Examining Liquidity of Exchanges and Assets and the Impact of External Events in Centralized Crypto Markets: A 2022 Study

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***Abstract*—Most cryptocurrencies are bought and sold on centralized exchanges that manage supply and demand via an order book. Besides trading fees, the high liquidity of a market is the most relevant reason for choosing one exchange over the other. However, as the different liquidity measures rely on the order book, external events that cause people to sell or buy a cryptocurrency can significantly impact a market's liquidity. To investigate the effect of external events on liquidity, we measure various liquidity measures for nine different order books comprising three currency pairs across three exchanges covering the entire year 2022. The resulting multivariate time series is then analyzed using different correlations. From the results, we can infer that as a cryptocurrency's market capitalization and the exchange's trading volume increases, so does its liquidity. At the same time, only a moderate correlation of liquidity between exchanges can be observed. Furthermore, our statistical observations show that external events, particularly the events around FTX and the Terra Luna crash, caused significant changes in liquidity. However, depending on the exchange's size and the cryptocurrency's market cap, the liquidity took a shorter or longer time to recover.**

***Index Terms*—Cryptocurrencies, Centralized Exchanges, Order Book Data, Liquidity**

I. Introduction

Cryptocurrencies are digital assets that use strong encryption to map financial transactions and digitally verify transfers [1]. In the past decade, cryptocurrencies emerged as a relevant asset class for both retail and professional investors [2]. This is due to several reasons. On the one hand, their high volatility offers numerous opportunities for quantitative investment strategies and trading. On the other hand, cryptocurrencies are seen as an alternative to traditional fiat currencies and thus serve within a portfolio to spread risk. Especially large asset management companies are increasingly confronted with the demand for novel products from their clients. This led, for example, to the launch of new indices that describe the development of the market capitalization of a set of cryptocurrencies and Exchange Traded Funds (ETFs) that make accessible to investors [3].

Cryptocurrencies can either be traded on a centralized or decentralized exchange [4]. In centralized exchanges, e.g., *Binance*, *Coinbase*, or *Kraken*, a third-party provider monitors all transactions and acts as an intermediary between buyer and seller. In decentralized exchanges, e.g., *PancakeSwap*, *Sushiswap*, or *Venus*, transactions are settled via smart contracts, which makes a third party irrelevant. The larger part is traded on centralized exchanges, where supply and demand are managed via an order book. An order book contains all open buy and sells orders and arranges them in levels [5]. In the case of a buy order (bid), this arrangement is made in descending order with the price, and in the case of a sell order (ask), in ascending order with the price. If a sell order and a buy order meet, i.e., they agree on a price for a cryptocurrency, a trade takes place, and their orders are removed from the order book. With respect to return, the associated costs for trading cryptocurrencies are the main reason for choosing an exchange. Besides the low transaction fees, the exchange should provide high liquidity, as otherwise, the average price achieved may deviate too much from the initially assumed price. Especially when investing larger volumes that correspond to several levels in the order book, such price differences strongly impact the achieved return. Various liquidity measures have been developed to quantify this effect, each requiring an order book as input. Market phases with significant changes in order books thus lead to a change in liquidity and thus directly influence the costs of trading. While existing work has measured the liquidity of various currency pairs on different exchanges, no work exists that dedicately includes external events in its considerations. However, such events are often the cause of increased trading volume.

In this paper, we want to investigate the effect of external events on the liquidity of currency pairs on centralized crypto exchanges. For this purpose, we investigate the order books of three currency pairs, BTC/USDT, ETH/USDT, and LTC/USDT, from three exchanges, namely *Binance*, *HitBtc*, and *CEXIO*, that cover the entire year 2022. As relevant events, we consider the incidents around *FTX* [6] and *Terra Luna* [7]. By surveying various measures of liquidity, we generate a multidimensional time series that captures different aspects of liquidity of nine different order books in five minute intervalls. By statistical investigations, we adress the following questions through a quantitative approach:

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RQ1 What are the measures' similarities or differences, and how should liquidity be measured?
RQ2 How does liquidity differ between different assets on different exchanges?
RQ3 Is the liquidity of different assets or exchanges independent of each other?
RQ4 Are there noticeable changes in liquidity over the course of 2022?

The remaining part of this work is structured as follows: Section II presents existing works that measure the liquidity of crypto exchanges. The different measures for liquidity used in our study are formalized in Section III. In Section IV we give details about the data collected within the year 2022, before we present the results in Section V. We discuss our results and threats to validity in Section VI. A conclusion and directions for future work are given in Section VII.

II. Related Work

A formal consideration of implicit costs arising from the structure of an order book is made using so-called liquidity measures [8]. One example of a primary liquidity measure is the spread, i.e., the difference between the best ask price and the best bid price. Especially for retail investors, whose trades mostly rely on the first few levels of the order book, the spread is the most relevant measure [9].

Dyhrberg et al. used data from three U.S. crypto exchanges to examine the extent to which Bitcoin is suitable for retail investors [10]. In their study, they were able to determine from the trading activities that a large part of the activities originates from retail investors. By measuring the spread of the order books, it was shown that the costs incurred are meager and even lower than those of traditional exchanges.

A more detailled study on emerging implicit costs for cryptocurrency trading, was presented by Angerer et al. [11]. In their work the authors measured several liquidity measures for a large set of target and base currencies based on a publicly available order book data set of four exchanges of 273 days, which are observed in 5-minute intervals. Their results confirmed the results of Dyhrberg and Foley, but also showed that the slippage effect can have a large impact for trading larger volumes. The slippage effect means that the execution of an order requires several orders on the opposite side, which leads to a distortion of the average price achieved. In many cases the costs caused by the slippage effect are significantly higher than the explicit costs [9]. The authors found several characteristics that indicate a small slippage effect. For example, exchanges that offer fewer currency pairs and allow investing through fiat currencies instead of fiat-pegged stablecoins provide higher liquidity in terms of slippage.

Although the various liquidity measures capture implicit costs in investing, they are not necessarily correlated. For a discussion of which measures are particularly relevant and suitable for different questions, see [8], [12]. In particular, the authors suggest which measures should be applied during phases of high and low volatility.

In a later work, Brauneis et al. compared the liquidity of three order books, where Bitcoin is traded against USD, with broader financial markets, e.g., foreign exchange markets [13]. Their results indicate that the liquidity on crypto exchanges is unrelated to broader financial markets, but rather related to the activity on the blockchain and exchange-specific attributes.

Our work builds on existing work but differs from existing work in two critical ways. First, we consider the most extended period of all studies. Second, no work exists that examines changes in liquidity throughout external events.

III. Measures for Liquidity

Besides explicit costs, e.g., exchange fees or taxes, implicit costs influence the profit/loss of an investor when trading cryptocurrencies. In liquid markets, these implicit costs are low. Various measures for quantifying liquidity exist, usually requiring information about individual trades or the order book [8], [14]. In this section, we introduce the liquidity measures that are used in our experiments, which are order book based as the exchanges of our interest only offer access to order book data. Our notation is similar to that used in the work of Angerer et al. [11].

The order book contains all open ask and bid offers for buying and selling a target currency, e.g., Bitcoin or Ether, using a quote currency, e.g., Tether. In our considerations, we always refer to Tether as the quote currency. All buy orders are sorted into levels given as pairs (P_1, Q_1), where P_1 denotes the price for the target currency in the quote currency and Q_1 denotes the quantity measured in target currency units for the ask and bide side, respectively. The best ask price $P_{\text{best ask}}$ refers to the lowest-priced sell order, and the best bid price $P_{\text{best bid}}$ refers to the highest-priced bid order. The average

$$P_{\text{mid}} = \frac{P_{\text{best ask}} + P_{\text{best bid}}}{2} \quad (1)$$

between the best ask price $P_{\text{best ask}}$ and the best bid price $P_{\text{best bid}}$ is called the mid-price and is usually referred to as the "price" of a target currency. The difference

$$\text{Spread} = P_{\text{best ask}} - P_{\text{best bid}} \quad (2)$$

is called the spread of the order book. In a perfect liquid market with $\text{Spread} = 0$, P_{mid} would be the price for selling and buying the target currency. To compare liquidity across different target currencies, one usually considers the relative spread given by

$$\text{Relative Spread} = \frac{\text{Spread}}{P_{\text{mid}}} \quad (3)$$

The relative spread is the most crucial liquidity measure for retail investors, who usually place small orders. However, when placing large orders requiring more levels in the order book to be traded against, the order book depth has to be considered. When placing larger orders, the average price paid for the target currency might significantly differ from the mid-price. The volume-weighted average price (VWAP), is another liquidity measure that quantifies the expected price for the bid and ask sides respectively

$$P_L^{\text{VWAP}} = \frac{\sum_{l=1}^{L} P_l \cdot Q_l}{\sum_{l=1}^{L} Q_l}. \tag{4}$$

The spread of the VWAP and its normalized spread is defined analogously as before, i.e.,

$$\text{Rel. Spread}_L^{\text{VWAP}} = \frac{\text{Spread}_L^{\text{VWAP}}}{P_{\text{mid}}} = \frac{P_{\text{ask},L}^{\text{VWAP}} - P_{\text{bid},L}^{\text{VWAP}}}{P_{\text{mid}}} \tag{5}$$

As a further measure for liquidity, we adopt the *Xetra Liquidity Measure* (XLM) used within the *Deutsche Börse Group* [9]. The XLM is based on the idea that liquidity corresponds to implicit costs. Given a buy order of volume vol in target currency units, the order requires $(P_1, \tilde{Q}_{\text{ask},1}), \ldots, (P_n, \tilde{Q}_{\text{ask},n})$ sell orders to be traded against. It is important to note that $\tilde{Q}_{\text{ask},1} = Q_{\text{ask},1}$ for $i < n$ and $\tilde{Q}_{\text{ask},n} \leq Q_{\text{ask},n}$. The implicit costs are then given by the sum of a liquidity premium and the adverse price movement, in the formula:

$$\text{XLM}_{\text{buy}}(\text{vol}) = \sum_{i=1}^{n} P_i \cdot \tilde{Q}_{\text{ask},i} - P_{\text{mid}} \cdot \text{vol}. \tag{6}$$

Analogously the XLM for the sell side is defined. The sum of the sell and buy side is usually referred to as the XLM, i.e.,

$$\text{XLM}(\text{vol}) = \text{XLM}_{\text{buy}}(\text{vol}) + \text{XLM}_{\text{sell}}(\text{vol}) \tag{7}$$

IV. Data

Daily market capitalization and trading volume data are from CoinMarketCap[1]. To make our exploratory data analysis more illustrative, we select three assets. Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). We choose these assets because they are popular, and have high availability but still differ drastically in terms of market capitalization. According to CoinMarketCap, the market capitalization of Bitcoin is about 67 times higher than that of Litecoin. Liquidity measures are calculated on order book snapshots, we retrieve these from the APIs of three selected exchanges, Binance[2], HitBtc[3] and CEXIO[4]. Binance was chosen because it has the highest trading volume of all exchanges and should therefore be the most liquid. HitBtc's trading volume is still among the higher ones, but it is about 16 times lower than Binance's. CEXIO's trading volume is about 289 times lower than HitBtc's, which is drastically lower than Binance's, so it serves as an example of an exchange that is presumably less liquid. Exchanges usually offer different quote currencies in which the asset can be traded. We chose Tether (USDT) as the quote currency on all three exchanges because it is usually the same as the USD rate. This, and the single quote currency, makes comparison easier.

[1]https://coinmarketcap.com/
[2]https://www.binance.com
[3]https://hitbtc.com
[4]https://cex.io

We calculate all liquidity measures based on order book snapshots at five-minute intervals, so there should be 105 120 observations per trading pair, for a total of 946 080. There may be missing values if there is no snapshot at a given time or if one side of the order book is missing, which was the case 7 407 times ($< 1\,\%$). Invalid observations may also occur because the data retrieved from the exchange's API may be non-sensible or errors may have occurred during data storage. This is the case, for example, when the spread is negative, which occurred 3 724 times ($< 1\,\%$). A more detailed breakdown is shown in Table I.

V. Results

We calculated all VWAP measures on an order book depth of 5, 10, 25 and 50 levels. As a value of 1 for the VWAP equals the spread, and the value of 1 for the relative VWAP equals the relative spread we will refer to VWAP at level 1 for better readability. The XLM is calculated with 10 000 and 100 000 as the targeted volume. Smaller quantities would be of interest to small investors, but that would mainly clear orders near the best bid or ask. However, due to practices such as wash trading or trading bots, it is questionable whether liquidity at these levels is real and if these orders are actually executed, so we consider a higher volume to be a more realistic representation of liquidity. The XLM measures could not be calculated for all order books as there must be sufficient volume. The XLM with a volume of 10 000 USDT could not be calculated 38 151 times (4 %), which is mainly due to LTC on CEXIO (38 125). For the XLM with a volume of 100 000 USDT, 135 569 values are missing (14 %), which is also mainly due to assets traded on CEXIO, more specifically LTC (98 750), followed by BTC (22 287) and ETH (13 372).

A. What are the measures' similarities or differences, and how should liquidity be measured??

A study by Aitken & Comerton-Forde shows that different liquidity measures may not have high correlations and the choice of measure may therefore affect the outcome of the analysis [8]. Thus, it is important to understand the commonalities and differences between the measures. Table IIa shows the correlation matrix of all relative spread measures. The correlation of the relative VWAP spread decreases from the middle of the spread toward lower levels of the order book. In general, there is a strong linear relationship between the relative VWAP spread of level 1 to 25. The correlation of XLM(10 k) to XLM(100 k) is 0.57, which is a strong linear relationship. However, not all order books could provide sufficient volume for a demand of 100 000 USDT, thus the actual relationship is weaker. The correlation between XLM and VWAP measures can be seen in the table table IIb. The correlation between XLM(10 k) and VWAP relative spread is highest at level 25, indicating that more levels are needed in the order book to deliver enough volume to satisfy the demand of 10 000 USDT. The same is true for an investment of 100 000 USDT, so the correlation between XLM(100 k) and the relative VWAP spread is highest at Level 50. In general, we can see that the measures

TABLE I: Asset Overview

Note: Volume and Market capitalization refer to the asset in general, not on the certain exchange. Amounts differ because missing or invalid observations got filtered and therefore excluded. Relative spreads are measured in 1e-3. Volume is Measured in 1e6, cap refers to market capitalization in 1e9, and values are rounded. XLM measures refer to XLM(vol).

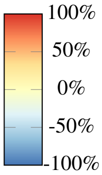
						vwap 1		vwap 5		vwap 25		vwap 50			
	Miss.	Inv.	Volume	Cap	Price	spr	rel. spr.	spr	rel. spr.	spr	rel. spr.	spr	rel. spr.	XLM(10k)	XLM(100k)
Binance															
BTC	31	3 663	29 949	536	28 146	0.47	0.02	1.46	0.05	5.94	0.20	10.71	0.35	0.59	1.99
ETH	33	58	15 277	240	1 990	0.02	0.01	0.15	0.07	0.74	0.38	1.36	0.71	0.49	2.57
LTC	39	2	691	6	80	0.05	0.56	0.26	2.92	0.87	9.74	1.65	18.68	8.45	20.74
HitBtc															
BTC	2 009	0	29 936	539	28 320	3.75	0.15	8.58	0.33	30.39	1.12	46.45	1.71	2.94	9.88
ETH	2 011	0	15 285	241	1 995	0.48	0.29	1.16	0.65	2.94	1.56	4.53	2.47	7.16	14.27
LTC	2 581	0	694	6	80	0.04	0.49	0.09	1.14	0.24	3.03	0.47	5.91	16.10	36.93
CEXIO															
BTC	263	0	29 969	537	28 241	88.25	4.12	189.85	8.10	1 035.23	44.91	4 761.83	203.23	62.79	638.42
ETH	221	0	15 277	240	1 990	1.80	0.81	8.09	4.05	50.89	30.50	258.89	158.51	46.34	1 017.05
LTC	219	1	691	6	80	0.78	2.03	1.68	25.51	16.70	230.09	55.53	489.41	6 357.33	2 171.42

TABLE II: Liquidity Measure Correlations

	vwap1 rel. spread	vwap5 rel. spread	vwap10 rel. spread	vwap25 rel. spread	vwap50 rel. spread
vwap1 rel. spread	1.00	0.77	0.64	0.57	0.37
vwap5 rel. spread	0.77	1.00	0.82	0.69	0.58
vwap10 rel. spread	0.64	0.82	1.00	0.81	0.67
vwap25 rel. spread	0.57	0.69	0.81	1.00	0.88
vwap50 rel. spread	0.37	0.58	0.67	0.88	1.00

(a) Correlations between VWAP measures

	XLM(10k)	XLM(100k)
vwap1 rel. spread	0.45	0.17
vwap5 rel. spread	0.55	0.33
vwap10 rel. spread	0.54	0.34
vwap25 rel. spread	0.67	0.69
vwap50 rel. spread	0.60	0.75



(b) Correlations between VWAP and XLM measures

have a similar meaning and change similarly. Nevertheless, we argue that XLM has a higher informative value because it directly reflects the cost involved in buying a given quantity of a given asset.

B. How does liquidity differ between different assets on different exchanges?

Table I is showing yearly averages of VWAP and XLM measures grouped by exchange and asset. Exchanges are ordered by their average trading volume according to CoinMarketCap. Binance has the highest, HitBtc comes second, and CEXIO last. We observe several differences between the exchanges and assets. First, we compare individual assets across exchanges to see if the liquidity of exchanges in general correlates with their trading volume. We can observe that asset VWAP spreads are smaller when exchanges have higher trading volumes. The only exception is LTC on HitBtc, where the spreads are lower than on Binance. This is similar to the relative VWAP spreads, which tend to be higher on exchanges with lower trading volume, again except LTC, which is lower on HitBtc than on Binance. This could indicate that HitBtc's LTC is more liquid than Binance's. A look at XLM values does not support this assumption. When the trading volume of an exchange decreases, the XLM measures increase, indicating less liquidity. The question of which asset in our set is the most liquid is difficult to answer using VWAP measures. The spread is generally higher for assets with higher trading volume and market capitalization, which is likely due to the trading price, with the exception of Binance, where the spread of ETH is smaller than the spread of LTC. A comparison of the VWAP relative spread between assets on different exchanges does not show consistent behavior. On HitBtc, the relative spread is usually lower for assets with higher trading volume and higher market capitalization, which is consistent with the previous observations. On Binance it is similar, but the relative VWAP spread at level one is lowest for ETH. On CEXIO, ETH has the lowest relative spread, followed by BTC and LTC. In terms of XLM measure, BTC is usually the most liquid, followed by ETH and LTC. The only exception is Binance, where ETH is more liquid and the most liquid market in our set (Binance ETH-USDT) if you invest a smaller amount. It has an XLM(10 k) value of 0.49, which means that the market impact for the so-called round trip (simultaneous purchase and sale of a position) of 10 000 USDT is 0.49. For an investment of 100 000 USDT, it would be 2.57[5].

C. Is the liquidity of different assets or exchanges independent of each other?

In contrast to the annual review, this section aims to provide a more detailed insight into the similarity of liquidity, in

[5]This is generally a low market impact. For instance, the XLM(25 k) value of one of the most liquid stocks on the German Stock Exchange is 2.8. See https://www.xetra.com/xetra-de/handel/marktquaelitaet/xlm-xetra-liquiditaetsmass

TABLE III: Asset Correlations using XLM(10k)

	BTC	ETH	LTC
BTC	1.00	0.44	0.30
ETH	0.44	1.00	0.48
LTC	0.30	0.48	1.00

100% 50% 0% -50% -100%

(a) Asset Correlations

		BTC	ETH	LTC
Binance	BTC	1.00	0.32	-0.08
	ETH	0.32	1.00	0.33
	LTC	-0.08	0.33	1.00
HitBtc	BTC	1.00	0.68	0.54
	ETH	0.68	1.00	0.58
	LTC	0.54	0.58	1.00
CEXIO	BTC	1.00	0.33	0.15
	ETH	0.33	1.00	0.27
	LTC	0.15	0.27	1.00

(b) Asset correlations separated by exchange

		Binance	HitBtc	CEXIO
BTC	Binance	1.00	0.21	0.13
	HitBtc	0.21	1.00	0.23
	CEXIO	0.13	0.23	1.00
ETH	Binance	1.00	0.08	0.03
	HitBtc	0.08	1.00	0.15
	CEXIO	0.03	0.15	1.00
LTC	Binance	1.00	0.09	-0.03
	HitBtc	0.09	1.00	0.39
	CEXIO	-0.03	0.39	1.00

(c) Correlations of assets between exchanges

particular, whether liquidity is correlated between assets and trading venues. To this end, we measure the Pearson correlation of the XLM(10 k) measure, as we believe it has the best explanatory power of the calculated measures. Table IIIa shows the correlation of the XLM measure between all assets across the entire dataset. All show moderate correlation, with ETH and LTC being the most correlated at 0.48, followed by BTC and ETH at 0.44, and finally BTC and LTC at 0.30. A breakdown by exchange provides a more detailed view, which can be seen in table IIIb and reveals different patterns. On HitBtc, there is a strong correlation of liquidity across all assets, with BTC - ETH having the highest correlation. On Binance, the correlation is mostly moderate, with BTC - LTC being the exception, showing almost no correlation. The assets on CEXIO mostly show a weak correlation, with BTC - ETH being the highest. Another angle on this matter is to see if, for example, the liquidity of an asset like BTC correlates with each other on different exchanges. As can be seen in table IIIc, assets show only a weak correlation between exchanges. The only exception is LTC, where there is a moderate correlation between HitBtc and CEXIO.

D. Are there noticeable changes in liquidity throughout 2022?

To see how liquidity has changed over 2022, we created daily averages of the XLM(10 k) measure for each asset on each exchange, which can be seen in Figure 1. The chart confirms our previous findings that assets on Binance are generally more liquid, followed by HitBtc and then CEXIO. As an asset itself, LTC is always the least liquid. In general, BTC is the most liquid, but on Binance and CEXIO this is only true for the first seven months of the year, after which ETH becomes more liquid on Binance. On CEXIO, BTC and ETH alternate as the most liquid assets. Significant changes in liquidity can also be seen over the course of 2022. Most assets saw a significant drop in liquidity in May, most likely caused by the collapse of the Terra ecosystem. After the swings, almost all markets returned to their previous state, with the exception of LTC on CEXIO, which continued to fluctuate in a less liquid state. The collapse of the Terra ecosystem had far-reaching consequences and led to major players becoming insolvent around June. We can observe that this affects liquidity for most assets, with the exception of LTC on CEXIO. Again, liquidity returned to its previous state for the most part. In the months of July to October, liquidity on the various exchanges did not behave uniformly. For BTC and ETH, liquidity on Binance and CEXIO suddenly dropped, but then slowly rose again. HitBtc did not experience this spike, but another one around mid-September. Towards the end of the year, especially in November, all assets became more illiquid, most likely due to the FTX crash. Assets on Binance mostly recovered to earlier liquidity and became more liquid towards the end of the year. On HitBtc, liquidity remained mostly at the same level, while on CEXIO, liquidity remained similar for BTC, while ETH became more liquid.

VI. Discussion

Our results show that there are differences in liquidity between assets on different exchanges and that the liquidity of exchanges is generally correlated with their trading volume. In addition, there is a moderate correlation in liquidity between different assets and exchanges and variation in liquidity between different assets on different exchanges. We would also like to emphasize the importance of understanding different measures of liquidity and their correlation with each other. Due to their higher explanatory power, we believe that XLM is a good option for measuring and interpreting liquidity. External events such as the Terra Luna crash and the FTX crash had a significant impact on liquidity and the recovery time does not show consistent behavior.

We would also like to point out that the limited number of assets and exchanges studied could pose a threat to validity. This also applies to the use of Tether as the only quote currency, as the study by Angerer et al. found that the choice of quote currency has an impact on liquidity [11]. Moreover, the XLM measure for LTC on CEXIO could not be calculated for each observation, so it can be assumed that the actual liquidity is worse.

VII. Conclusions

In this study, we examined the liquidity of exchanges and assets and the impact of external events on centralized crypto exchanges over the course of 2022. We measured several measures of liquidity for nine different order books with three

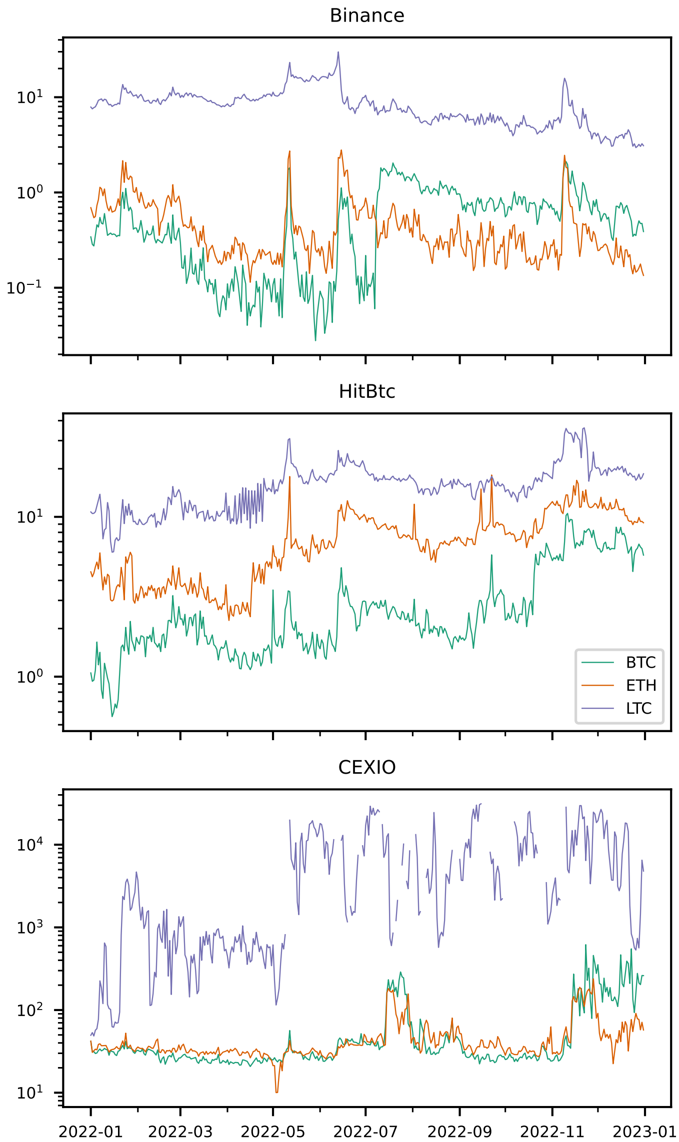


Fig. 1: Daily averages of the XLM(10 k) measure of BTC, ETH, and LTC divided by exchange.

currency pairs on three exchanges and analyzed the resulting multivariate time series using correlation and time series plots. We find that there are differences in liquidity across assets on different exchanges and that the liquidity of exchanges is generally correlated with their trading volume. We found only a moderate correlation of liquidity between different assets and exchanges, and variation in liquidity between different assets on different exchanges during 2022. The study also found that external events such as the Terra Luna crash and the FTX crash had a significant impact on liquidity, and the recovery time varied across assets and exchanges. We believe our results can help traders and investors make more informed decisions about investing in crypto exchanges. For future work, we plan to expand the number of assets and exchanges studied and examine the impact of different quote currencies on liquidity. In addition, correlations could also be time-shifted, which we will investigate with more appropriate measures. In general, future research could benefit from learning more about liquidity in decentralized exchanges and how it compares to centralized exchanges. In addition, a comparative study of liquidity on crypto exchanges and traditional exchanges would be interesting.

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