Order Book Liquidity on Crypto Exchanges

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Abstract

We analyze intraday liquidity for a range of cryptocurrencies across different exchanges. Among the liquidity measures used, slippage is most interesting for crypto traders, as it directly impacts their profit/loss. We find evidence that slippage can be explained by liquidity measures indicating that trades are timed. We report various liquidity patterns that allow traders to increase their profits by minimizing liquidity-dependent trading costs. We further find indications that crypto exchanges can control liquidity by the number of offered currency pairs.

Keywords: Cryptocurrencies; Liquidity; Market microstructure

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1 Introduction

In recent years, cryptocurrencies have gained in importance in various ways. An increasing number of investors have come to acknowledge cryptocurrencies as a separate asset class. This has been supported by the rise of altcoins, several of which outperformed Bitcoin in recent years and broadened the investment opportunities within this new asset class. These developments have spurred new research on cryptocurrencies, which is reflected by a rapidly growing number of papers on topics in this area. Most of the literature, however, still focuses on Bitcoin and on data derived from price series, such as returns or volatilities. Liquidity, while of high importance for cryptocurrency investors, has received less attention. One major reason for this is data availability. While price data are widely available, order book data are harder to come by.

From an academic point of view, liquidity and its development over time is an important indicator of (and requirement for) market efficiency. From an investor's point of view, liquidity impacts transaction costs, which in turn impact the investor's profit/loss from trading.

An attractive trading place provides the infrastructure to trade (in our case crypto) assets with high reliability at low costs. This operational efficiency is a necessary but not sufficient condition for higher forms of market efficiency. An important aspect in this regard are the total transaction costs, which can be split in explicit and implicit costs. Explicit costs include but are not limited to trading, clearing and settlement fees for exchanges as well as service and commission fees for market intermediaries. These costs are typically easy to measure and compare due to their transparency. Implicit costs however, such as those associated with (il)liquidity, are not transparent and are usually much harder to measure. While a negative relation between liquidity and implicit trading costs seems intuitive, this is quite vague as it does not refer to a particular concept or aspect of liquidity. Different aspects of liquidity give rise to different liquidity measures. Simple proxies such as trading volume may serve as a rough indicator for liquidity, but cannot capture its more specific aspects, which are often more subtle.

In this paper, we investigate various aspects of the liquidity of cryptocurrencies. In particular, we are interested in differences in liquidity among currency pairs, across exchanges, and over time. Insights from this analysis are of interest for academics, investors, trading places, and regulators.

For investors, the comparison of liquidity and the associated transaction costs of currency pairs and trading places provides information that helps in making decisions what to buy, where to buy it, and when to buy. Trading venues may use the results to reevaluate their trading systems, market design, and listings. E.g., they may consider to add designated sponsors for liquidity contribution to shift from a pure order-driven to a hybrid market. These liquidity providers are valuable for order book markets whenever liquidity for trading pairs is weak, i.e. the spreads are too large or the volumes at the best levels of the order books are too low. The 24/7 continuous trading may also be reviewed. Auction models or continuous trading with interrupting auctions are more suitable for currency pairs with low liquidity to bring together a higher number of traders. Additional liquidity attracts more traders and the exchange can gain a higher trading volume and market share.

Finally, our results are also relevant for regulators. For example, market competition issues are one of the typical concerns of regulators. In a consolidated (fragmented) market, there is low (high) competition among the exchanges, but high (low) competition among the traders, which leads to low (high) liquidity costs and high (low) explicit transaction costs. The optimal degree of fragmentation is very critical to ensure investor protection. Fragmentation in the crypto-world does not only happen across exchanges, but also within one particular trading place, as they usually offer many trading pairs with different base currencies.

The remainder of the paper is organized as follows. Section 2 describes the related literature. Section 3 presents the data. Section 4 provides the methodology and discusses the liquidity measures used. Section 5 discusses the results, and Section 6 concludes.

2 Literature

Research on market liquidity started in the late 1960s with Demsetz (1968) who analyzed bid-ask spreads in dealer markets. The literature created influential theoretical (e.g., Akerlof, 1970 for a market with information asymmetries; Kyle, 1985 for strategic behavior of insiders), empirical (e.g., Huang and Stoll, 1996 for transaction costs in auction and dealer markets; Christie and Schultz, 1994 for collusion in the NASDAQ dealer market), and experimental models (e.g., Plott and Sunder, 1982 for information dissemination in experimental auction markets; Friedman, 1993 for experimental comparison of auction and dealer markets).

The present paper is related to several strands of the literature. Research on cryptocurrencies in finance and economics is still in an early stage. The majority of papers in this area focuses on the potential real effects of cryptocurrencies as a payment and transaction mechanism. Ciaian et al. (2016), Harvey (2016), Böhme et al. (2015), and Raskin and Yermack (2016) provide a broad perspective on the economics of cryptocurrencies and the blockchain technology they are built upon. Pagnotta and Buraschi (2018) propose valuation models for digital currencies. Easley et al. (2019) and Huberman et al. (2020) study bitcoin mining fees and the incentives of miners in equilibrium.

Brauneis et al. (2020) mention that few papers use full order book data to study the liquidity of cryptocurrency markets. Dyhrberg et al. (2018) study the trading dynamics of Bitcoin on US-based crypto exchanges. Makarov and Schoar (2018) study arbitrage opportunities across exchanges. In most applications low-frequency measures have been used in isolation [what is meant by "in isolation?" = without basis of comparison] in cryptocurrency markets Brauneis and Mestel (2018) test the predictability of cryptocurrency returns. Al-Yahyaee et al. (2020) study the efficiency of cryptocurrency markets and find inefficiencies which are driven by illiquidity and volatility of the cryptocurrencies.

Anand et al. (2005), Back and Baruch (2005) and Ranaldo (2004) point out the advantages of limit order books which include, but are not limited to low transaction costs (brokerage, commissions, spreads and fees, etc), pre- and post-trade transparency, efficient price discovery through comprehensive information aggregation, less information asymmetry and more competitive market microstructure.

The nature of liquidity provisioning in LOB markets differs from that in quote-driven markets in one important aspect. The limit order suppliers -– i.e. the de-facto market makers — face very low entry and exit barriers. They can freely provide or withdraw liquidity from the market depending on the market conditions. This is in contrast to the designated market makers in quote-driven markets who have a commitment to provide liquidity. This important aspect of liquidity provisioning in LOB markets is captured by the "free-entry and free-exit" hypothesis by Brockman and Chung (2002).

Previous literature has widely documented the informativeness of limit order books and their contribution in decreasing the information asymmetry. Cao et al. (2009) studied the informational content of order book levels behind the best bid and ask. Harris and Panchapagesan (2005) find that limit order books are informative about future price movements. The state of order book (tightness, depth and imbalance) in a financial market is ascertained using a number of measures (such as spread, volume and impact costs).

This paper contributes to the literature in various ways. First, we focus on liquidity, whereas most of the previous studies on cryptocurrencies analyzed other aspects. Second, instead of confining ourselves to Bitcoin, we analyze a large number of altcoins. We also contribute to the sparse literature which takes deeper levels of order books into account, i.e. prices and quantities beyond the best bid and ask, when evaluating limit order book liquidity. Third, in contrast to order books from other exchanges, full limit order books of the crypto exchanges are unique in providing 24/7 trading data.

3 Data

3.1 Raw Data

Order book data from the exchanges Binance, Kraken, Huobi, and OKEx are provided by CryptoTick (https://www.cryptotick.com/). The time frame is Jan. 1, 2019, until Sept. 30, 2019 (273 days). The data are delivered in the form of single files per currency pair, exchange, and trading day. Date and time of the trading days are standardized on Coordinated Universal Time (UTC).

The data set represents all levels from each side of the order book which were provided to CryptoTick by the exchanges. Some exchanges report all available orders, some only display a limited number of orders. For example, Binance reported only the best 20 bids and asks until mid-June 2019.

The time horizon of our sample covers many new listings/delistings on the exchanges, so some currency pairs appeared/disappeared between January and September 2019. Occasionally, some trading days are also missing if they are not reported by Cryptotick due to suspended trading or unavailability of data for unknown causes.

These 24/7 limit order book data allow for reconstructing (part of) the limit order books to evaluate the liquidity of currency pairs. Unlimited trading hours may shift or center liquidity to specific times during the day. Trading reflected in our limit order books is not interrupted by auctions, which is different from, e.g., XETRA with opening, intraday, and closing auction for German stocks.

3.2 Data Processing

Each file starts with an order book snapshot which lists all available price levels on each side of the order book at the beginning of the day. The following entries document updates to the current order book status. We created 5-minute order book snapshots containing up to 20 levels on each side (if available), which results in 288 order book snapshots per day. Order books at 5-minute intervals are widely used in the literature. They represent a good compromise between computation time and informational content of the data, allowing for reasonable processing effort without sacrificing important information.

Table 1: Number of Base Currencies, Target Currencies and Trading Pairs by Exchange

This table reports the number of base currencies (column 2), the number of target currencies (column 3), and the number of trading pairs (column 4) by the four exchanges (column 1).

Exchange	# of Base Currencies	# of Target Currencies	# of Trading Pairs
BINANCE	11	161	514
HUOBI	4	22	57
KRAKEN	7	21	79
OKEX	5	160	436

Some filters are applied to ensure data quality. First, we exclude all days with order books which report negative or zero bid-ask spreads at 5-minute snapshots. Any such observations should have led to matching and removing the corresponding orders from the order book. Second, we omit all days with order books which report a negative quantity for an order as this is economically meaningless. Both issues are an indication of incorrect raw data. If we were not able to identify and solve the cause of the error for a trading pair on a day, we omit the whole day of the observation. This occurs very rarely in our sample, so our results should not be significantly affected.

3.3 Descriptive Statistics

The crypto exchanges in our sample offer a range of crypto trading pairs. For this paper, we label the crypto which is reported as quantity in the order book as the "target currency" and the crypto or fiat currency which is reported as the price in the order book as the "base currency". Each combination of a target currency with a base currency yields a currency pair (or trading pair).

Table 1 reports for each exchange the number of base currencies, the number of target currencies, and the number of the trading pairs which were traded from January 2019 until September 2019. While the number of base currencies for each exchange is rather modest between four and twelve, the number of target currencies and trading pairs differ substantially across exchanges. Binance and OKEx have a broader offer with 162 and 160 offered target currencies resulting in 515 and 436 trading pairs, respectively. In contrast, Huobi and Kraken are more focused with only 22 and 21 target currencies (57 and 79 trading pairs). This points to different business policies or strategies on the part of different crypto exchanges (wider selection with Binance and OKEx, specialization on selected currency pairs with Huobi and Kraken).

Next, we examine the types of the base currencies and distinguish between three types: fiat currencies (US dollar, euro etc.), stablecoins (Tether and other US dollar pegged coins), and other cryptocurrencies (Bitcoin, Ether, etc.).

Table 2 reports the number of target currencies and trading pairs by the exchanges and our selected base currency types. Huobi is the only exchange which offered all three of the base types. Binance and OKEx did not have fiat currencies while Kraken did not offer any stablecoins. The four fiat trading pairs for Huobi are the US dollar vs. Tether, Bitcoin, Ether, and Ripple. These four currencies are very popular and serve as base currencies as well. So, these trading pairs can be used entry and exit points between the fiat and the crypto trading world. The other three exchanges provide either stablecoins or fiat currencies.

Since the exchanges differ in the base currency types, we now investigate which base currencies

Table 2: Number of Target Currencies and Trading Pairs by Exchange and Base Type

This table reports the number of target currencies (column 3) and the number of trading pairs (column 4) by the four exchanges (column 1) and the base currency type (column 2).

Exchange	Base Type	# of Target Currencies	# of Trading Pairs
BINANCE	cryptocurrency	157	377
BINANCE	stablecoin	57	137
HUOBI	cryptocurrency	20	33
HUOBI	fiat currency	4	4
HUOBI	stablecoin	20	20
KRAKEN	cryptocurrency	20	29
KRAKEN	fiat currency	19	50
OKEX	cryptocurrency	140	276
OKEX	stablecoin	143	160

Table 3: Number of Target Currencies by Exchange and Base Currency

This table reports the number of target currencies (column 4) by the four exchanges (column 1) and the base currencies (column 2). Column 3 defines the type of the corresponding base currency in column 2.

Exchange	Base Currency	Base Type	# of Target Currencies
BINANCE	BBTC	cryptocurrency	1
BINANCE	BNB	cryptocurrency	92
BINANCE	BTC	cryptocurrency	150
BINANCE	ETH	cryptocurrency	131
BINANCE	TRX	cryptocurrency	1
BINANCE	XRP	cryptocurrency	2
BINANCE	PAX	stablecoin	29
BINANCE	TUSD	stablecoin	24
BINANCE	USDC	stablecoin	27
BINANCE	USDS	stablecoin	2
BINANCE	USDT	stablecoin	55
HUOBI	BTC	cryptocurrency	20
HUOBI	ETH	cryptocurrency	13
HUOBI	USD	fiat currency	4
HUOBI	USDT	stablecoin	20
KRAKEN	BTC	cryptocurrency	20
KRAKEN	ETH	cryptocurrency	9
KRAKEN	CAD	fiat currency	7
KRAKEN	EUR	fiat currency	18
KRAKEN	GBP	fiat currency	2
KRAKEN	JPY	fiat currency	4
KRAKEN	USD	fiat currency	19
OKEX	BTC	cryptocurrency	127
OKEX	ETH	cryptocurrency	118
OKEX	OKB	cryptocurrency	31
OKEX	USDK	stablecoin	18
OKEX	USDT	stablecoin	142

Table 4: Number of Trading Pairs and Target Currencies traded parallel

This table reports the number of target currencies (panel (a)) and the number of trading pairs (panel (b)) traded parallel on the four exchanges. The first row reports the absolute number and the second row reports the relative number of the target currencies and the trading pairs. The columns 1 to 4 report the number of exchanges (one exchange for column 1 to four exchanges for column 4).

(a) Target Currencies

	1	2	3	4
Frequency	182	54	10	11
Rel. Freq.	70.8%	21.0%	3.9%	4.3%

(b) Trading Pairs

	1	2	3	4
Frequency	714	117	30	12
Rel. Freq.	81.8%	13.4%	3.4%	1.4%

are offered by each exchange and report the most interesting findings. Table 3 shows the exchanges in the first column, the base currency of the associated exchange in the second column, the type of the base currency in the third column, and the number of target currencies for the corresponding base currency. We report the total number of currencies which are traded in our sample period (including new listings and delistings).

Bitcoin and Ether are those cryptocurrencies that are part of the highest number of trading pairs, especially on Binance and OKEx with over 100 trading pairs. Tether on OKEx serves as the base currency for 142 target currencies, while it only accounts for 55 target currencies on Binance and 20 on Huobi. Binance offers further stablecoins and other cryptocurrencies such as Baby Bitcoin (BBTC), Tron (TRX), Ripple (XRP), and USD Coin (USDS) which are of limited importance and will be disregarded for the rest of the paper. Binance and OKEx released their own coins, Binance Coin (BNB) with 92 and OKB with 31 target currencies. The vast variety of investment opportunities is difficult to grasp and assess for investors.

Kraken is the only exchange in our sample which, in addition to the US dollar (or stablecoins pegged to US dollar) also provides fiat currencies, namely the euro (EUR), Canadian dollar (CAD), Japanese yen (JPY), and Pound Sterling (GBP). This may be appealing to investors from those countries/areas as it allows them to directly express the value of the target currency in their home fiat currency, and it also removes the currency risk and transaction costs between the US dollar and their home currency. Generally, US dollar-based investors have more opportunities via fiat trading pairs and USD-pegged stablecoins.

Table 4 reports how many trading pairs and target currencies are traded on how many of the four exchanges in our sample. Roughly 72% of the target currencies and 82% of the trading pairs are traded on just one exchange. Only eleven (4.26%) identical target currencies and twelve (1.37%) identical trading pairs are offered on each of the exchanges. This is probably inconvenient for investors who have to maintain several wallets to trade in a variety of crypto assets. Limiting the comparative evaluation of the exchanges in terms of liquidity to the trading pairs in common could bias the results. For example, Binance and OKEx offer a wider range of trading pairs compared to Huobi and Kraken, so the probable higher total liquidity maybe spread over multiple pairs. This would let the a single trading pair from Binance and OKEx appear less liquid compared to the corresponding pair on Huobi and Kraken. From an investor's perspective, this is only relevant for those who wish to trade in these pairs entirely. To understand the overall market better and to target a larger audience, our approach focuses on measuring liquidity by considering all trading pairs on the exchanges and applying suitable liquidity measures regardless of the target currency, base currency, and trading pairs.

4 Methodology

We choose liquidity measures which can be applied to all trading pairs and make them comparable regardless of their target and base currencies. There are liquidity measures which keep the units of either the target or base currencies, for example liquidity measures based on trading volume. Trading volume can be reported as a quantity which equals the number of the target currency units traded for our case. Transactions can also be measured by multiplying the trade volume with the average price of the trade. As a result we disregard the transaction data and solely derive the liquidity measures from the limit order books themselves We account for transactions in an indirect way with our order book slippage measure we explain in detail in section 4.1. The main focus of this paper is the investors' perspective on limit order books and what they can learn from them.

Since trading is possible 24/7 and we work with data at five minute intervals, the resulting liquidity measures at this frequency would be quite noisy. For this reason, we generate daily values for the liquidity measures by taking the average of our studied measures for the day. The resulting values are much less noisy than, e.g., liquidity measures calculated from order book snapshots taken at a daily frequency.

First, we want to compare the liquidity depending on the base currency type of the trading pair. We are interested in the differences in liquidity given the base currency is either a fiat currency, a stablecoin, or another cryptocurrency. We analyze this by grouping the results for our chosen liquidity measures by the base currencies similar to Table 2. We also take a closer look at the the specific base currencies like in Table 3, leaving out BBTC, TRX, XRP, and USDS on Binance since they only account for a small fraction of all target currencies for their corresponding base currency type.

In the following subsection, we present and discuss the liquidity measures chosen for this study. All of them are based solely on order book data, in particular on prices and quantities of different order book levels which reflect liquidity provision by investors.

4.1 Order Book Slippage

Slippage measures the difference between the expected trading price and the actual trading price. Slippage can also be anticipated pre-trade by estimating the trading price from order book data. Brauneis et al. (2020) and Gomber et al. (2015) estimate transaction costs by roundtrip costs of predefined order book sizes. This measure evaluates how good order books can absorb large liquidity demands. Higher transaction costs indicate lower liquidity and vice versa. A crucial element of this measure is to define the order book sizes. Brauneis et al. (2020) takes the 99% quantile of the aggregate trade size distribution. A necessary condition to use this methodology is that the the studied assets are traded in the same currency so that they are not exposed to exchange rate risks. If there are exchange rate fluctuations, the measures are not comparable over time. This is the case for our sample since our sample has several base currencies and they are exposed to exchange rate fluctuations.

For the reasons discussed above, we select a measure for the intraday slippage in a limit order book. As outlined in Section 3, we reconstruct the order book at five-minute intervals which results in 288 snapshots per day. One way to measure slippage is by the number of order book levels the mid price moves from one such snapshot to the next. First, we find the level L which minimizes the absolute difference between the bid price at level L at time t and the mid price at time $t-1$.

$$l_{\text{bid}} = \arg\min_{l} \left(|P_{bid,1,t} - P_{mid,t-1}|, |P_{bid,2,t} - P_{mid,t-1}|, ..., |P_{bid,l,t} - P_{mid,t-1}|, ..., |P_{bid,L,t} - P_{mid,t-1}| \right) \tag{1}$$

Next, we proceed analogously for the ask side of the order book:

$$l_{\text{ask}} = \arg\min_{l} \left(|P_{ask,1,t} - P_{mid,t-1}|, |P_{ask,2,t} - P_{mid,t-1}|, ..., |P_{ask,l,t} - P_{mid,t-1}|, ..., |P_{ask,L,t} - P_{mid,t-1}| \right) \tag{2}$$

We combine the results from equations 1 and 2 by taking the maximum of their results:

$$l = \max(l_{\text{bid}}, l_{\text{ask}}). \tag{3}$$

By construction at least one of the two values is equal to one. Lower values of l indicate higher liquidity in the order book.

For each trading day, we calculate 288 values of l (one value per five-minute time interval). For further analysis, we aggregate these values in two ways: First, we compute the simple average across all observations of l for each trading day. This filters out short-term fluctuations and can be interpreted as a measure of the average level of slippage for a currency pair on a given trading day. Second, we compute the maximum 5-minute slippage, which can be interpreted as the worst-case slippage recorded for a currency pair on a given trading day. The difference between the two is a simple measure of slippage risk.

This slippage measure accounts for two liquidity-consuming factors simultaneously. On the one hand, best bid and ask orders may be cancelled and disappear from the order book. From a narrow order book liquidity perspective, this is a removal of liquidity. However, this effect is expected to be very low for our slippage measure since we do not expect that mid-price changes are driven by order cancellations a lot, and there is no corresponding evidence in the literature to the best of our knowledge.

On the other hand, liquidity can be consumed by trades, i.e. when matched orders disappear from the order book. The impact of the trade depends on the trade size and the current state of the order book in terms of liquidity. In general, larger trades and lower order sizes at the levels closest to the mid-price lead to higher values for our slippage measure. Trades are expected to be the main driver of large order book slippage.

One advantage of this measure is that it captures the liquidity dynamics of the order books without putting too much emphasis on the exact numbers. Abstracting from prices and reducing the information to price levels allows for a comparison of trading pairs with different base currencies. From an investor's point of view, slippage is highly relevant. They can use the measure to identify trading pairs with low liquidity and adjust their order submission strategies to minimize slippage, execution and pick-off risk.

4.2 Order Book Spread

Order book spread measures the liquidity implied by the prices of orders at the best bid and ask levels. The lowest-priced sell limit order is the best ask price and the highest-priced buy limit order is the best bid price. The difference between these prices is the quoted spread. Chung et al. (2004) outline that investors only submit limit orders to the order book with respect to the profitability of their order. Since cryptocurrencies are subject to high volatility, we can expect higher spreads to account for price volatility. In general, the bid-ask spread reflects explicit costs (transaction and order processing costs) as well as implicit costs (adverse selection costs and waiting costs). Brockman and Chung (1999), Chan (2000) as well as de Jong et al. (1996) find that a large fraction of the spread is highly persistent and related to adverse selection costs. Brauneis et al. (2020) outlines that order book data at the best bid and ask prices provide good real-time estimates of liquidity in crypto markets.

The quoted spreads are defined in prices, this means for our data set that they are denominated in the base currency. Computing the relative spread, i.e. dividing the quoted spread by the mid-quote, removes this denomination and makes the results comparable across all currencies and exchanges.

$$\text{Relative Spread} = \frac{P_{\text{best ask}} - P_{\text{best bid}}}{P_{\text{mid}}} = \frac{\text{Quoted Spread}}{P_{\text{mid}}} \tag{4}$$

with

$$P_{\text{mid}} = \frac{P_{\text{best ask}} + P_{\text{best bid}}}{2} \tag{5}$$

Gomber et al. (2015) interpret the relative spread as a liquidity premium which has to be paid to execute an order immediately. Investors face a trade-off between the payment of this liquidity premium and the waiting costs until their order is executed.

So far, we have only looked at the best prices. The literature, for example Cao et al. (2009), provides evidence that levels deeper in the order book are less prone to noise and carry more relevant information about the liquidity of limit order books. Volume-weighted average prices (VWAP) can be used to incorporate prices and volumes beyond the best bid and best ask orders. The VWAP for the bid and ask side are calculated as:

$$P_L^{\text{VWAP}} = \frac{\sum_{l=1}^{L} P_l * Q_l}{\sum_{l=1}^{L} Q_l}, \tag{6}$$

where l represents the levels of the corresponding bid and ask sides, Q_l equals the quantity at level l, and P_l equals the price at level l.

The VWAP spread and the VWAP relative spread at level L are calculated analogously to the (best) bid-ask spread:

$$\text{Spread}_L^{\text{VWAP}} = P_{\text{ask},L}^{\text{VWAP}} - P_{\text{bid},L}^{\text{VWAP}} \tag{7}$$

$$\text{Relative Spread}_L^{\text{VWAP}} = \frac{P_{\text{ask},L}^{\text{VWAP}} - P_{\text{bid},L}^{\text{VWAP}}}{P_{\text{mid}}} \tag{8}$$

Besides level one, the best bid and ask level, we calculate the VWAP spreads for the levels 5, 10, 15, 20, 25, 50, 75, 100, and 150, i.e. incorporating up to the best 150 orders on both sides of the order book if available.

4.3 Order Book Depth

The liquidity impact of orders at the best prices is higher and lasts longer if they carry substantial volume. Cao et al. (2009) highlight that orders at the best prices are noisy and less informational efficient than prices at deeper levels of the order book. The reasons are that these orders are matched first and disappear if market orders are submitted with larger volume than the best orders or new limit orders with low volume undercut the existing best orders. This leads to volatile best prices and quantities which do not persist long in the order book. We expect that we can cancel or smooth these noisy orders out by observing only the five minute order book snapshots and averaging the results for the day to get an unbiased state of the liquidity of the order book.

Goettler et al. (2005) and Valenzuela et al. (2015) argue that a greater depth around the best price levels reflects a relatively high consensus on the true price while a preponderance of volume at price levels further away from the mid-price indicates higher uncertainty about the price.

We define depth as the sum of the product of the price and quantity from the best price until the selected level. We calculate depth separately for both sides of the order book to gain information on differences between buy and sell:

$$\text{Depth}_{\text{ask},L} = \sum_{l=1}^{L} (P_{\text{ask},l} * Q_{\text{ask},l}) \tag{9}$$

$$\text{Depth}_{\text{bid},L} = \sum_{l=1}^{L} (P_{\text{bid},l} * Q_{\text{bid},l}) \tag{10}$$

This measure of the depth highlights the accumulated volume the order book contains at the different price levels. We take the product of the quantity and the prices to cancel out the target currency and to report the volume in terms of the base currency. This allows us to compare the results among exchanges for a given base currency. We do not compare the results in terms of the target currency because there are too many most of them are only traded at one exchange.

4.4 Order Book Imbalance

While depth itself captures a relevant aspect of liquidity, the difference between the bid and ask depth, which is known as *order imbalance*, contains additional information. Biais et al. (1995) find evidence that a higher order imbalance is linked to higher trading costs. Bonart and Gould (2017) argue that order book imbalance is a strong predictor of order flow due to traders who cancel their limit orders to submit market orders.

We calculate the order imbalance by subtracting the bid depth from the ask depth at our selected levels.

$$\text{OBI}_L = \sum_{l=1}^{L} (P_{\text{ask},l} * Q_{\text{ask},l} - P_{\text{bid},l} * Q_{\text{bid},l}) = \text{Depth}_{\text{ask},L} - \text{Depth}_{\text{bid},L} \tag{11}$$

Similar to the spread, a normalization is required to make the measure comparable across different base currencies. To this end, we divide the order imbalance (the difference between ask and bid

Table 5: Slippage by Base Type

This table reports the average mean slippage (column 3) and the average maximum slippage (column 4) by the four exchanges (column 1) and the base currency types (column 2). The numbers in the brackets report the standard errors of the corresponding averages.

Exchange	Base Type	Mean Slippage	Max Slippage
BINANCE	cryptocurrency	1.97 (0.011)	12.5 (0.079)
BINANCE	stablecoin	3.24 (0.034)	15.5 (0.203)
HUOBI	cryptocurrency	2.95 (0.055)	19.3 (0.358)
HUOBI	fiat currency	2.71 (0.055)	15.7 (0.409)
HUOBI	stablecoin	6.86 (0.148)	39.4 (0.724)
KRAKEN	cryptocurrency	1.63 (0.016)	10.5 (0.136)
KRAKEN	fiat currency	2.32 (0.023)	14.3 (0.180)
OKEX	cryptocurrency	1.48 (0.023)	8.04 (0.185)
OKEX	stablecoin	2.02 (0.065)	13.0 (0.451)

depths) by the sum of the ask and bid depth measures for the same order book levels.

$$\mathrm{NOBI}_L = \frac{\sum_{l=1}^{L} (P_{\mathrm{ask},l} * Q_{\mathrm{ask},l} - P_{\mathrm{bid},l} * Q_{\mathrm{bid},l})}{\sum_{l=1}^{L} (P_{\mathrm{ask},l} * Q_{\mathrm{ask},l} + P_{\mathrm{bid},l} * Q_{\mathrm{bid},l})} = \frac{\mathrm{OBI}_L}{\mathrm{Depth}_{\mathrm{ask},L} + \mathrm{Depth}_{\mathrm{bid},L}} \tag{12}$$

This measure overcomes some drawbacks of the order book depth. The target and base currencies are cancelled out which allows us to compare the results among all base currencies and exchanges. Second, the order book imbalance measure is standardized to values between -1 and 1 and can be interpreted easily. -1 is the extreme case that there are only bid orders in the order book, 0 stand for a balanced order book with equally high depth at level L and 1 is the other extreme case that there are only ask orders in the order book. Accordingly, negative (positive) NOBI corresponds to a preponderance of ask (bid) orders in value terms of the base currency.

To measure the effect of order book imbalance in general, we take the absolute value of NOBI for the absolute normalized order book imbalance (ANOBI):

$$\mathrm{ANOBI}_L = |NOBI_L| \tag{13}$$

5 Results

5.1 Slippage

Table 5 summarizes the results for slippage grouped by exchange and base type. The third column shows the daily average of the mean slippage over the 288 intraday observations, while the fourth column provides the daily average of the maximum slippage an order book experienced within a day. The numbers in brackets are the standard errors of the corresponding measures.

The mean (maximum) slippage ranges from 1.48 (8.04) for OKEx' cryptocurrencies to 6.86 (39.4) for Huobi's stablecoins. The large differences between the average means and maximums of intraday slippage indicates a high liquidity risk: Depending on the exact time at which an order is submitted, liquidity may vary significantly. Every now and then during a trading day, liquidity drops sharply, which creates a risk for investors who submit *new* orders without current information on the state of the order book. *Existing* limit orders face pick-off risk which informed and fast traders can exploit.

Focusing on those exchanges that offer currency pairs with stablecoins as base currencies (Binance, Huobi, and OKEx), the mean slippage as well as the maximum slippage are higher for stablecoins than for either fiat currencies or cryptocurrencies. Among these exchanges, slippage is highest for trades at Huobi. The data from Kraken show higher slippage for currency pairs with fiat currencies as base currency compared to cryptocurrencies as base currency. So, for the exchanges Binance, Kraken and OKEx, the investors provide more liquidity to cryptocurrencies than to fiat currencies and stablecoins. This is a surprising result since these base cryptocurrencies are exposed to considerably higher price volatility.

For Huobi, which offers all three types of base currencies, the fiat currencies have the lowest slippage among the base types. OKEx and Binance, which only offer stablecoins and other cryptocurrencies, have lower slippage than the corresponding types on Huobi. This suggests that from the viewpoint of an exchange, offering the choice of fiat currencies as base currency takes away liquidity from the stablecoins and other cryptocurrencies.

5.2 Spreads

Table 6 shows the average relative spreads for the best level, level 5, level 10, level 15, and level 20 grouped by exchange and base currency type. We observe a number of differences between the exchanges and base currency types.

For cryptocurrencies other than stablecoins, the spreads are about 0.55% for Binance, Huobi and Kraken, but 1.9% for OKEx. Sizable differences also arise for stablecoins between Binance (0.59%), Huobi (0.23%), and OKEx (1.26%). The differences in the fiat currencies between Huobi (0.12%) and Kraken (1.25%) are primarily driven by high spreads for GBP, JPY and CAD. USD on Kraken has an average spread of 0.38 for the best level which is still significantly higher than the corresponding spread on Huobi.

The results suggest that the specialization on selected trading pairs benefits the results of exchanges in terms of liquidity overall, Binance and OKEx offer 514 and 436 trading pairs while Huobi and Kraken offer only 57 and 79 trading pairs. Even though the best relative spread for Kraken's other cryptocurrencies is larger than the best spread of Binance's cryptocurrencies, the former along with Huobi's cryptocurrencies report higher liquidity in terms of lower spreads from level-5 than

Table 6: Spread Measures by Exchange and Base Currency

This table reports the average relative spreads in percent (%) for the best level (column 3), level 5 (column 4), level 10 (column 5), level 15 (column 6), and level 20 (column 7) by the four exchanges (column 1) and base currency types (column 2). The numbers in the brackets report the standard errors of the corresponding average relative spreads.

Exchange	Base Type	L1 Rel. Spread	L5 Rel. Spread	L10 Rel. Spread	L15 Rel. Spread	L20 Rel. Spread
BINANCE	cryptocurrency	0.552 (0.003)	1.53 (0.012)	2.78 (0.023)	4.21 (0.037)	5.92 (0.0558)
BINANCE	stablecoin	0.589 (0.018)	1.14 (0.031)	2.62 (0.0832)	4.9 (0.153)	7.37 (0.226)
HUOBI	cryptocurrency	0.539 (0.008)	1.17 (0.019)	1.99 (0.0358)	3.38 (0.0886)	4.76 (0.126)
HUOBI	fiat currency	0.12 (0.004)	0.283 (0.010)	0.622 (0.0268)	1.04 (0.0426)	1.44 (0.0575)
HUOBI	stablecoin	0.231 (0.005)	0.459 (0.010)	0.769 (0.0163)	1.12 (0.0254)	1.52 (0.0367)
KRAKEN	cryptocurrency	0.576 (0.0112)	1.19 (0.024)	2.18 (0.0426)	3.3 (0.0644)	4.44 (0.0875)
KRAKEN	fiat currency	1.25 (0.044)	2.05 (0.057)	4 (0.122)	7.15 (0.202)	12.4 (0.434)
OKEX	cryptocurrency	1.9 (0.052)	4.76 (0.094)	11.3 (0.513)	17.1 (0.698)	21.2 (0.75)
OKEX	stablecoin	1.26 (0.053)	3.12 (0.105)	6.73 (0.585)	9.29 (0.295)	11.9 (0.383)

Table 7: Correlation between Spread Measures

This table reports the correlation matrix between level-1 relative spread, level-5 relative spread, level-10 relative spread, level-15 relative spread, and level-20 relative spread. The stars after the correlation coefficients indicate that their correlation is significantly different from zero at the 1%-significance level.

	L1 Rel. Spread	L5 Rel. Spread	L10 Rel. Spread	L15 Rel. Spread
L1 Rel. Spread				
L5 Rel. Spread	0.81*			
L10 Rel. Spread	0.57*	0.61*		
L15 Rel. Spread	0.50*	0.64*	0.86*	
L20 Rel. Spread	0.56*	0.67*	0.77*	0.86*

Table 8: Correlation between Slippage and Spreads

This table reports the correlation between the mean slippage (first column) as well as the maximum slippage (second column) and the level-1 relative spread (first row), the level-5 relative spread (second row), the level-10 relative spread (third row), the level-15 relative spread (forth row), as well as the level-20 relative spread (fifth row). The stars after the correlation coefficients indicate that the coefficients are significantly different from zero for the 1% significance level.

	Mean Slippage	Max Slippage
L1 Rel. Spread	-0.17*	-0.20*
L5 Rel. Spread	-0.22*	-0.26*
L10 Rel. Spread	-0.11*	-0.14*
L15 Rel. Spread	-0.15*	-0.18*
L20 Rel. Spread	-0.17*	-0.20*

the cryptocurrencies of Binance and OKEx. Considering the 377 trading pairs for Binance against 33 for Huobi and 29 for Kraken in the cryptocurrencies, the liquidity of Binance in terms of spreads is surprisingly good for other cryptocurrencies. The concentration of liquidity is more obvious by comparing the relative spreads of the stablecoins of Huobi versus the stablecoins by Binance and OKEx. Even though Binance and OKEx pursue a similar strategies, i.e. offering many trading pairs in cryptocurrencies and stablecoins, their liquidity as measured by relative spreads differ a lot.

The spreads increase with higher levels of the order books, and the higher the spreads at the best level, the steeper the increase in spreads. Compared to the other exchanges and base types, the very flat spread increase in order book levels for the fiat currencies and stablecoins on Huobi stand out. We can see a strong relationship for the relative spread among the order book levels which are to some extent to be expected given the nested structure of the spread measures (higher levels contain lower levels). Table 7 presents the correlation among the spreads at different order book levels and supports this findings.

Table 8 reports the correlations between the spread measures and the slippage measures. All correlations are negative and significant: Higher spreads go hand in hand with higher (average and maximum) slippage, with level 5 relative spreads and slippage values showing the highest correlation.

This result is plausible. Larger spreads indicate higher trading costs, which is not attractive for investors and leads to reluctance in placing market orders and paying the associated liquidity premium. Investors rather submit limit orders if liquidity is scarce. Vice versa, tighter spreads increase the probability of slippage. Consuming liquidity becomes cheaper, and traders increasingly move to using market orders. These results are in line with related literature from equity markets by Ranaldo (2004). The findings also support the equilibrium of liquidity supply and demand of liquidity in limit order books by Handa and Schwartz (1997).

5.3 Depth

Tables 9 and 10 display the results for ask depth and bid depth, respectively, from order book levels 1 to 20. By construction, depth is denoted in units of the base currency. For example, the level 1 ask depth in Table 9 for BTC on Binance equals 0.329 BTC. We omit the base currencies which only exist on one exchange and cannot be compared across exchanges. We sort the remaining base currencies in four groups: Bitcoin, Ether, US dollar, and USD-pegged stablecoins. While Bitcoin and Ether show more depth on the bid side, USD and USD-pegged stablecoins show more depth on the ask side on average.

For Bitcoin as the base currency, Binance and Kraken provide higher depth than Huobi and OKEx across all order book levels. While their depth values are very similar for the first and fifth price levels, Kraken provides more depth compared to Binance if we go deeper in the order book. Kraken also has high depth for Ether, while Binance has the lowest depth among the exchanges for Ether as the base currency. This outlines that Binance collect more liquidity in terms of depth for Bitcoin than for Ether. Despite the large number of trading pairs Binance offers in BTC, this does not seem to negatively impact depth.

The comparison across exchanges for the USD as base currency leads to similar results as for the spread measures. Huobi provides higher liquidity in terms of depth than Kraken for both the bid and ask side. Kraken provides similar depth on the bid and ask side, while the ask side of Huobi carries more depth for the first and fifth price levels. The deeper we look in the order book, the more the accumulated volumes move apart.

The stablecoins show less depth compared to their corresponding fiat currency, the USD. This is intuitive at first glance, as investors may prefer to trade in the real USD than a stablecoin version of it. However, fiat trading pairs are very limited, and investors who restrict themselves to fiat as base currency automatically exclude out a wide range of cryptocurrencies from their investment universe. For the stablecoins we can see a negative relationship between the number of trading pairs and depth.

Comparing the results with the spread measures hints at a positive relation between the depth and spread measures. A lower spread is usually associated with higher depth among all order book levels in our sample. We also find a negative relation between slippage and depth for each base currency with the only exception of Huobi's USD trading pairs. Higher depth is associated with lower slippage, which is an intuitive results as well.

5.4 Order Book Imbalance

Table 11 reports the normalized order book imbalances (NOBI) grouped by crypto exchanges and base currencies. We can see that the average NOBI is negative for all levels for each base currencies for the exchanges Binance, Kraken and OKEx. Except for the Huobi's fiat currency, all exchanges and base currency types indicate a preponderance of buying orders from level-10 on. This indicates

Table 9: Ask Side Depth

This table reports the average level-1 ask depth (column 3), the average level-5 ask depth (column 4), the average level-10 ask depth (column 5), the average level-15 ask depth (column 6), and the average level-20 ask depth (column 7) in terms of the corresponding base currency (column 2) by the four exchanges (column 1) and the base currency. The numbers in the brackets report the standard errors of the corresponding averages.

Exchange	Base Currency	L1 Ask Depth	L5 Ask Depth	L10 Ask Depth	L15 Ask Depth	L20 Ask Depth
BINANCE	BTC	0.329 (0.0103)	2.1 (0.0548)	4.46 (0.111)	6.77 (0.166)	8.97 (0.212)
HUOBI	BTC	0.145 (0.0025)	1.19 (0.0322)	2.33 (0.0591)	3.37 (0.0762)	4.41 (0.0898)
KRAKEN	BTC	0.306 (0.0064)	2.08 (0.0405)	5.39 (0.122)	9.39 (0.218)	13.1 (0.341)
OKEX	BTC	0.0631 (0.002)	0.459 (0.0196)	0.917 (0.0439)	1.42 (0.0681)	1.99 (0.092)
BINANCE	ETH	0.879 (0.0076)	5.76 (0.0547)	12 (0.127)	17.7 (0.207)	23.8 (0.302)
HUOBI	ETH	2.35 (0.0537)	12 (0.329)	20.8 (0.485)	30.5 (0.757)	39.3 (0.969)
KRAKEN	ETH	3.55 (0.0816)	20.3 (0.706)	57.5 (2.02)	96.8 (3.53)	128 (4.65)
OKEX	ETH	0.91 (0.0244)	7.23 (0.379)	15.5 (0.858)	24.1 (1.35)	32.8 (1.88)
HUOBI	USD	4706 (522)	156991 (28672)	419948 (71680)	539540 (78370)	668694 (84430)
KRAKEN	USD	2307 (54.4)	15743 (370)	45004 (1142)	82555 (2344)	118909 (3596)
BINANCE	PAX	1114 (23.2)	9014 (300)	21551 (804)	35861 (1486)	50158 (2155)
BINANCE	TUSD	2129 (69.2)	15411 (583)	38206 (1365)	54017 (1925)	63632 (2139)
BINANCE	USDC	1156 (40.7)	8338 (204)	18984 (417)	31411 (720)	43418 (1101)
OKEX	USDK	686 (84.8)	5157 (754)	10707 (1331)	16443 (1681)	22657 (2217)
BINANCE	USDT	1041 (16.3)	6818 (89.4)	14958 (177)	23130 (262)	31490 (347)
HUOBI	USDT	963 (24.6)	6391 (175)	14866 (406)	24192 (623)	33922 (802)
OKEX	USDT	332 (9.23)	2629 (95.6)	5645 (225)	8594 (339)	11477 (430)

Table 10: Bid Side Depth

This table reports the average level-1 bid depth (column 3), the average level-5 bid depth (column 4), the average level-10 bid depth (column 5), the average level-15 bid depth (column 6), and the average level-20 bid depth (column 7) in terms of the corresponding base currency (column 2) by the four exchanges (column 1) and the base currency. The numbers in the brackets report the standard errors of the corresponding averages.

Exchange	Base Currency	L1 Bid Depth	L5 Bid Depth	L10 Bid Depth	L15 Bid Depth	L20 Bid Depth
BINANCE	BTC	0.392	2.67	5.15	7.02	8.47
		(0.0151)	(0.0684)	(0.103)	(0.124)	(0.135)
HUOBI	BTC	0.146	1.38	2.74	3.96	5.11
		(0.0025)	(0.0352)	(0.0622)	(0.079)	(0.0916)
KRAKEN	BTC	0.38	2.49	5.88	10.1	14.4
		(0.0089)	(0.0532)	(0.102)	(0.176)	(0.29)
OKEX	BTC	0.0869	0.733	1.31	1.92	2.6
		(0.0027)	(0.0274)	(0.044)	(0.0631)	(0.0878)
BINANCE	ETH	1.22	6.75	16.5	26.1	35
		(0.007)	(0.054)	(0.129)	(0.206)	(0.289)
HUOBI	ETH	2.59	18.4	29.9	40.9	50.7
		(0.0546)	(0.541)	(0.664)	(0.809)	(0.998)
KRAKEN	ETH	4.65	24.7	63.5	103	133
		(0.118)	(0.652)	(1.95)	(3.28)	(4.22)
OKEX	ETH	1.15	11.5	57.5	34.9	44.9
		(0.0335)	(0.485)	(20.2)	(1.55)	(2.1)
HUOBI	USD	3751	97143	442571	608334	743027
		(717)	(17995)	(73177)	(87762)	(97323)
KRAKEN	USD	2428	15532	40661	72862	108608
		(61.6)	(350)	(852)	(1473)	(2326)
BINANCE	PAX	1013	8190	19226	31993	46400
		(27.2)	(485)	(927)	(1500)	(2083)
BINANCE	TUSD	2067	14601	35812	48294	56376
		(74.5)	(514)	(1216)	(1662)	(1930)
BINANCE	USDC	1380	8789	18369	29597	42319
		(50.5)	(246)	(440)	(696)	(1134)
OKEX	USDK	680	4422	10286	15643	21753
		(82.9)	(461)	(901)	(1331)	(1541)
BINANCE	USDT	995	7049	16041	25397	34975
		(13.4)	(89.2)	(191)	(286)	(375)
HUOBI	USDT	897	6145	14595	23742	32837
		(21.8)	(165)	(389)	(597)	(766)
OKEX	USDT	397	3644	7654	11266	14535
		(10.1)	(169)	(299)	(416)	(508)

Table 11: Normalized Order Book Imbalance (NOBI) by Exchange and Base Currency

This table reports the average normalized order book imbalance (NOBI) for level-1 (column 3), level-5 (column 4), level-10 (column 5), level-15 (column 6), and level-20 (column 7) by the exchanges (column 1) and base currency types (column 2). The numbers in the brackets are the standard errors of the corresponding average NOBIs.

Exchange	Base Type	L1 NOBI	L5 NOBI	L10 NOBI	L15 NOBI	L20 NOBI
BINANCE	cryptocurrency	-0.0742	-0.1460	-0.2120	-0.2300	-0.2250
		(0.0010)	(0.0014)	(0.0016)	(0.0017)	(0.0017)
BINANCE	stable coin	-0.0197	-0.0008	-0.0055	-0.0070	-0.0135
		(0.0022)	(0.0022)	(0.0026)	(0.0027)	(0.0028)
HUOBI	cryptocurrency	0.0022	-0.0955	-0.1490	-0.1660	-0.1580
		(0.0022)	(0.0032)	(0.0034)	(0.0035)	(0.0035)
HUOBI	fiat currency	0.0624	0.0353	0.0162	0.0058	0.0081
		(0.0063)	(0.0078)	(0.0099)	(0.0096)	(0.0094)
HUOBI	stable coin	0.0368	0.0153	-0.0080	-0.0247	-0.0276
		(0.0021)	(0.0020)	(0.0026)	(0.0031)	(0.0035)
KRAKEN	cryptocurrency	-0.0578	-0.0771	-0.0691	-0.0685	-0.0760
		(0.0033)	(0.0037)	(0.0044)	(0.0047)	(0.0049)
KRAKEN	fiat currency	-0.0267	-0.0264	-0.0086	-0.0046	-0.0163
		(0.0025)	(0.0034)	(0.0035)	(0.0034)	(0.0034)
OKEX	cryptocurrency	-0.0128	-0.2080	-0.2760	-0.2790	-0.2580
		(0.0037)	(0.0044)	(0.0048)	(0.0053)	(0.0058)
OKEX	stable coin	-0.0353	-0.1140	-0.1490	-0.1510	-0.1400
		(0.0051)	(0.0055)	(0.0058)	(0.0061)	(0.0063)

a preference of the investors to exchange their base currencies for the target currencies.

The fiat currency (USD) of Huobi is the only one which has a positive order book balance on average through all levels indicating a preponderance of selling orders. However, from level-10 on, the imbalance is not significantly different from zero anymore which is an evidence for balanced order books for deeper levels. This fits our assumption that this special case is an entry and exit point to the crypto world.

In general, the best order book levels do not reflect the whole order book appropriately. For Huobi, the level-1 NOBI is not significant different from zero indicating balanced order book. The order book imbalances of the cryptocurrencies and stable coins from Huobi become negative from the fifth and tenth level on. We can also observe strong changes of NOBI for the other exchanges and base types, for example a sharp decline for the other cryptocurrencies of Binance and both base currency types of OKEx as well as an insignificant l-5 NOBI for Binance's stable coins. This supports previous literature and our results that deeper order book carry more robust information.

To compare order book imbalance to our slippage measure, we report the absolute normalized order book imbalance (ANOBI) grouped by crypto exchanges and base currencies in table 12. We can observe that the results do not deviate much for the level-1 ANOBI between the base currency types among the exchanges ranging from 0.08 to 0.19, but show the differences clearer at deeper level of the order books. The ANOBIs increase considerably to level-10 and level-15 and settle there with no significant changes to level-20 overall with Huobi's stable coins as an exception. This confirms the findings from table 12 that deeper levels of the order books carry more reliable information about the overall order book imbalance. This also supports the literature that the best

Table 12: Absolute Normalized Order Book Imbalance (ANOBI) by Exchange and Base Currency

This table reports the average absolute normalized order book imbalance (ANOBI) for level-1 (column 3), level-5 (column 4), level-10 (column 5), level-15 (column 6), and level-20 (column 7) by the exchanges (column 1) and base currency types (column 2). The numbers in the brackets are the standard errors of the corresponding average ANOBIs.

Exchange	Base Type	L1 ANOBI	L5 ANOBI	L10 ANOBI	L15 ANOBI	L20 ANOBI
BINANCE	cryptocurrency	0.119 (0.0008)	0.187 (0.0012)	0.249 (0.0014)	0.271 (0.0014)	0.275 (0.0013)
BINANCE	stable coin	0.12 (0.0016)	0.121 (0.0016)	0.143 (0.0019)	0.155 (0.0019)	0.16 (0.0019)
HUOBI	cryptocurrency	0.0988 (0.0015)	0.148 (0.0027)	0.185 (0.0030)	0.202 (0.0030)	0.203 (0.0029)
HUOBI	fiat currency	0.104 (0.0047)	0.112 (0.0056)	0.142 (0.0067)	0.141 (0.0064)	0.136 (0.0065)
HUOBI	stable coin	0.082 (0.0015)	0.0721 (0.0014)	0.0882 (0.0019)	0.104 (0.0023)	0.118 (0.0025)
KRAKEN	cryptocurrency	0.132 (0.0022)	0.151 (0.0025)	0.171 (0.0030)	0.18 (0.0033)	0.186 (0.0034)
KRAKEN	fiat currency	0.128 (0.0017)	0.168 (0.0023)	0.175 (0.0024)	0.166 (0.0023)	0.16 (0.0023)
OKEX	cryptocurrency	0.187 (0.0025)	0.286 (0.0032)	0.346 (0.0036)	0.358 (0.0038)	0.354 (0.0040)
OKEX	stable coin	0.171 (0.0037)	0.216 (0.0038)	0.241 (0.0041)	0.255 (0.0042)	0.254 (0.0043)

Table 13: Correlation of Slippage and Order Book Imbalance

This table reports the correlation between the mean slippage as well as the maximum slippage average and the absolute normalized order book imbalance (ANOBI) in Panel (a) as well as the normalized order book imbalance (NOBI) in Panel (b) for the order book levels 1, 5, 10, 15, and 20 each. The stars for the correlation values indicate that the correlations are significantly different from zero at the 1% significance level.

(a) Absolute Normalized Order Book Imbalance

	Mean Slippage	Max Slippage
L1 ANOBI	-0.19*	-0.21*
L5 ANOBI	-0.27*	-0.29*
L10 ANOBI	-0.31*	-0.31*
L15 ANOBI	-0.32*	-0.31*
L20 ANOBI	-0.32*	-0.30*

(b) Normalized Order Book Imbalance

	Mean Slippage	Max Slippage
L1 NOBI	0.15*	0.13*
L5 NOBI	0.21*	0.22*
L10 NOBI	0.24*	0.23*
L15 NOBI	0.24*	0.22*
L20 NOBI	0.22*	0.19*

levels are noisy and rather uninformative.

Comparing the slippage results in table 5 and the level-15 ANOBI results in table 12, there is an overall negative relationship between the two variables. Higher order book imbalances indicate lower slippage risk. OKEx' stable coins and other cryptocurrencies as well as Binance's other cryptocurrencies have the three highest average ANOBIs and account for three of the four lowest slippage results. Vice versa Huobi's stable coins and fiat currency as well as Binance's stable coins have the lowest average ANOBIs and constitute three of the four highest slippage results. Huobi's and Kraken's other cryptocurrencies are the exceptions here. Since higher order book imbalance is associated with higher higher transaction costs and lower liquidity, these results are intuitive.

Next, we evaluate if the bid and ask side of the order book contribute differently to order book slippage. Table 13 reports the correlations between the imbalance measures and the mean slippage in the second column as well as the maximum slippage in the third column.

Panel (a) shows the results for the absolute normalized order book imbalance (ANOBI). We find significantly negative correlations for all order book levels. There is a jump in the correlation from the best level to the fifth level of –0.08 for the mean as well as the maximum slippage and from the fifth to the tenth level of –0.04 for the mean slippage only. These jumps may indicate uninformative and noisy best levels. For the other levels the results are stable around –0.3, so there is no obvious difference in the relation of ANOBI with the two slippage measures. These results are as expected. Since a higher imbalance is associated with lower liquidity and higher trading costs, submissions of market orders should decrease. These results agree with the results.

Panel (b) in Table 13 presents the correlations between the normalized order book imbalance (NOBI) and the slippage measures. The correlations are significantly positive with values ranging from 0.19 and 0.24 for the fifth to the twentieth level. There is again a large jump from the first to the fifth level.

Keeping in mind that order book imbalance is calculated as the accumulated ask volume minus the accumulated bid volume, there is strong evidence that the a higher depth on the bid side contributes more strongly to lower slippage. This result is very interesting. As long as the order book provides sufficient possibilities for investors to sell their target currencies, the risk of slippage tends to decrease. Vice versa, lower depth on the bid side is associated with higher risk of slippage.

This may explain large drawdowns of prices because investors tend to sell their target currencies if they observe a decline in volume of buy orders.

5.5 Regression Results for Slippage

The results of the spread measures and order book imbalance indicate that slippage is endogenous. We outlined the negative relationship between slippage and the spreads and imbalances which is intuitive on the first sight.

On the other hand, it would be also comprehensible if higher slippage is associated higher spreads and higher order book imbalance. A large slippage of the order book can cause a large spread which has to be filled by new orders submitted to the order book. This may take a long time so that the order book would remain with a large spread. In addition, if order book slippage is exogenous, i.e. it is caused by actions outside the order book, slippage should occur independently of the current spread in the market. However, since we can observe a strong negative relationship, we can assume a causal relation from spread to slippage.

Likewise, slippage can also cause order book imbalance. A large trade can consume liquidity in terms of depth from one side of the order book. Again, if slippage is exogenous, it should occur independently of the order book imbalance, but we find a significantly negative relationship which suggests a causal relation from imbalance to slippage.

We want to study effect of spread and imbalance and their interaction on slippage with regression models. We select the level-5 VWAP spread and the level-10 ANOBI as these levels indicate high correlation with slippage according to table 8 and table 13. However, for other combinations of spread and imbalance levels we find similar results.

Table 14 reports regression results for four types of regressions: a pooled OLS, a fixed effects model with currency pair individual effects, a fixed effects model with time effects, and a fixed effects model with both currency pair individual and time effects. The signs of the coefficients are as expected for all models even though the magnitudes differ. Higher spreads and order book imbalances are associated with lower slippage risk. We also include an interaction term to account for the collinearity of the level-5 VWAP relative spread and the level-10 ANOBI. The interaction term is not significant for the OLS model, but significantly negative for the fixed effect models.

To decide which model to use, we run a F-test for individual and/or time effects. We find significant results that there are significant individual and time effects, so we choose the model with individual and time fixed effects. If L5 VWAP relative spread increases by one percent, the slippage decreases between 0.53% and 0.41% depending on the present L10 ANOBI level due to the interaction term. If L10 ANOBI increases by one percent, the slippage changes between a decrease of 0.08% and an increase of 0.02% depending on the present L5 VWAP relative spread level due to the interaction term. It is important to include the interaction term to account for correlation among the spread and the imbalance due to its significance. Economically, the effect of spread seems to be stronger than the effect for the imbalance. The results provide strong evidence that slippage can be explained by the liquidity measures. We reason that large trades which causes slippage are timed for high liquidity in the currency pairs.

Next, we check if the results differ for negative imbalanced and positive imbalanced order books as indicated in section 5.4. We run two individual and time fixed effect regressions for negative imbalanced order books and positively imbalanced order books. The results are reported in table15,

Table 14: Regression Results: OLS vs Fixed Effects

This table reports regression results, the estimated coefficients with their corresponding standard errors in brackets and significance levels by stars, for four log-log models. Maximum slippage (dependent variable) is regressed on the level-5 VWAP relative spread (row 1), the level-10 absolute normalized order book imbalance (ANOBI) (row 2) and the interaction term of the two explanatory variables (row 3). The models are a pooled OLS model (column 2), a fixed effects model with currency pair individual effects (column 2), a fixed effects model with time effects (column 3), and a fixed effects model with both currency pair individual and time effects (column 4). In the bottom row, the results for a F test for individual and/or timed effects are presented.

	Dependent variable:			
	log(Max Slippage)			
	Pooled OLS	*Fixed Effects*		
		Pair	*Time*	*Pair & Time*
	(1)	(2)	(3)	(4)
log(L5 VWAP Spread)	-0.566***	-0.452***	-0.592***	-0.535***
	(0.005)	(0.007)	(0.004)	(0.007)
log(L10 ANOBI)	-0.035***	-0.069***	-0.050***	-0.061***
	(0.009)	(0.010)	(0.008)	(0.009)
log(L5 VWAP Spread):log(L10 ANOBI)	0.002	-0.009***	-0.003**	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.422***			
	(0.020)			
Individual and/or Time Effects		YES***	YES***	YES***
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 15: Regression Results: Negative Imbalance vs Positive Imbalance

This table reports the results of two individual and time fixed effect models. Model (1) reports the regression results for observations with negative order book imbalances and model (2) reports the regression results for for observations with positive order book imbalances. The estimated coefficients are presented with their corresponding standard errors in brackets and significance levels by stars.

	Dependent variable:	
	log(Max Slippage)	
	(1)	(2)
log(L5 VWAP Spread)	-0.537***	-0.487***
	(0.010)	(0.013)
log(L10 ANOBI)	-0.060***	-0.048***
	(0.012)	(0.014)
log(L5 VWAP Spread):log(L10 ANOBI)	-0.009***	-0.006**
	(0.003)	(0.003)
Note:	*p<0.1; **p<0.05; ***p<0.01	

column (1) for negative imbalance and column (2) for positive imbalance.

We can see that the effects of the spreads and imbalances are stronger for negative imbalanced books than for positive imbalanced books. These results support our assumption that higher depth on the bid side contributes more strongly to lower slippage than the other way around.

For a preponderance of selling orders, the coefficient of the spread is lower than for the negative imbalance. The effect of imbalance itself does not seem to be significantly different for negative or positive imbalances. This indicates that the observation that order book slippage is different for negative and positive order book imbalance is mainly driven of spreads and traders are willing to pay higher spreads to sell their currencies than they are to buy new currencies.

6 Conclusion

The rise of altcoins of which outperformed Bitcoin in recent years and broadened the investment opportunities within this new asset class. Crypto exchanges open the doors to the crypto investment world for investors and enable them to trade 24/7 a wide range of cryptocurrencies. These exchanges differ in many characteristics. For example, crypto markets are highly fragmented and weakly regulated as well as allow for 365 days a year and a 24 hour trading a day with direct market access for all traders. We study four crypto exchanges over a time period of nine months with intraday data.

From investors' perspectives, their requirements for all exchanges are the same, they want to buy and sell assets at low costs. Illiquidity accounts for a considerable fraction of these costs. We evaluate the liquidity of crypto exchanges and their currency pairs in terms of spread, imbalance and slippage. We account for the special feature of crypto currency pairs, various base currencies and base currency types, using standardized liquidity measures. This allows us to compare the results across all exchanges and trading pairs.

We find evidence that spread and imbalance can explain the occurrence of slippage and by that the contradicting results for liquidity. Lower spreads and imbalances indicate higher liquidity, but are correlated with higher slippage, an indication of lower liquidity. We assume that large orders which cause slippage are timed for phases of high liquidity. A preponderance of selling orders over buying orders contributes more to higher slippage than the other way around. This could explain price drawdowns and panic selling behavior of traders if they observe a decline in selling opportunities (lower bid volume) or an increase in offers to sell (higher ask volume). We conclude that traders are willing to pay higher spreads to sell their currencies than they are to purchase new ones.

We further find evidence that our studied crypto exchanges follow different strategies in serving traders which affect the liquidity in terms of spread, imbalance and slippage. Specializing on fewer trading pairs and base currencies increases the liquidity in terms of spreads and imbalance on average. Offering fiat currencies results in higher order volume than offering fiat pegged stablecoins on average.

Our study is focused on the investor's perspective, but we also want to mention the importance for the other market participants. We highlight the fragmentation of the market not only due to the many existing exchanges around the globe, but also within exchanges by various trading pairs and base currencies that effect liquidity. It will be interesting to study how the existing crypto exchanges react to missing liquidity of currency pairs. How regulators should tackle this fragmentation and ensure investor protection are open questions for future research. Another open question for future research is how quick the order books of currency pairs on crypto exchanges recover after slippage events in terms of liquidity and prices. This Market resiliency is a dimension of market efficiency and is sparsely studied in the literature.

References

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84(3):488–500. Publisher: Oxford University Press.

Al-Yahyaee, K. H., Mensi, W., Ko, H.-U., Yoon, S.-M., and Kang, S. H. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. *The North American Journal of Economics and Finance*, 52:101168.

Anand, A., Chakravarty, S., and Martell, T. (2005). Empirical evidence on the evolution of liquidity: Choice of market versus limit orders by informed and uninformed traders. *Journal of Financial Markets*, 8(3):288–308.

Back, K. and Baruch, S. (2005). Working Orders in Limit-Order Markets and Floor Exchanges. SSRN Scholarly Paper ID 838584, Social Science Research Network, Rochester, NY.

Biais, B., Hillion, P., and Spatt, C. S. (1995). An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse. SSRN Scholarly Paper ID 6970, Social Science Research Network, Rochester, NY.

Bonart, J. and Gould, M. D. (2017). Latency and liquidity provision in a limit order book. *Quantitative Finance*, 17(10):1601–1616. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2017.1296177.

Brauneis, A. and Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters*, 165:58–61.

Brauneis, A., Mestel, R., Riordan, R., and Theissen, E. (2020). How to Measure the Liquidity of Cryptocurrencies? SSRN Scholarly Paper ID 3503507, Social Science Research Network, Rochester, NY.

Brockman, P. and Chung, D. Y. (1999). Bid-Ask Spread Components in an Order-Driven Environment. SSRN Scholarly Paper ID 146738, Social Science Research Network, Rochester, NY.

Brockman, P. and Chung, D. Y. (2002). Commonality in Liquidity: Evidence from an Order-Driven Market Structure. *Journal of Financial Research*, 25(4):521–539. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1475-6803.00035.

Böhme, R., Christin, N., Edelman, B., and Moore, T. (2015). Bitcoin: Economics, Technology, and Governance. *Journal of Economic Perspectives*, 29(2):213–238.

Cao, C., Hansch, O., and Beardsley, X. (2009). The Information Content of an Open Limit-Order Book. *Journal of Futures Markets*, 29:16–41.

Chan, Y.-C. (2000). The price impact of trading on the stock exchange of Hong Kong. *Journal of Financial Markets*, 3(1):1–16.

Christie, W. G. and Schultz, P. H. (1994). Why do NASDAQ Market Makers Avoid Odd-Eighth Quotes? *The Journal of Finance*, 49(5):1813–1840. Publisher: [American Finance Association, Wiley].

Chung, K. H., Van Ness, B. F., and Van Ness, R. A. (2004). Specialists, Limit-Order Traders, and the Components of the Bid-Ask Spread. SSRN Scholarly Paper ID 495243, Social Science Research Network, Rochester, NY.

Ciaian, P., Rajcaniova, M., and Kancs, d. (2016). The economics of BitCoin price formation. *Applied Economics*, 48(19):1799–1815. Publisher: Taylor & Francis Journals.

de Jong, F., Nijman, T., and Röell, A. (1996). Price effects of trading and components of the bid-ask spread on the Paris Bourse. *Journal of Empirical Finance*, 3(2):193–213.

Demsetz, H. (1968). The Cost of Transacting*. *The Quarterly Journal of Economics*, 82(1):33–53.

Dyhrberg, A. H., Foley, S., and Svec, J. (2018). How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets. *Economics Letters*, 171:140–143.

Easley, D., O'Hara, M., and Basu, S. (2019). From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics*, 134.

Friedman, D. (1993). How Trading Institutions Affect Financial Market Performance: Some Laboratory Evidence. *Economic Inquiry*, 31(3):410–435. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1465-7295.1993.tb01302.x.

Goettler, R. L., Parlour, C. A., and Rajan, U. (2005). Equilibrium in a Dynamic Limit Order Market. *The Journal of Finance*, 60(5):2149–2192. Publisher: [American Finance Association, Wiley].

Gomber, P., Scheickert, U., and Theissen, E. (2015). Liquidity dynamics in an electronic open limit order book: an event study approach. *European Financial Management*, 21:52–78.

Handa, P. and Schwartz, R. A. (1997). Limit Order Trading. SSRN Scholarly Paper ID 8200, Social Science Research Network, Rochester, NY.

Harris, L. E. and Panchapagesan, V. (2005). The information content of the limit order book: evidence from NYSE specialist trading decisions. *Journal of Financial Markets*, 8(1):25–67.

Harvey, C. R. (2016). Cryptofinance. SSRN Scholarly Paper ID 2438299, Social Science Research Network, Rochester, NY.

Huang, R. D. and Stoll, H. R. (1996). Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics*, 41(3):313–357.

Huberman, G., Leshno, J., and Moallemi, C. C. (2020). Monopoly without a Monopolist: An Economic Analysis of the Bitcoin Payment System. SSRN Scholarly Paper ID 3025604, Social Science Research Network, Rochester, NY.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, 53(6):1315–1335. Publisher: [Wiley, Econometric Society].

Makarov, I. and Schoar, A. (2018). Trading and Arbitrage in Cryptocurrency Markets. SSRN Scholarly Paper ID 3171204, Social Science Research Network, Rochester, NY.

Pagnotta, E. and Buraschi, A. (2018). An Equilibrium Valuation of Bitcoin and Decentralized Network Assets. SSRN Scholarly Paper ID 3142022, Social Science Research Network, Rochester, NY.

Plott, C. R. and Sunder, S. (1982). Efficiency of Experimental Security Markets with Insider Information: An Application of Rational-Expectations Models. *Journal of Political Economy*, 90(4):663–698. Publisher: University of Chicago Press.

Ranaldo, A. (2004). Order aggressiveness in limit order book markets. *Journal of Financial Markets*, 7(1):53–74.

Raskin, M. and Yermack, D. (2016). Digital Currencies, Decentralized Ledgers, and the Future of Central Banking. SSRN Scholarly Paper ID 2773973, Social Science Research Network, Rochester, NY.

Valenzuela, M., Zer, I., Fryzlewicz, P., and Rheinländer, T. (2015). Relative liquidity and future volatility. *Journal of Financial Markets*, 24:25–48.