquidity in other financial markets, such as equity and foreign exchange markets. In addition, they will reveal whether liquidity on the three bitcoin exchanges under consideration is driven by blockchain-specific and exchange-specific (local) factors.

4.1. Trading

We start with results on trading activity on the three cryptocurrency exchanges. The upper part of Table 2 shows that the average one-minute number of transactions ranges from 19.64 (Bitstamp) to 46.66 (Coinbase Pro). The average dollar volume for single transactions is lowest on Coinbase Pro (USD 1,623) and highest on Bitstamp (USD 3088).[15] The trade size distribution is heavily skewed, as evidenced by the large difference between the mean and median volumes.

We estimate one-minute price volatility based on returns calculated from the first observed transactions in each interval, i.e., $|\ln(P_{t,1}/P_{t-1,1})|$. We normalize this volatility estimate by the factor $\sqrt{(60/timegap)}$, such that, irrespective of the actual time elapsed between two transactions, we obtain an estimate of the sixty-second-volatility. We estimate a similar volatility measure based on quote midpoints. We find price volatility to be highest on Bitstamp (14.41 bp) and lowest on Coinbase Pro (12.46 bp). Midpoint volatility is similar to price volatility on Bitfinex and Coinbase Pro, but markedly lower than price volatility on Bitstamp. The discrepancy between price volatility and midpoint volatility on Bitstamp may be an indication of high bid–ask spreads on this exchange. We return to this issue in Section 4.2.

The lower part of Table 2 displays results for trading activity and volatility based on the synchronized data set. They are almost identical to those obtained from the exchange-specific data sets.

The last two lines of Table 2 show the order imbalance based on the number of transactions (OI) and the USD volume (OIV). Both imbalance measures are close to 0 on Bitfinex. On Bitstamp and Coinbase Pro, on the other hand, both are positive. This finding is consistent with our earlier result that the fraction of buyer-initiated trades is above 50% on Bitstamp and Coinbase Pro while it is slightly below (but close to) 50% on Bitfinex.

Fig. 2 shows how trading activity and volatility evolve over the time of the day (in UTC time).[16] Similar to Dyhrberg et al. (2018) we find daily trading activity to peak at 17:00 UTC. This roughly coincides with the market opening on NYSE and NASDAQ in US

[15] We note that some trades observed in our dataset are not in line with the minimum order size rules reported on the exchanges' websites. This is most likely due to partial executions being reported as multiple transactions in the data. We observe several transactions with a size of 1 Satoshi (1/100mio BTC).

[16] We also investigated for our four measures of trading activity temporal patterns over the days of the week. All measures show little variation between Tuesday and Friday but are markedly lower on Saturdays and Sundays, and slightly lower on Mondays. A graphical representation of these results can be found in the online appendix.

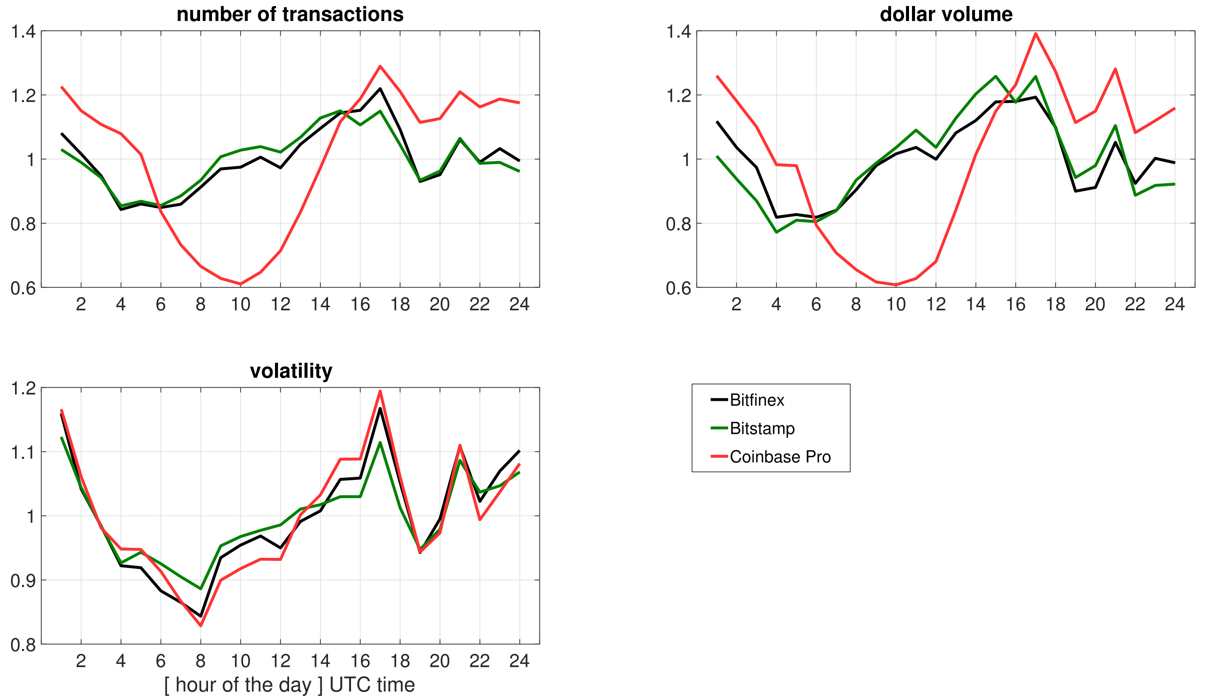

Fig. 2. Temporal patterns over the course of one day, covering hours 1 to 24 in UTC time. All subplots depict relative deviations from the overall mean. The upper left subplot shows the number of transactions, the upper right subplot plots the US dollar volume, the lower plot refers to volatility respectively. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

equity markets but is one hour before the 4 pm London foreign exchange fix during which benchmark prices for many currency pairs are determined (on this see Melvin and Prins (2015)). The final settlement price for the bitcoin futures contract traded on the Chicago Mercantile Exchange is also determined at 4 pm London time.[17] We observe the lowest trading activity between 04:00 and 06:00 UTC on Bitfinex and Bitstamp and between 09:00 UTC and 11:00 UTC on Coinbase Pro. Volatility is lowest around 08:00 UTC on all three venues.

4.2. Liquidity

In this section we provide an in-depth analysis of percentage quoted and effective bid–ask spreads, price impacts and the cost of a roundtrip trade on the three trading venues under investigation.[18]

The results, shown in Table 3 were obtained using the synced data set. Quoted and effective bid–ask spreads indicate that Coinbase Pro and Bitfinex are the most liquid platforms. The mean quoted spread on Coinbase Pro (0.52 bp) is moderately lower than that on Bitfinex (0.82 bp), while the latter has a slightly lower mean effective spread (1.29 bp) than Coinbase Pro (1.33 bp). Spreads on Bitstamp, in contrast, are larger by an order of magnitude, at 7.11 bp (quoted spread) and 7.76 bp (effective spread).[19] To put these results into perspective, consider a stock trading at USD 40. Given the minimum tick size in US equity markets the smallest admissible quoted spread for this stock is USD 0.01. Given a stock price of USD 40 a 1 cent spread corresponds to 2.5 bp.

[17] The final settlement price for the futures contract traded on the CBOE (discontinued in 2019) was determined at 3 pm central time. The daily settlement prices on both CME and CBOE are determined at the end of the regular trading hours in the US, around 8 pm London time. The prices that are used to calculate the CRIX cryptocurrency index (Trimborn and Härdle, 2018) are determined at 12:00 UTC.

[18] Note that descriptive statistics for the other liquidity measures defined in Section 3.2, US dollar volume, number of transaction, and the two order imbalance measures, were already provided in Table 2.

[19] Dimpfl and Maeckle (2020) report that spreads on Kraken, another large cryptocurrency exchange, are of a similar order of magnitude than those on Bitstamp. They report an average quoted spread of 7.865 bp for a sample covering April 2017 to February 2019. Because of the higher execution costs on Bitstamp (and similarly so on Kraken) traders may want to avoid this venue. However, there is a number of reasons why there is still significant trading activity on Bitstamp. The majority of transactions are small. The median trade size on Bitstamp is 354 USD and the median quoted spread amounts to 5.9 bp over our sample period. These numbers imply that the execution costs for a median-sized trade on Bitstamp are 0.104 USD (354 USD multiplied by the half-spread). Traders may consider this cost to be negligible. In addition, other frictions exist. Cryptocurrency exchanges differ in the ways how traders can transfer and withdraw fiat money to and from their accounts. These differences result in cost and speed differences between the trading venues. Furthermore, not all traders can freely choose where to trade. As a case in point, during our sample period Bitfinex did not accept US residents as customers. Finally, traders may prefer to trade on a venue in their home country, e.g. because they are more familiar with its legislative regime.

Table 3
Descriptive statistics for liquidity measures derived from the synced data set. QS, ES, PI and CRT refer to percentage quoted spread, effective spread, price impact and cost of a roundtrip (for volumes of USD 500, USD 2000, USD 40,000 and USD 100,000), respectively, all measured in basis points ([bp]). AvgD is the average BBO depth and is reported in USD thousand. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

	Bitfinex			Bitstamp		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
QS [bp]	0.82	0.19	1.84	7.11	5.90	6.19
ES [bp]	1.29	0.21	5.73	7.76	6.07	8.26
PI [bp]	0.61	0.00	4.66	0.87	0.02	5.55
CRT 500 [bp]	1.01	0.25	2.02	7.80	6.56	6.45
CRT 2k [bp]	1.29	0.37	2.27	8.50	7.25	6.78
CRT 40k [bp]	4.86	4.13	4.31	15.39	13.76	8.93
CRT 100k [bp]	9.49	8.65	6.31	21.97	19.55	10.81
AvgD [USD 1,000]	43.46	23.74	98.65	13.92	7.26	42.80
	Coinbase Pro			Exchange average		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.
QS [bp]	0.52	0.01	1.96	2.82	2.36	2.39
ES [bp]	1.33	0.01	6.57	3.46	2.64	4.37
PI [bp]	0.49	0.00	4.47	0.66	0.17	2.95
CRT 500 [bp]	0.81	0.01	2.25	3.21	2.73	2.56
CRT 2k [bp]	1.07	0.02	2.51	3.62	3.13	2.75
CRT 40k [bp]	4.07	3.20	4.55	8.11	7.29	4.34
CRT 100k [bp]	7.93	6.83	6.51	13.13	11.78	6.04
AvgD [USD 1,000]	67.57	45.16	74.60	41.65	31.48	44.92

We therefore conclude that the percentage quoted spread of an average-priced stock in the US equity market, even if that stock trades at a 1 cent spread, is three to five times higher than the quoted bitcoin spreads on Coinbase Pro and Bitfinex.[20]

Table 3 also reveals that effective spreads are higher than quoted spreads on all three venues. Such a result may obtain when the size of market orders exceeds the depth available at the best bid or ask quote and therefore the orders walk up or down the book. In fact, Dyhrberg et al. (2022) report that, due to the economically insignificant tick sizes and the extensive use of trading bots quoting very small order sizes, undercutting is very frequent on cryptocurrency exchanges. The undercutting, in turn, results in very narrow top-of-book quoted spreads while even small market orders (e.g. USD 500) might walk up or down the order book, resulting in higher effective spreads. Our findings support their argument.

The two upper panels of Fig. 3 plot the quoted and effective spread, separately for each exchange, over time. The graphs reveal that both quoted and effective spreads have decreased over time. The figure confirms the ranking of the three exchanges (i.e. spreads are similar on Coinbase Pro and Bitfinex but are markedly and consistently higher on Bitstamp), and shows that this ranking is stable throughout the sample period. The lower average quoted spreads on Coinbase Pro documented in Table 3 above appear to be due to the first part of the sample period. From mid-2018 onward quoted spreads on Coinbase Pro and Bitfinex are hardly distinguishable.

The effective bid–ask spread can be decomposed into the price impact and the realized spread. The former measures the losses of liquidity suppliers to traders with superior information. The middle left panel of Fig. 3 shows the price impact (calculated as described in Section 3.2) for the three exchanges. It is lowest on Coinbase Pro (mean 0.49 bp), followed by Bitfinex (0.61 bp) and Bitstamp (0.87 bp). These values are much closer to each other than those for the quoted and effective spreads presented above, implying that differences in adverse selection costs do not explain the spread differences between the exchanges. The price impact is roughly half of the effective spread at Bitfinex and Coinbase Pro, and a little less than one tenth of the effective spread at Bitstamp. These results suggest that liquidity supply is very profitable on Bitstamp and less profitable on the two other trading venues.

The difference between the effective half-spread and the price impact (known as the *realized half-spread*) is an estimate of the gross revenue of the suppliers of liquidity. Realized half-spreads are positive on Coinbase Pro (at 1.33/2 - 0.49 = 0.17 bp), virtually zero on Bitfinex (0.03 bp) and large and positive on Bitstamp (3.01 bp). Some of these differences may be explained by differences in the fee schedule of the three trading venues. Unfortunately we cannot perform a more detailed analysis for two reasons. First, as explained in Section 2, the fee schedules depend on the total volume transacted by a trader during a 30-day window, which we do not observe. Second, there have been several changes to the fee schedules during our sample period. We note, though, that the differences in the quoted, effective and realized spreads between Bitstamp and the other two venues are much too large to be explained by differences in execution fees.

The depth at the best quotes measures the average volume (in USD) that can be traded at the current best bid and ask prices. It is highest on Coinbase Pro (at USD 67,570), followed by Bitfinex (USD 43,460) and Bitstamp (USD 13,920). The middle right panel

[20] This estimate is likely to be conservative. For a sample of 300 US stocks (Anand et al., 2021) report an average percentage quoted spread of 18.6 bp in October 2016, ranging from 4.0 bp for large stocks (those in the top three market capitalization deciles) to 51.9 bp for small stocks (those in the three bottom deciles). Concerning liquidity on FX markets, Mancini et al. (2013) investigate liquidity for the 9 most heavily traded exchange rates on the EBS platform from January 2007 to December 2009. For the most liquid rate (= EURUSD) these authors find a mean relative quoted spread of 1.1 bp, while the spread is 8.3 bp for the least liquid (= USDCAD) of the analyzed pairs.

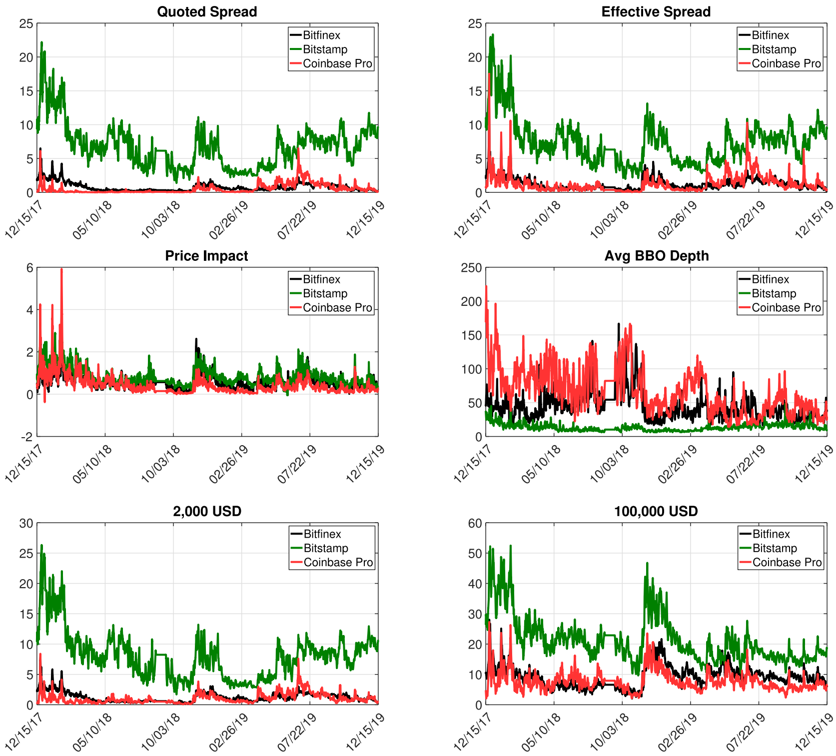

Fig. 3. Liquidity measures quoted spread, effective spread, price impact average BBO depth as well as the percentage cost of a roundtrip trade when buying/selling target volumes of USD 2,000 and 100,000 over time for all three exchanges. All measures are derived from synced one-minute-intervals, all subplots show a moving average of 1,440 one-minute intervals (24 h). The unit of measurement is basis points and USD 1,000 for the average BBO depth. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

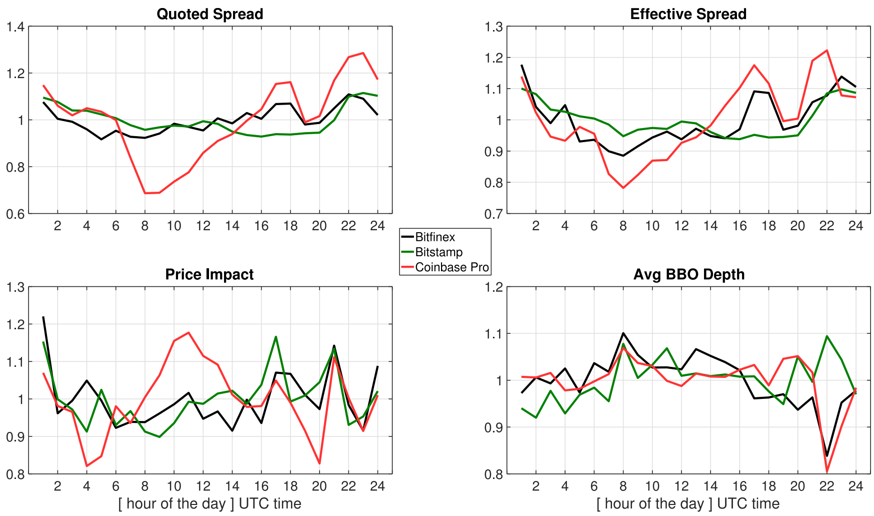

Fig. 4. Temporal patterns over the course of one day, covering hours 1 to 24 in UTC time. All subplots depict relative deviations from the overall mean. The upper left subplot shows the quoted spread, the upper right subplot plots the effective spread, the lower left plot refers to price impact and the lower right plot shows the average BBO depth respectively. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

of Fig. 3 shows that this ranking is rather stable throughout the sample period. Thus, Coinbase Pro simultaneously has the lowest quoted spreads and the highest depth while Bitstamp has the highest spreads and the lowest depth.

Fig. 4 shows how liquidity evolves over the time of day (in UTC). All measures are normalized (i.e. they are divided by the exchange-specific mean). Spreads on Coinbase Pro show marked daily peaks between 17:00 and 18:00 and again between 22:00

and 23:00 and a daily low between 08:00 and 09:00. Interestingly, these peaks and troughs roughly coincide with those of volatility (see Fig. 2 above).

It thus appears that the daily pattern of spreads on Coinbase Pro is related to volatility. Quoted and effective spreads on Bitfinex and Bitstamp show less variation over the trading day.

The price impact also shows the largest variation over the day on Coinbase Pro, with a daily high at 11:00 and lows at 04:00 and 20:00. In contrast, the quoted depth does not show much variation during most of the trading day but then has a pronounced daily low at 22:00 on two venues, Bitfinex and Coinbase. Interestingly, depth is at its daily high at the same time on Bitstamp, a finding that again points to a low level of integration across trading venues.

The quoted bid–ask spread and quoted depth reported above only capture the liquidity that is available at the best quotes. For traders wishing to trade a quantity exceeding the depth at the best bid or ask, the liquidity further up or down the order book is important. We assess it by calculating, separately for each exchange, weighted average prices for buy and sell orders of specific sizes as described in Section 3.2. We then calculate the percentage cost of a roundtrip trade CRT, defined as the difference between the weighted average prices for a buy and a sell order of equal size relative to the average of these two prices. Corresponding to our analyses for QS, ES, PI and $AvgD$ we investigate the evolution over time of CRT for each specific order size. Fig. 3 shows the results for two order sizes, USD 2,000 (lower left panel) and USD 100,000 (lower right panel). Those for the other order sizes (USD 500 and USD 40,000) are very similar.

Coinbase Pro and Bitfinex are the most liquid exchanges irrespective of the order size considered. This finding is consistent with the result, reported above, that these venues offer the lowest quoted spreads and the highest depth. Bitstamp, on the other hand, is, by a large margin, the least liquid of the three exchanges. Additionally, we find a high correlation between the CRT measures for different trade sizes. Thus, considering the liquidity beyond the best quotes does not change the conclusion that Bitstamp is the least liquid of the exchanges we investigate.

We note that the cost of a roundtrip trade on Coinbase Pro and Bitfinex is low when compared to the transaction costs in equity markets. Considering an order size of USD 100,000, the cost of a roundtrip is usually at or below 10 bp (the averages are 9.49 bp on Bitfinex and 7.93 bp on Coinbase Pro, see Table 3). This corresponds to a cost of less than USD 0.04 for a roundtrip trade in a stock with a price of USD 40.

4.3. Determinants of liquidity

In this section we analyze in detail the determinants of bitcoin liquidity for all three markets jointly.

For this purpose we estimate daily time-series regressions. The dependent variable is the change in liquidity. We use the same four measures of liquidity as in Section 4.2, the relative quoted spread, the relative effective spread, the relative price impact, and the percentage cost of a roundtrip trade of size USD 100,000.[21]

The choice of independent variables is inspired by Hameed et al. (2010) and Karnaukh et al. (2015). Like these authors we include a set of general financial market variables which are related to the liquidity of equity and FX markets. Including these variables allows us to test whether bitcoin liquidity depends on the same factors that determine liquidity in other financial markets. Because bitcoin belongs to a new asset class, cryptocurrencies, it is plausible that bitcoin liquidity is related to variables describing market conditions in cryptocurrency markets in general. These constitute our second group of explanatory variables. As noted earlier, the specific design features of bitcoin and the transparency of the ledger suggest that blockchain-related variables may affect bitcoin liquidity. Finally, as also argued earlier, the regulatory environment (e.g. the absence of a no trading through-rule) and frictions such as mining fees that impede the free movement of inventories between exchanges may result in bitcoin liquidity having an exchange-specific (local) component. We therefore also include explanatory variables relating to market condition on the trading venue under investigation. Note that for most of these variables we use lagged daily changes instead of levels. Details are provided in Table 4. In what follows we briefly describe the individual variables included in the four groups described above.

- *General financial market variables.* This group comprises variables that capture market conditions, such as lagged returns, volatility and liquidity on equity and FX markets. In particular, we consider the lagged return of the S&P500, the contemporaneous and lagged change in the squared return of the S&P500 as measures of volatility (sourced from Refinitiv Eikon), the lagged change of the value weighted average bid–ask spread of the S&P 500 component stocks (estimated based on CRSP closing bid–ask spreads), the lagged return of the EURUSD exchange rate, the contemporaneous and lagged change in the squared return of the EURUSD exchange rate, and the lagged change in the average bid–ask spread of the EURUSD exchange rate (sourced from Refinitiv Eikon). Besides conditions on equity and FX markets, we also include the lagged change in the TED spread (source: https://fred.stlouisfed.org/series/TEDRATE) which is a proxy for the perceived credit risk and funding liquidity in the interbank market. Brunnermeier and Pedersen (2009) argue that funding constraints deteriorate FX market liquidity and might induce liquidity spirals, an effect that could also apply to cryptocurrency markets. In addition we consider the lagged change in the VIX volatility index as a proxy for investor sentiment in financial markets (sourced from Refinitiv Eikon). Finally we take into account that spread data for the bitcoin exchanges which are open seven days a week are available on every day of our sample period, while those of our independent variables that relate to trading on traditional financial markets are not. Therefore we include a dummy variable D which takes on the value 1 on Saturdays and Sundays, days without trading on

[21] Fig. 3 implies that the CRT measures for different order sizes are highly correlated. We therefore confine the analysis to the largest order size category, i.e. USD 100,000.

Table 4
Description of independent regression variables to determine bitcoin market liquidity: General financial market variables (upper panel), global cryptocurrency variables (second panel), technical variables concerning the Bitcoin Blockchain (third panel), and exchange-specific (local) variables (lower panel).

Variable	Description	Δ/level	lag
$Return_{SP500}$	Return of the SP500 index	level	1
$Return^2_{SP500}$	Squared return of the SP500 index	Δ	0 and 1
$Quoted\ Spread_{SP500\_constit}$	Value weighted spread of SP500 index constituents	Δ	1
$Return_{EURUSD}$	Return of the EURUSD spotrate	level	1
$Return^2_{EURUSD}$	Squared return of the EURUSD spotrate	Δ	0 and 1
$Quoted\ Spread_{EURUSD}$	Spread of the EURUSD spotrate	Δ	1
TED	TED spread	Δ	1
VIX	CBOE volatility index	Δ	1
$Dummy\ (non-trading\ day)$	Weekend dummy	Δ, -1/0/1	0
$Return_{BTC}$	Volume weighted bitcoin return from exchanges	level	1
$Return^2_{BTC}$	Squared bitcoin return	Δ	0 and 1
$Return_{CRIX}$	Return of the CRIX index	level	1
$Return^2_{CRIX}$	Squared return of the CRIX index	Δ	0 and 1
$Quoted\ Spread_{Cryptomarket}$	Volume weighted spread of crypto markets	Δ	1
$Turnover^{off-chain}_{BTC}$	Turnover of bitcoin traded off-chain (exchanges)	Δ	1
$Confirmation\ Time$	Median confirmation time on-chain in min	Δ	1
$Mempool\ Size$	Size of the mempool on-chain in MB	Δ	1
$Fees$	Total daily fees w/o block reward in mio USD	Δ	1
$Network\ Hashrate$	Network hashrate in exahashes/s	Δ	1
$Turnover^{on-chain}_{BTC}$	Turnover of bitcoin traded on-chain	Δ	1
$Turnover_i$	Exchange-specific turnover	Δ	1
$Order\ Imbalance_i$	Exchange-specific order imbalance	Δ	1
$Dependent\ Variable_i$	Exchange-specific liquidity measure (*QS, ES, PI, CRT*)	Δ	1

traditional financial markets.[22] Including this dummy allows us to analyze whether Bitcoin liquidity is affected by the fact that other financial markets are closed.

- *Global cryptocurrency variables.* We include the lagged bitcoin return (sourced from coinmarketcap.com, a site which reports volume weighted average prices and trading volume across hundreds of markets), the lagged return of the CRIX cryptocurrency index (Trimborn and Härdle, 2018), the contemporaneous and lagged changes in the squared return on bitcoin and CRIX as measures of volatility, the lagged change in the volume weighted average spread of bitcoin markets (derived from value weighted spreads for bitcoin on 5 major exchanges and obtained from bitcoinity.org) and the lagged change in the total bitcoin trading volume on all bitcoin exchanges (referred to as off-chain volume and sourced from coinmarketcap.com).
- *BTC Blockchain variables.* We include several variables relating to the usage of the Bitcoin Blockchain. The median confirmation time in minutes captures the speed with which transactions are included in the blockchain. The mempool size in megabytes is an estimate of blockchain 'congestion'. Transaction fees are an estimate of how costly an on-chain transaction is while the network's hashrate is a measure of the mining activity. Finally, we include the total bitcoin volume exchanged via the Bitcoin Blockchain (referred to as on-chain volume and sourced from blockchain.info; this website reports estimates of the number of bitcoins traded on-chain, excluding change, i.e. bitcoins which are returned to the sender). Again and for all variables we use lagged first differences.
- *Exchange-specific (local) variables.* We include, for each of the three exchanges in our sample, the lagged change in the turnover and in the order imbalance. We further include the first lag of the dependent variable (i.e. the change in the quoted spread, the effective spread, the price impact, and the cost of a roundtrip trade, respectively). These variables are derived from our high-frequency dataset. We use simple averages of all observations belonging to a trading day in UTC time.

Table 4 summarizes our independent variables. To address multicollinearity concerns we calculated all pairwise correlations between the independent variables. Of all pairs of variables that are included in the same regression[23] the two that are most strongly correlated are the lagged S&P500 return and the lagged change in the VIX, with a correlation of −0.82. All other correlations are below 0.75 in absolute terms and variance inflation factors (VIF) are well below 2, expect for the lagged S&P500 return (VIF 3.36) and the lagged change in the VIX (VIF 3.62).

We follow a procedure similar to that in Karnaukh et al. (2015) and first estimate models in which we only include one group of independent variables (models 1 to 4). In a second step we use those variables for which we obtain at least three significant coefficients (at the 10% level or better) in models 1 to 4 to build our encompassing model (model 5).[24] All models are estimated by OLS. To account for liquidity differences between the three exchanges in our sample we include dummy variables identifying

[22] Note that we use the *change* in the dummy variable (i.e., the numerical values of the variable are −1, 0 and 1) because we are interested in changes in liquidity from trading days to non-trading days and vice versa.

[23] The lagged change in exchange-specific turnover is very highly correlated across exchanges, the largest correlation coefficient being 0.918 (Bitstamp and Coinbase). However, these variables are never jointly included in a regression.

[24] This procedure guarantees that we include the same explanatory variables in the encompassing models for all four liquidity measures.

Table 5
Results for regression model 1: financial markets variables. Regression parameters are estimated using OLS for first differences in the relative quoted spread (QS), the relative effective spread (ES), the relative price impact (PI) and the percentage cost of a roundtrip trade (CRT) of the BTCUSD exchange rate as dependent variables. To calculate CRT we choose order sizes of USD 100,000 on both sides of the order book. See Table 4 for definitions of the independent variables. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

Variable	Model 1 - Dependent variable			
	$\Delta QS_{i,t}$	$\Delta ES_{i,t}$	$\Delta PI_{i,t}$	$\Delta CRT_{i,t}$
$Constant$	−0.002	0.001	0.004	0.000
$Return_{SP500,t-1}$	−0.144	0.443	0.157	17.43
$\Delta Return^2_{SP500,t}$	−27.28	−3.984	63.03	374.9
$\Delta Return^2_{SP500,t-1}$	66.67	150.4	23.88	492.27*
$\Delta Quoted\ Spread_{SP500\_constit,t-1}$	−897.6	−945.1	−100.2	5.282
$Return_{EURUSD,t-1}$	5.527	17.24**	7.890***	42.89**
$\Delta Return^2_{EURUSD,t}$	−539.8	−2003**	−534.6**	−939.2
$\Delta Return^2_{EURUSD,t-1}$	−1099*	−269.5	219.4	66.87
$\Delta Quoted\ Spread_{EURUSD,t-1}$	−0.002	0.001	0.001	−0.026
ΔTED_{t-1}	0.662	−0.873	−0.340	−2.896
ΔVIX_{t-1}	0.019	0.040	0.013	0.235***
$\Delta Dummy\ (non-trading\ day)$	0.175***	0.113**	−0.041***	1.252***
$Dummy\ Bitstamp$	0.001	0.025	0.006	−0.008
$Dummy\ CoinbasePro$	0.001	0.004	−0.002	0.008
R^2	0.017	0.011	0.014	0.078
adj R^2	0.011	0.005	0.008	0.073

***/**/* denote statistical significance at the 1%/5%/10% level respectively.

observations from Bitstamp and Coinbase Pro. Thus, the constant in the regression models relates to Bitfinex while the coefficients on the two dummy variables capture differences between Bitfinex and the other two trading venues.

In the following we first present the results for the four individual models 1 to 4 and then proceed to the results for the encompassing model 5.

Table 5 documents that the general financial market variables (model 1) hardly affect the liquidity on the bitcoin exchanges, irrespective of which of the four dependent variables we consider. Bitcoin liquidity appears to be unrelated to equity market returns, squared returns and liquidity. The only exception here is that the cost of a roundtrip trade is positively related to lagged equity market volatility, as evidenced by positive coefficients on the lagged squared S&P 500 return and the lagged VIX. The relation between bitcoin liquidity and the FX market is slightly more pronounced. The four measures of bitcoin liquidity are positively related to lagged EURUSD returns and negatively related to squared EURUSD returns; five of the eight coefficients are significant. It thus appears that bitcoin liquidity decreases following positive EURUSD returns and also decreases when FX volatility goes up. Bitcoin liquidity is unrelated to funding liquidity as measured by the lagged TED spread. This is in sharp contrast to the results for FX markets reported in Mancini et al. (2013) and Karnaukh et al. (2015) where both authors find a strong negative relation between changes in FX liquidity and TED spreads.

The coefficient on the non-trading-day dummy is positive in three regressions, implying that quoted and effective spreads as well as the cost of a roundtrip trade are higher on weekend days on which other financial markets are closed. At the same time, price impacts are lower on weekend days, consistent with the view that less information is released on those days. Interestingly, the coefficients on the Bitstamp and Coinbase Pro dummy variables are insignificant in all models. Thus, while (as documented earlier) liquidity levels differ across the trading venues, changes in the four liquidity measures (after controlling for the independent variables included in our regression) do not.

Table 6 shows the results of the regressions of our bitcoin liquidity measures on the global cryptocurrency markets explanatory variables (model 2). In contrast to the equity and FX market variables considered in model 1, there is substantial evidence of a relation between bitcoin liquidity and this set of variables. The results are also highly consistent across the four liquidity measures we consider. The explanatory power of the regression is also markedly higher than for model 1, as evidenced by higher adjusted R^2s. They range from 0.03 for the quoted spread to 0.15 for the effective spread and the price impact (as compared to values around 0.01 for model 1). All four liquidity measures are negatively related to past bitcoin returns and are positively related to current and lagged bitcoin volatility as well as contemporaneous CRIX volatility. Three of them are also positively related to lagged CRIX volatility. Further, there is evidence of a negative relation between the liquidity measures on the three trading venues under investigation and the lagged weighted average spread across a larger set of bitcoin markets, a finding that points to negative serial correlation in liquidity.

Table 7 presents results for the regressions using data from the Bitcoin Blockchain as independent variables (model 3). We find confirmation time to be unrelated to bitcoin liquidity. Mempool size is negatively related to all four liquidity measures but significantly so only for two, the price impact and the cost of a roundtrip trade. The lagged hashrate is negatively related to the bitcoin spreads (and significantly so in three cases), implying that it becomes cheaper to trade bitcoin when mining activity is higher. All four liquidity measures are positively and significantly related to the lagged fees paid to miners on the blockchain. This positive relation implies that, when it gets more expensive to transfer bitcoin via the blockchain, it also gets more expensive to transfer them off-chain, i.e. on an exchange. We offer the following explanation for this finding. As argued earlier, trades on

Table 6
Results for regression model 2: global cryptocurrency markets variables. Regression parameters are estimated using OLS for first differences in the relative quoted spread (QS), the relative effective spread (ES), the relative price impact (PI) and the percentage cost of a roundtrip trade (CRT) of the BTCUSD exchange rate as dependent variables. To calculate CRT we choose order sizes of USD 100,000 on both sides of the order book. See Table 4 for definitions of the independent variables. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

Variable	Model 2 - Dependent variable			
	$\Delta QS_{i,t}$	$\Delta ES_{i,t}$	$\Delta PI_{i,t}$	$\Delta CRT_{i,t}$
$Constant$	−0.002	−0.003	0.002	−0.005
$Return_{BTC,t-1}$	−0.705	−1.768***	−0.769***	−4.330***
$\Delta Return^2_{BTC,t}$	14.47***	55.29***	20.61***	108.2***
$\Delta Return^2_{BTC,t-1}$	17.13***	37.05***	14.54***	143.1***
$Return_{CRIX,t-1}$	0.247	0.461	0.183	2.464*
$\Delta Return^2_{CRIX,t}$	8.983**	37.52***	10.93***	49.45***
$\Delta Return^2_{CRIX,t-1}$	−0.595	17.12***	5.310***	40.34***
$\Delta Quoted\ Spread_{Cryptomarket,t-1}$	−4.951***	−15.10***	−3.722***	−23.36***
$\Delta Turnover^{off-chain}_{BTC,t-1}$	0.116	−1.279	0.160	0.798
$Dummy\ Bitstamp$	0.001	0.025	0.006	−0.008
$Dummy\ CoinbasePro$	0.001	0.005	−0.002	0.008
R^2	0.032	0.151	0.149	0.118
adj R^2	0.028	0.147	0.145	0.114

***/**/* denote statistical significance at the 1%/5%/10% level respectively.

Table 7
Results for regression model 3: BTC Blockchain variables. Regression parameters are estimated using OLS for first differences in the relative quoted spread (QS), the relative effective spread (ES), the relative price impact (PI) and the percentage cost of a roundtrip trade (CRT) of the BTCUSD exchange rate as dependent variables. To calculate CRT we choose order sizes of USD 100,000 on both sides of the order book. See Table 4 for definitions of the independent variables. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

Variable	Model 3 - Dependent variable			
	$\Delta QS_{i,t}$	$\Delta ES_{i,t}$	$\Delta PI_{i,t}$	$\Delta CRT_{i,t}$
$Constant$	0.002	0.013	0.008	0.015
$\Delta Confirmation\ Time_{t-1}$	0.043	0.028	0.005	0.118
$\Delta Mempool\ Size_{t-1}$	−0.000	−0.004	−0.002**	−0.012**
$\Delta Fees_{t-1}$	0.142***	0.709***	0.226***	0.719***
$\Delta Network\ Hashrate_{t-1}$	−0.006**	−0.008*	−0.001	−0.026***
$\Delta Turnover^{on-chain}_{BTC,t-1}$	−3.019	25.61***	15.27***	−20.08**
$Dummy\ Bitstamp$	0.001	0.025	0.006	−0.008
$Dummy\ CoinbasePro$	0.001	0.005	−0.002	0.008
R^2	0.007	0.077	0.103	0.018
adj R^2	0.004	0.074	0.100	0.015

***/**/* denote statistical significance at the 1%/5%/10% level respectively.

cryptocurrency exchanges are settled by the exchanges, not by a centralized institution. Therefore, if a trader wants to sell bitcoin on a venue, the trader first needs to transfer bitcoins to the exchange wallet. The higher the miner fees are, the more expensive that transfer will be. This, in turn, means that it is more expensive to shift funds between trading venues to exploit price and/or liquidity differences. The relation between bitcoin liquidity and the lagged on-chain turnover is complex. Posted liquidity appears to increase, as evidenced by (insignificantly) lower quoted spreads and (significantly) lower cost of a roundtrip trade. In contrast, effective spreads and price impacts increase significantly. This is consistent with higher on-chain turnover predicting an increase in informed trading. The observation that, at the same time, posted liquidity *increases* is puzzling. We return to this finding below.

Table 8 shows results of regressions of bitcoin liquidity on exchange-specific variables (model 4). Two of the explanatory variables, lagged turnover and the lagged dependent variable, are statistically significant in all four regressions. All four bitcoin liquidity measures are significantly positively related to lagged turnover and significantly negatively related to their own lagged values. The latter result implies that bitcoin liquidity is negatively serially correlated and confirms the finding of a negative relation between exchange-specific spreads and lagged weighted spreads across a larger set of bitcoin markets from model 2. The strong and positive relation between our liquidity measures and lagged turnover is somewhat puzzling because it implies that trading bitcoin becomes more expensive when turnover is high. However, while this finding is in contrast to what most theoretical models predict, it is in line with recent empirical evidence for large cap stocks presented by Bogousslavsky and Collin-Dufresne (2022).

Table 8

Results for regression model 4: exchange-specific variables. Regression parameters are estimated using OLS for first differences in the relative quoted spread (QS), the relative effective spread (ES), the relative price impact (PI) and the percentage cost of a roundtrip trade (CRT) of the BTCUSD exchange rate as dependent variables. To calculate CRT we choose order sizes of USD 100,000 on both sides of the order book. See Table 4 for definitions of the independent variables. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

Variable	Model 4 - Dependent variable			
	$\Delta QS_{i,t}$	$\Delta ES_{i,t}$	$\Delta PI_{i,t}$	$\Delta CRT_{i,t}$
$Constant$	−0.001	−0.000	0.005	0.004
$\Delta Turnover_{i,t-1}$	88.71**	222.9***	91.63***	675.4***
$\Delta Order\ Imbalance_{i,t-1}$	−0.208	−0.566**	−0.199**	0.263
$\Delta DependentVariable_{i,t-1}$	−0.259***	−0.365***	−0.350***	−0.230***
$Dummy\ Bitstamp$	0.001	0.032	0.009	−0.011
$Dummy\ CoinbasePro$	0.002	0.005	−0.003	0.009
R^2	0.066	0.120	0.105	0.054
adj R^2	0.064	0.118	0.103	0.051

***/**/* denote statistical significance at the 1%/5%/10% level respectively.

Table 9

Results for regression model 5: full model. The model includes those independent variables for which we obtained at least three equally-signed significant coefficients in models 1–4. Regression parameters are estimated using OLS for first differences in the relative quoted spread (QS), the relative effective spread (ES), the relative price impact (PI) and the percentage cost of a roundtrip trade (CRT) of the BTCUSD exchange rate as dependent variables. To calculate CRT we choose order sizes of USD 100,000 on both sides of the order book. See Table 4 for definitions of the independent variables. Data is collected from Bitfinex, Bitstamp, and Coinbase Pro between 12/15/2017 and 12/15/2019.

Variable	Model 5 - Dependent variable			
	$\Delta QS_{i,t}$	$\Delta ES_{i,t}$	$\Delta PI_{i,t}$	$\Delta CRT_{i,t}$
$Constant$	−0.001	0.006	−0.001	−0.001
$Return_{EURUSD,t-1}$	5.298	5.866	2.757	23.17
$\Delta Dummy\ (non-trading\ day)$	0.229***	0.292***	0.014	1.565***
$Return_{BTC,t-1}$	−1.207***	−2.578***	−0.983***	−7.681***
$\Delta Return^2_{BTC,t}$	13.41***	48.15***	17.00***	99.02***
$\Delta Return^2_{BTC,t-1}$	13.07**	30.95***	11.96***	125.3***
$\Delta Return^2_{CRIX,t}$	7.868**	30.61***	9.755***	47.46***
$\Delta Return^2_{CRIX,t-1}$	−2.843	12.98***	5.353***	29.75***
$\Delta Quoted\ Spread_{Cryptomarket,t-1}$	−2.380**	−5.010***	−1.415***	−17.80***
$\Delta Fees_{t-1}$	0.063	0.531***	0.179***	0.300**
$\Delta Network\ Hashrate_{t-1}$	−0.005*	−0.004	0.000	−0.019**
$\Delta Turnover^{on-chain}_{BTC,t-1}$	6.287	25.56***	9.162***	48.91***
$\Delta Turnover_{i,t-1}$	99.07**	158.7***	63.95***	401.1***
$\Delta DependentVariable_{i,t-1}$	−0.241***	−0.313***	−0.323***	−0.171***
$Dummy\ Bitstamp$	0.001	0.031	0.009	−0.010
$Dummy\ CoinbasePro$	0.002	0.005	−0.003	0.009
R^2	0.104	0.259	0.278	0.232
adj R^2	0.097	0.254	0.272	0.226

***/**/* denote statistical significance at the 1%/5%/10% level respectively.

We present the results of the encompassing model (model 5) in Table 9.[25] As described earlier we include as explanatory variables those variables that delivered three or more significant coefficients in the individual models.[26] The explanatory power of the encompassing model is considerably higher than that of the best individual model (adjusted R^2 ranging from 0.10 for the quoted spread to 0.27 for the price impact as compared to values between 0.06 (model 4 for the quoted spread) and 0.15 (model 2 for the effective spread and the price impact) for the best individual model). This finding implies that the different sets of explanatory variables indeed capture different information.

The results of the encompassing model are remarkably consistent across the four liquidity measures under investigation. The positive coefficient for the non-trading day dummy in three regressions implies that trading costs in bitcoin markets are higher on weekend days when other financial markets are closed. As was the case in model 1, the respective coefficient in the price impact regression is insignificant, consistent with the view that information release and/or informational asymmetries are not higher on non-trading days than on trading days.

[25] In Section 3 we described a shortened sample that excludes the period from September 15, 2018 to May 31, 2019. When we re-estimate model 5 for this shortened sample period we obtain qualitatively similar results. They are included in the internet appendix.

[26] Deviating from this rule we keep exchange specific dummy variables in the full model irrespective of their significance in the individual models to control for exchange specific effects.

The four measures of bitcoin liquidity are unrelated to lagged FX returns, are significantly negatively related to lagged bitcoin returns and are positively related to contemporaneous and lagged bitcoin and CRIX volatility. The negative relation of the bitcoin liquidity measures to the lagged quoted spread averaged over a larger number of trading venues continue to hold.

The four measures of bitcoin liquidity are positively related to on-chain volume (significantly so in three cases). Thus, the puzzling result from model 3 that quoted spreads and the cost of a roundtrip trade decrease while price impacts and effective spreads increase disappears once the full set of explanatory variables is included. Our four liquidity measures are also positively related to lagged fees (significantly so in three cases) and are negatively related to the hashrate (significant in two cases). As mentioned earlier these findings imply that trading bitcoins on an exchange becomes more expensive when on-chain activity increases and when the cost of transacting on-chain increases, and become less expensive when mining activity increases. Taken together these results suggest that on-chain and off-chain transactions are, to a certain degree, substitutes. Our findings complement those of Makarov and Schoar (2020) and Dyhrberg (2020). These authors find that cross border market frictions (capital control regulations, fiat currency conversions, clearing time for international bank transfers) impede the flow of arbitrage capital between cryptocurrency exchanges. Our results suggest that blockchain-related frictions impede the flow of liquidity between trading venues.

Finally, the impact of the local factors remains strong in the encompassing model. The positive relation between the four liquidity measures and lagged turnover documented in model 4 above persists in the encompassing model. Similarly, we confirm the finding of significant negative serial correlation in the liquidity measures.

Overall the results of our regression analysis allow two main conclusions. First, the liquidity on bitcoin exchanges appears to be largely independent of other financial markets such as the equity or foreign exchange markets. Second, local factors appear to be much more important in explaining bitcoin liquidity than global factors.

5. Conclusion

In this paper we study BTCUSD liquidity and provide an in-depth analysis of the local and global determinants of liquidity. We find that the bitcoin exchanges are highly liquid. The bid–ask spreads are lower than those of large-cap stocks on equity exchanges. The analysis of the determinants of liquidity reveals that bitcoin liquidity is decoupled from the liquidity of other asset classes such as equities and foreign exchange. In fact, bitcoin liquidity largely depends on factors specific to cryptocurrencies and the blockchain. Specifically, bitcoin market liquidity is driven by the recent past of risk and returns for cryptocurrencies, and the costs with which the blockchain is clearing on-chain transactions. These results are generally consistent with what one would expect based on classic economics models. Market microstructure theory has identified adverse selection costs and, to a lesser extent, inventory holding costs as the main drivers of bid–ask spreads. Thus, to the extent that the time series variation in the degree of informational asymmetry and the inventory holding cost is driven by cryptocurrency-specific variables, we would expect that bitcoin liquidity depends on those variables rather than on general financial market variables.

It is also worth noting that the current infrastructure of bitcoin markets runs counter to the intention of the creator of bitcoin, Satoshi Nakamoto. They originally designed the Bitcoin Blockchain as a response to the fractional reserve banking system and the financial crisis. Nakamoto embedded the following in the first block of the blockchain: "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks''. Bitcoin was designed as an anonymous, decentralized system in competition with central bank controlled money supply. Exchanges have circumvented the philosophy by introducing a non-anonymous centralized reserve of bitcoin on each exchange. Crypto-exchanges require customers to fully reveal their identity. Customers of cryptocurrency exchanges must also transfer funds (fiat and cryptocurrency) and control over these funds to the exchange, similar to the banking system. The introduction of a centralized bitcoin repository and of brokerages would lead us even further away from the decentralized and anonymous system envisioned by Nakamoto. Usurping the financial system may be more difficult than originally thought.

CRediT authorship contribution statement

Alexander Brauneis: Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Roland Mestel:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Ryan Riordan:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Erik Theissen:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2022.08.004.

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