Price Discovery in Cryptocurrency Markets: Trades versus Liquidity Provision [*]

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Abstract

This paper studies Uniswap V3 and centralized exchanges, and quantifies the price impact of different order types: swaps, mints, burns, market and limit orders. Price discovery occurs predominantly through swaps in the Uniswap V3 and both market and limit orders in the centralized exchange. Liquidity posted near current market prices have permanent price impact, although it is smaller compared to limit orders. We find evidence of active liquidity provision. Liquidity providers with large orders, higher priority of execution, and more sophisticated trading strategies have higher price impact. Our findings emphasize the informational value of trading activities in decentralized financial markets.

Keywords: Price discovery, order flow, decentralized finance

JEL Classifications: E44, F31,G18, G20, G28

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1 Introduction

One of the central functions of financial markets is the price discovery process – the process of incorporation of new information into asset prices by matching buyers and sellers. Cryptocurrencies are trades in two different structures – centralized exchanges (CEX) that are organized as traditional limit order books (LOBs) and decentralized exchanges (DEX) that operate on blockchains using smart contracts and govern and set up prices algorithmically. These different market structures offer different levels of security, speed of execution, transparency and trading costs which are the key factors for the informed traders' choice of trading venue and corresponding instruments.

In this paper we use detailed transaction-level and liquidity data to quantify the contribution to price discovery of trades ('swaps'), liquidity deposits ('mints') and liquidity withdrawals ('burns') in the DEX (Uniswap V3) versus market and limit orders in CEX (Binance). This is an important question to understand the choice of trading venues by informed traders, and whether decentralized markets are viable and have the potential to replace LOB infrastructure.

In traditional markets, information can be transmitted via limit and market orders (Brogaard, Hendershott, and Riordan 2019). In May 2021, Uniswap V3 introduced key innovations such as liquidity posted in a specific price range. By allowing more flexibility, liquidity providers (LPs) can now simulate limit orders. Liquidity provision – 'mint' – for a token at a price above (below) the market price is equivalent to a sell (buy) limit order in this token while liquidity withdrawal – 'burn' – is analogous to limit order cancellations. Introduction of this functionality in Uniswap V3 could also attract participation of informed LPs and a natural question is whether changes in liquidity provision convey information about future returns.

In this paper we employ an information analysis based on vector autoregression (VAR) (Hasbrouck 1991a), which allows us to determine the price impact of swap and liquidity orders in a dynamic setting. Our results show that both swaps and liquidity order significantly contribute to price discovery of ETH/USDC, which is the most liquid pair traded on the Uniswap exchange. In particular, we find swaps in the DEX market have comparable price impact to market orders in the CEX market, and a variance decomposition reveals that swap trades contribute most to the price discovery process.

We find that actions of LPs in both markets can also reveal information about future returns. Examining aggressive orders placed close to the market price, the price impact of limit orders are about thirteen times larger than price impacts of aggressive burns and about twenty-four times larger than price impacts of aggressive mints. In contrast, non-aggressive orders far away from the market price have either insignificant or opposite signs. Comparing swaps with mints and burns in the DEX, we find that the price impact of swaps is about five times larger than the price impact of burns and about ten times larger than the price impact of mints. In contrast, for the centralized exchange, the price impact of limit orders is about three times as large as the price impact of market orders.

We also find evidence of heterogeneous price impact, across dimensions of transaction size, priority of execution and measures of trader sophistication. When conditioning our analysis on order size, we observe that the longer lasting impact of order flow can be mainly attributed to larger trades on CEX and larger swaps on DEX. This is in contrast with "stealth trading" evidence from traditional markets (Barclay and Werner 1993; Chakravarty 2001). We also show that larger mint and burn orders, with the above median order size, contribute the most to price discovery by LPs.

We then classify transactions by priority of execution. Our results indicate that top positioned mints and burns, defined as orders with higher priority of execution, show more significant price impact.[1] This suggests that active LPs strategically compete for priority execution to minimize adverse selection costs and reposition stale liquidity orders.

Furthermore, we measure sophistication of active LPs – those that combine liquidity provision with aggressive trading via swap orders as well as those who actively reposition liquidity – tend to be more informed. Alternative measures of LP activity, such as the

1. Order priority is usually based on gas fees, although this can be a noisy proxy.The emergence of Flashbots MEV-geth introduces an off-chain sealed-bid auction mechanism, allowing traders to bid for execution priority irrespective of gas fees. For example, Lehar and Parlour (2023) reports that a significant percentage of Ethereum blocks violate gas price rankings, indicating the prevalence of zero gas fees for priority transactions.

number and frequency of liquidity orders, is not associated with informed trading.

Finally, we test a potential alternative explanation to information in DEX markets, where permanent price impact of DEX orders are due to exploiting price differences between CEX and DEX markets. We identify arbitrage opportunities as differences in DEX and CEX prices, exceeding 0.5%. We show the permanent price impact of DEX swaps, mints and burns during periods when price gaps are both below and above 0.5%. Our results are therefore robust to periods when there is no apparent arbitrage trading.

Related literature. Decentralized finance is a blockchain-based form of finance that uses smart contracts to auto-execute in financial markets without the need for traditional intermediaries (Schär 2021; John, Kogan, and Saleh 2022).

The early literature on DEX focuses on the role of LPs in DEX, and the co-existence of DEX and centralized LOBs (Lehar and Parlour 2021; Aoyagi and Ito 2021), the role of liquidity provision (Caparros, Chaudhary, and Klein 2023; Fang 2022; Lehar, Parlour, and Zoican 2022; Neuder et al. 2021), empirical differences between DEX and CEX markets (Barbon and Ranaldo 2021; Han, Huang, and Zhong 2021; Capponi, Jia, and Yu 2022; Foley, O'Neill, and Putniņš 2023; Alexander et al. 2023; Heimbach, Wang, and Wattenhofer 2021), the role of arbitrage and front-running in DEX markets (Daian et al. 2019; Wang et al. 2022) and the theoretical foundation of AMM functions and informed trading (Hasbrouck, Rivera, and Saleh 2022, 2023; Park 2022; Angeris and Chitra 2020; Angeris et al. 2021; Angeris, Chitra, and Evans 2022; Cartea, Drissi, and Monga 2023; Cartea et al. 2023; Aoyagi 2020).

Our paper contributes to an understanding of the incentives for informed trading. Within this literature, our paper is closest to Capponi, Jia, and Yu (2022) which shows that trades with high gas fees have higher informational content on DEX, as they improve the likelihood of their trade execution in the next block and assign higher gas tips to miners, and Han, Huang, and Zhong (2021), that argues price differences between Binance and Uniswap have predictability for order flow. Our main innovation in this context is to consider the relative contribution of swap and liquidity orders on price discovery.

A second focus is on understanding the determinants of liquidity provision (Lehar and Parlour 2021; Capponi and Jia 2021; Foley, O'Neill, and Putniņš 2023). These papers document that liquidity provision is dependent on factors such as adverse selection risk, and the amounts provided in the pool are related to the underlying volatility of the pair, and the share of informed trading in the pool. Turning to whether LPs are passive or active, Fang (2022) show evidence of passive LPs that chase return fees but do not necessarily reallocate capital in accordance with adverse selection risk. Caparros, Chaudhary, and Klein (2023) show that blockchain scaling solutions such as Polygon and Arbitrum allow more active liquidity and re-positioning of trades, and Lehar, Parlour, and Zoican (2022) compare low and high fee pools on Uniswap v3, finding low fee pools typically attract institutional LPs that re-balance more often, whereas retail LPs typically concentrate in high fee pools. We contribute to this literature by studying the information set of LPs. Interestingly, we find LPs strategically re-balance in response to information on future returns, and that net liquidity posted close to the market price has permanent price impact. This is consistent with the effects of limit orders in traditional financial markets (Brogaard, Hendershott, and Riordan 2019).

The remainder of the paper is structured as follows. Section 2 introduces the institutional setting and data for both centralized and decentralized exchanges. In section 3 we conduct our empirical analysis of information of market orders and liquidity provision. Section 4 concludes.

2 Institutional setting and data

2.1 Centralized vs Decentralized Exchanges

Cryptoassets can currently be traded either on CEX or on DEX. CEXs, such as Binance and Coinbase, use LOBs, similar to traditional exchanges. In LOBs, market orders are matched with outstanding limit orders, i.e. traders need to find a counterparty for their orders to be executed. However, once orders are matched, the execution is quickly processed by the exchange server.

Decentralized exchanges, such as Uniswap and Curve, operate on the blockchain, using a set of smart contracts. Most commonly, liquidity is provided through an "automated market maker" (AMM). Each asset pair, for example, USDC/ETH, comprises a separate liquidity pool. LPs can deposit ('mint') or withdraw ('burn') liquidity from the pool. Liquidity demanders can then exchange, or swap, one token for another in the pool at the current pool price. In contrast to LOB, all trades are executed against the AMM, eliminating the need for a counterparty search. Importantly, execution on DEXs is also more secure, because traders and LPs keep custody of their assets. However, these advantages of DEX come at a cost. Every transaction on the blockchain has to be validated, before it is actually recorded. Validating takes time and traders have to compensate validators with so-called "gas fees" for processing their transactions. Gas fees represent a fixed cost per transaction and are paid in addition to the usual exchange fees that traders pay to LPs both on CEX and DEX. Thus, execution on DEX is costly and not immediate.[2]

Based on aggregate monthly DEX trading volume averages approximately 10% during the sample period of Uniswap V3, from May 2021 to May 2023.[3] In our further analysis, we concentrate on the largest CEX, Binance, and the largest DEX, Uniswap v3. Appendix A provides details of trading mechanics on Uniswap v3.[4]

2.2 DEX Data

Our sample of DEX data consists of two most liquid pools on Uniswap V3, USDC/ETH 0.05% (DEX(5) henthforce) and USDC/ETH 0.3% (DEX(30) henthforce), over a sample period of May 6, 2021 until July 12, 2022.[5]

We obtain the trade history data for Uniswap V3 DEX (5) and DEX (30) pools through the Subgraph API.[6] Trade data includes fields with pool address, fee tier, block number, amounts of tokens swapped, and the pool price after the transaction. Using

2. Lehar and Parlour (2021) provide a detailed introduction to decentralized exchanges. Barbon and Ranaldo (2021) compare transaction costs on CEX and DEX, highlighting that the major difference in execution costs on DEX arises due to existence of high gas fees.

3. Reference is based on data aggregated from major CEX and DEX exchanges at the Block https://www.theblock.co/data/decentralized-finance/dex-non-custodial/dex-to-cex-spot-trade-volume.

4. See also Lehar, Parlour, and Zoican (2022) and Caparros, Chaudhary, and Klein (2023) for further details and numerical examples of trading on Uniswap v3.

5. Our sample period starts with the launch of Uniswap v3 on May 6, 2021.

6. https://thegraph.com/hosted-service/subgraph/uniswap/uniswap-v3

these data, we compute the buy (sell) ETH volume for each minute, denoted as buy (sell) order flow, $swap(k)^{buy}$ ($swap(k)^{sell}$), where $k = 5$ for 0.05% pool and $k = 30$ for 0.3% pool. Net swap order flow is defined as $swap(k) = swap(k)^{buy} - swap(k)^{sell}$. For the ease of interpretation, we switch the order of the tokens in all our analyses, i.e. our base token (X) is ETH and our quote token (Y) is USDC.

We source DEX liquidity data from Kaiko, a cryptocurrency market data provider that delivers industrial-grade, regulatory-compliant data to businesses. Kaiko's DEX liquidity data includes liquidity events (mints/burns) and liquidity snapshots. Liquidity event data includes fields with pool address, fee tier, block number, token pair, wallet id, amount minted or burned, and the corresponding tick range. Liquidity snapshots are similar to LOB snapshots, showing the total amount of liquidity deposited within each tick range, $[i, i + l]$.[7] Liquidity snapshots are reconstructed from liquidity events data. Notably, the range of price levels, provided by Kaiko, is constrained to ±10% around the current price of each block.

Figure 1 displays an example of liquidity distribution centered around the current market price for ETH/USDC 0.5% pool. The upper panel shows the distribution separately for each token, with values for ETH (token X) shown on the right axis and values for USDC (token Y) on the left axis. The x axis shows the relative distance in ticks from the current market price, scaled to 0. For example, there are around 400 ETH and around 400,000 USDC deposited in the current tick range [0;10]. Outside the current tick range, there is only one token deposited (see Appendix A for details). Liquidity deposited for tick ranges above the current tick contains only ETH (token X), and corresponds to the ask side of the LOB (selling ETH for USDC). Liquidity deposited for tick ranges below the current tick contains only USDC (token Y), and corresponds to the bid side of LOB (buying ETH with USDC). The lower panel of the figure shows same liquidity distribution with all ETH values converted to USDC.

[Insert Figure 1 approximately here]

We use liquidity snapshots to construct market depth within 2% of the current market

7. Liquidity deposited within each tick range is similar to market depth for traditional LOB.

price, *depth*. Specifically, we compute $depth^{ask}$ ($depth^{bid}$) as the total amount of token X (Y), deposited within 2% (or 200 ticks) of the current market price (in USDC).

We use liquidity events to construct the imbalances of liquidity minted on the ask side (token X) and the bid side (token Y), *mint*. For each mint of $[x_p; y_p]$ posted on a price range $[p_a, p_b]$, we first compute total liquidity deposited, L_p, for this position from Equations (10) and (11) in Appendix A.[8] We then split the total price range $[p_a, p_b]$ into two sub-ranges: liquidity minted close to the current price (*best*) and liquidity minted or burned away from the current price (*away*). We use 5 tick ranges threshold to define the cut-off points for these two ranges. This five ticks range corresponds to 50 basis points interval around the current price for DEX(5) pool and 300 basis points around the current price for DEX(30) pool. The choice of these parameters ensures that about a quarter of all mints and burns are within our *best* sub-range. Table 1 presents the distribution of mints and burns distances from the current price in the DEX pools.

[Insert Table 1 approximately here]

Next, we dis-aggregate L_p into the quantity of x (y) minted at a particular sub-range, again using Equations (10) and (11).[9]

We then define *mint* as the difference in the quantities of $mint^{ask}$ and $mint^{bid}$ minted for each minute on a given price sub-range. A positive imbalance of minted liquidity, *mint*, shows that LPs have minted more of token X (ask) than token Y (bid) within a given time interval. For traditional LOB, it would indicate a larger amount of sell limit orders posted on the ask side, relative to buy limit orders on the bid side, indicating overall higher willingness of LPs to sell. By the same logic, we define *burn* as the difference in the quantities of $burn^{ask}$ and $burn^{bid}$ burned for each minute on a given price sub-range. A positive imbalance of burned liquidity, *burn*, shows that LPs have burned more of token X (ask) than token Y (bid) within a given time interval. For traditional LOB, it would indicate a larger amount of limit orders cancellations on the ask side, relative to the bid side, suggesting overall lower willingness of LPs to sell.

8. See Caparros, Chaudhary, and Klein (2023) for further details and numerical example.
9. We verify the validity by checking that the sum of the estimated quantities of x (y) at these three price sub-ranges actually equals the total quantity of x (y) minted or burned for each transaction.

2.3 CEX Data

Our sample of CEX data consists of the ETH-USDC pair traded on Binance over the same sample period as DEX pools, May 6, 2021 until July 12, 2022. We obtain Binance tick-level data from CryptoTick, a subsidiary of CoinAPI. Similar to DEX data, we define the one-minute market order flow in the CEX market, $market = market^{buy} - market^{sell}$, where $market^{buy}$ and $market^{sell}$ are buy and sell market order flow respectively. We construct the end-of-minute mid-price series using LOB snapshots from CryptoTick. The mid-price is calculated as the average of the last best bid and ask in each minute. We then calculate the log return, ret, as the log price difference.

We construct the market depth on the ask (bid) side, $depth^{ask}$ ($depth^{bid}$), as the sum of the best 50 ask (bid) orders at the end of each minute.[10] We would also like to construct liquidity imbalances for CEX data, similar to $mint$ and $burn$ for DEX pools. However, we do not have the order-level data for CEX, making it impossible to track separately limit order submissions and cancellations. Instead, we approximate the net new limit orders added to the ask (bid) side within each minute, $limit^{ask}$ ($limit^{bid}$), as the change in the depth on the ask (bid) side, adjusted for the buy (sell) order flow:

$$\begin{aligned} limit^{ask} &= \Delta depth^{ask} + market_{buy}, &(1)\\ limit^{bid} &= \Delta depth^{bid} + market_{sell}, &(2)\\ limit &= limit^{ask} - limit^{bid}. &(3)\end{aligned}$$

In addition, we divide $limit$ into two price ranges: liquidity added at the best ask ($limit^{ask,best}$) and bid ($limit^{bid,best}$) and away from the best ask/bid ($limit^{ask,away}$ and $limit^{bid,best}$ respectively). We then define the liquidity imbalance at (away from) the best ask/bid as the difference between the new liquidity added at (away from) the best ask

10. Our data only covers first 50 orders on each side of the book. However, first 50 orders cover the range of prices within 1.5%-1.7% of the current mid-price, which is close to our measure of market depth within 2% for DEX pools. We also apply winsorization to the bid and ask side at the 1% level to remove extreme outliers.

and the best bid:

$$limit^{best} = limit^{ask,best} - limit^{bid,best} \quad (4)$$

$$limit^{away} = limit^{ask,away} - limit^{bid,away}. \quad (5)$$

Higher values of $limit^{best}$ ($limit^{away}$) imply a larger amount of the new liquidity added at best prices (away from) to the ask side, relative to the bid side within a given minute.

2.4 Summary statistics

Table 2 reports summary statistics of order flows, individual trade sizes and trade frequencies (per minute), separately for DEX pools (DEX(5) and DEX(30)) and ETH/USDC pair traded on Binance (CEX). All data are in one-minute frequency, with ETH amounts converted to units of USDC.

[Insert Table 2 approximately here]

The Panel A of Table 2 shows the distribution of ETH swaps and market order flow. Whereas order flow is balanced between purchases and sales both on DEX and CEX, we observe a significantly higher average amount of ETH traded on DEX. Around 270K (in USDC) is traded per active minute in the low-fee pool and 360K in the high-fee pool. In contrast, the average corresponding amount on CEX is around 20K.[11]

This larger volume is mostly due to significantly larger average trade sizes of USDC 100K-200K on DEX, compared to the average trade of USDC 1.5K on CEX (as reported in the Panel B of Table 2). This result is not surprising, given the existence of gas fees on DEX that represent a fixed cost for each transaction. Barbon and Ranaldo (2021) also confirm that gas fees represent a significant part of transaction costs on DEX, such that DEX can currently only compete with CEX on larger trades. Further, Panel C shows that trades are much more frequent on CEX, with 25 trades on average per minute in our sample. In contrast, we observe only 3 trades for the low-fee DEX pool and 0.45 trades for the high-fee DEX pool per minute.

11. We report statistics only for minutes with non-zero values of all variables.

Overall, DEXs are mostly used for larger trades that happen less frequently, whereas CEXs are mostly used for more frequent, but smaller trades. Within DEX, we observe that low-fee pools are used for execution of relatively "small" (but more frequent) trades with the average size of USDC 100K. High-fee pools are used for execution of the largest trades on the market, with the average size of USDC 200K.

[Insert Table 3 approximately here]

Table 3 reports summary statistics of market depth and liquidity provision in both DEX pools and CEX. Panel A reports statistics for market depth (average of ask side and bid side). For DEX, market depth is measured at the end of each minute as total liquidity deposited within 2% of the current market price (in USDC). For CEX, it is measured as the sum of the first 50 orders on the ask or bid side (in USDC). On aggregate, DEX pools are significantly deeper, with around 8 million USDC deposited to the pool. In contrast, average market depth on CEX is only around 0.4 million USDC on each side.

Panel B shows the distribution of liquidity events, i.e. mints and burns for DEX pools and the new limit order flows on CEX. We observe significantly larger mints/burns of around 1.4-3 million USDC for a low-fee pool, compared to 0.38-0.9 million USDC for a high-fee pool. These results are consistent with previous findings of Lehar, Parlour, and Zoican (2022), who analyze co-existence of low- and high-fee pools on DEX. Their findings also suggest that low-fee pools are used by larger and more active (i.e. institutional) LPs, whereas the high-fee pools are rather used for liquidity provision by smaller and more passive (i.e. retail) LPs.

Limit order flow on CEX is much lower on average than on DEX, just around 18-20 thousands. However, changes in liquidity on CEX are much more frequent than on DEX pools, taking place practically every minute. Mints are more frequent than burns on both DEX pools – there are more time periods with minted liquidity than burnt liquidity. This is because withdrawing (or burning) liquidity from the pool is costly. Hence, we expect LPs to burn their positions (and subsequently re-mint them) only when their mid-price deviates significantly from the current market price. Whereas burns happen less frequently, they are on average larger than mints for both DEX pools (see also Panel C for individual order sizes).

Panel D presents frequency that particular order types is submitted within every minute. Probability that during a particular minute interval a mint order is submitted in DEX(5) equals to about 4% (and similar for burns). For DEX(30) this probability is 9% (and 6% for burns). In the most extreme case, we observed 27 mint orders submitted within the same minute in DEX(5) (7 burn orders).

Existence of fixed gas fees on Ethereum prevents LPs to update their positions frequently on DEX. Hence, we observe larger but less frequent liquidity changes on DEX. Greater depth of DEX pools is especially attractive for large traders, as it minimizes price impact of their trades. For CEX, we observe more frequent but smaller liquidity changes, since there is no cost associated with limit order re-submission. Further, CEX are more attractive for small traders, for whom price impact of their trades is of less importance than low execution costs (in absence of gas fees).

3 Empirical Evidence

3.1 Research hypotheses

H1: *DEX LPs have the following price impact of mints and burns: a) Positive impact of (net) mints on ask side, b) Positive impact of (net) mints on bid side, c) Positive impact of (net) burns on ask side, d) Positive impact of (net) burns on bid side.*

Figure 2 illustrates the effects of mint and burn liquidity orders on prices. The current price is denoted by P_0, and the "long-run" price is given by P_{30}. Panel (a) considers the price impact of mints. Net positive mints on the bid (ask) side can have negative (positive) price impact. Price impact can occur due to active re-positioning, in response to adverse selection risk due to changes in the fundamental price. For example, if LPs believe the base currency token is appreciating, they can post liquidity to buy the token at bid, leading to negative price impact. In contrast, they may also re-post liquidity to a higher price, in revising stale quotes, leading to positive price impact.

Liquidity re-positioning also allows the for the cancellation of orders via burns. Panel (b) of Figure 2 considers the price impact of burns, and shows that net positive burns on the bid (ask) side can have negative (positive) price impact. LPs can re-position liquidity due to information on returns. In response to the base currency token appreciating, they can burn liquidity at ask if they are concerned about being "picked off", minimising adverse selection risk. Alternatively, they can burn liquidity on the bid side if they believe these quotes are now stale, leading to negative price impact.

[Insert Figure 2 approximately here]

H2: *Price impact of LPs is increasing in a) Transaction size, b) Priority of execution, c) Sophistication (re-positioning frequency, conducting swap trades)*

This hypothesis examines strategies utilized by active LPs, investigating whether those who undertake large transactions, prioritize execution through higher gas fees, and engage in both liquidity provision and aggressive trading behaviors (i.e., combining mint/burn operations with swap orders) are more informed and thus have a more substantial impact on the market.

We hypothesize that larger transactions generally have a more significant and lasting price impact, suggesting that the size of an order is indicative of the trader's information level and market influence. The effect of transaction size should be evident in both market orders and swaps in the DEX market, where large orders lead to a more permanent price impact compared to smaller ones.

We investigate the role of execution priority, revealing that transactions classified by their execution priority, determined by their position within the block, also exhibit varying levels of price impact. More active LPs are likely to pay higher transaction fees to attain a higher position within the block. This allows LPs to re-position more effectively to mitigate adverse selection risk.

The sophistication of LPs, reflected in their strategic behavior such as mixing order types (liquidity provision with trading) and the frequency of their liquidity updates, can also contribute to the market's price dynamics. We hypothesize that LPs engaging in these sophisticated strategies tend to have a more significant impact on prices, suggesting their actions are more informed.

3.2 Price impact tests

3.2.1 Baseline estimation

We start our analysis with a VAR with order flow of both decentralized and centralized exchanges, and a benchmark CEX return (as used in the literature, e.g., Capponi, Jia, and Yu (2022)).

$$AY_t = \alpha + \sum_{j=1}^{25} A_j Y_{t-j} + \epsilon_t, \tag{6}$$

where

$$\begin{aligned} Y_t = [&swap(30),\ swap(5),\ mint(30)^{best},\ mint(30)^{away},\ burn(30)^{best},\ burn(30)^{away}, \\ &mint(5)^{best},\ mint(5)^{away},\ burn(5)^{best},\ burn(5)^{away},\ market,\ limit^{best},\ limit^{away},\ ret]. \end{aligned} \tag{7}$$

In our analysis, we will use variables from both Uniswap V3 pools. We assume the following structure in our VAR methodology:

1) We assume zero contemporaneous effects across swap, mints, burns and CEX market and limit orders. This is a safe assumption to make as LPs often burn and mint liquidity simultaneously, making it difficult to determine the order of causality. Trading volume and liquidity provision are jointly determined objects, and it is a challenge to determine the feedback dynamics of swap and liquidity orders.

2) shocks to order flow can cause shocks to returns contemporaneously, however shocks to returns cause changes in order flow with a delay. This follows the structural VAR methodology outlined in Hasbrouck (1991a).

To test for significance of the impulse responses, we construct a distribution of cumulative Impulse Response Functions (CIRFs) derived from 1,000 computations utilizing the Wild bootstrap method. The significance of the CIRF is determined relative to the empirical distribution obtained from the 1,000 bootstrapped CIRFs. In the Wild Bootstrap method, we first generate residuals based on the actual residuals of the VAR model and a random value drawn from the Rademacher distribution. We then simulate data using both a small set of observations from the real data (equivalent to the number of lag observations) and the generated residuals. This simulated data is subsequently used to estimate the CIRF, a process we repeat 1,000 times.[12]

[Insert Table 4 approximately here]

Table 4 summarizes the results and reports the CIRFs of market and swap net order flows (buy − sell), CEX net limit order flow (ask side − bid side of LOB) and DEX net minted and burned order flow (token X − token Y). We record coefficients at horizons of 0, 1, 10 and 30 minutes after the shock.

Cumulative price impact of a 1 USDC Million shock to market order flow leads to 0.126 percentage point change in the ETH-USDC return 30 minutes after the shock (Panel A). We find that price impact of swap order flow in the DEX market is of a similar magnitude: for the low fee pool, a shock to swap order flow has a price impact of 0.124 percentage points 30 minutes after the shock. For the high fee pool, a shock to swap order flow has a price impact of 0.203 percentage points 30 minutes after the shock. All cumulative impulse responses to liquidity taking order flow shocks are statistically significant at the 1% level.

Turning to the price impact of centralized liquidity orders, Figure 3 displays the aggressive and non-aggressive strategies LPs can conduct. Panel (a) considers aggressive orders placed close to the current price, and panel (b) considers non-aggressive orders placed far away from the current price. In summary, we hypothesize limit orders posted at the best bid-ask have a negative effect on returns. In contrast, limit orders posted further away from the best bid-ask have a positive effect on returns.

[Insert Figure 3 approximately here]

Quantitatively, the price impact coefficients are of a similar order of magnitude to the effect of market orders, which is consistent with evidence in equities markets (Brogaard,

12. The procedures outlined in the MATLAB VAR Toolbox by Ambrogio Cesa-Bianchi. See https://sites.google.com/site/ambropo/MatlabCodes?authuser=0.

Hendershott, and Riordan 2019). A 1 USDC Million increase in $limit^{best}$ decreases returns by 0.317 per cent at a horizon of 30 minutes. In contrast, a 1 USDC Million increase in $limit^{away}$ increases returns by 0.074 per cent 30 minutes after the shock. We argue that the significant price impact of limit orders is due to strategic liquidity provision. Informed LPs in the centralized market reposition liquidity toward a price range further away from the best bid-ask in anticipation of future price increases.

Similar to centralized limit orders, we can test hypothesis H1 on whether net flows of mints and burns in the DEX market close to the current price ($best$) carry information about future price changes. For DEX(5), positive net flow of mint orders submitted in a range close to the current price predicts future price decreases of 1.3 basis points. Positive net flow of burn orders in DEX(5) that withdraw liquidity in a range close to the current price predicts future price increases of 2.5 basis points. These coefficients are substantially smaller than the price impact estimates of market orders and swaps. While they are also nominally smaller than the price impacts of CEX limit orders, given that limit orders are substantially smaller in magnitude, a price impact of 1 standard deviation shock to DEX liquidity order flow is comparable to the price impact of 1 standard deviation shock to CEX limit order flow.

In DEX(5), burns of ETH that are further away from the current price tend to have a negative price impact, with smaller economic values of -0.006. This finding suggests that LPs burn their net liquidity on the ask side that is further away from the current price, in anticipation that prices will go down, leaving their positions inactive. DEX(5) mint orders submitted further away from the current price tend to have insignificant long-term price impacts. Both mints and burns in DEX(30) show no significant long-term price impacts (see Panel C).

Our findings suggest that LPs in the DEX market have similar behavior to liquidity suppliers in the CEX market, engaging in active liquidity re-positioning across alternative price-ranges. For example, if LPs expect prices to fall, they are more willing to increase their net provision of ETH at the current price, and decrease their net liquidity provision further away from the current price. Conversely, if LPs expect prices of ETH to rise, they decrease their net provision of ETH close to the current tick range, and increase their provision of ETH for prices further away.

The liquidity re-positioning hypothesis is applicable only to DEX(5) and not to DEX(30). This is because DEX(5) has a smaller tick size for price ranges compared to DEX(30), thereby increasing the incentive for informed LPs to engage in concentrated provision based on their price expectations. Further, all swaps are first routed to DEX(5) pool to minimize transaction costs. Only the residual order flow from large trades is then executed at DEX(30) pool, after cheaper liquidity at DEX(5) has been depleted. With trades arriving more frequently to DEX(5) pool, there is a larger incentive for LPs to re-position more frequently in anticipation of informed trades. Lehar, Parlour, and Zoican (2022) also show that large (i.e. professional) LPs are active in low-fee pools and small (i.e. retail) investors prefer to passively provide liquidity in high-fee pools.

Figure 4 visualizes the CIRF coefficients for different types of order flows.

[Insert Figure 4 approximately here]

3.2.2 Variance decomposition

We have shown that the average permanent price impacts across different orders. While this demonstrates evidence that different types of orders convey information about future prices, it does not directly determine each order type's contribution to overall price discovery. In order to complete the picture we employ the Hasbrouck (1991b) variance decomposition to weight the impulse responses functions by the variance of innovations in each order type to calculate the total contribution to price discovery by order type. The results of the variance decomposition is given in Table 5.

[Insert Table 5 approximately here]

In total, swap orders contribute about 25% to price discovery while market orders in the CEX market account for only 0.71%. This reflects the fact that despite a higher average price impact, order size of swaps is substantially higher than that of the market order.

All mints, burns and limit orders individually as well as in aggregate contribute less than 1%. This suggests that although there is evidence that changes in liquidity carry information in both markets, their contribution to price discovery is relatively small.

3.3 Heterogeneity in price impact: transaction size, priority of execution and mixed trades

In this section we test hypothesis H2 on the determinants of price impact of LPs. We explore in more detail various patterns in strategies of active LPs in the DEX market. In particular, we explore if traders and LPs that submit large orders, pay for priority of execution, and combine active liquidity provision with aggressive trading (submitting both mint/burns with swap orders), relocate liquidity (simultaneously burn and mint liquidity) and submit orders most frequently tend to be more informed than others. We also explore the role of arbitrage activity in price discovery in the DEX market.

3.3.1 Transaction size

We test whether informativeness of order flow depends on the order size. Both traders and LPs who submit large orders in general have more incentives to gather information given their large exposure to the market.

We re-run the VAR specification in Equation (6) where we now condition on the order size. For market orders and swaps, we examine separately buy and sell order flow, conditional on its size. We classify sell (buy) order flow as large ($large$) if it is above the median size of the distribution of non-zero minute-level sell (buy) order flows, and as small ($small$) otherwise. For mints (burns), we classify orders as large ($large$), if they are above the median size of the distribution of all mints (burns) in our sample.[13].

[Insert Table 6 approximately here]

Table 6 presents the estimation results of the corresponding CIRFs at $n = 30$ minutes horizon. Large buy and sell market orders have more permanent price impact than small

13. We cannot perform the same analysis for limit orders on CEX because we do not have order-level data. Therefore, we just leave $limit^{best}$ and $limit^{away}$ as in previous VAR specifications

orders in the CEX market. This is in line with our hypothesis that large orders have more information content. Small orders in the CEX market have larger price impact than large orders, however it is insignificant at longer horizon ($n = 30$).

For large swaps, we also observe more permanent price impacts in both pools. These trades are typically coincident with high gas fees. Capponi, Jia, and Yu (2022) find that trades executed with higher gas fees typically have more information content. Small swaps in the DEX market have opposite sign price impacts. This suggests that small traders are uninformed and tend to lose money in a similar fashion to noise-traders in traditional markets. They do not contribute to the permanent price impact of aggregate order flow.

Results for mints and burns also broadly support our hypothesis: large mint and burn orders submitted in DEX(5) exhibit significant long-term price impacts. In contrast, small mints and burns do not convey information. As before, we do not find any significant price impacts of mints and burns in DEX(30), since liquidity provision in this pool is mostly done by small (i.e. retail) providers who tend to be uninformed.

3.3.2 Execution priority

We test if informed LPs are willing to pay high gas fee in order to reposition liquidity ahead of other traders or before the information is revealed to public. Capponi, Jia, and Yu (2022) show that in Uniswap V2 the high-fee DEX trade flow is considerably more informative than the low-fee DEX trade flow. In this section we perform analysis to identify whether active LPs in DEX are also actively expediting the execution of their submission strategies.

Transactions in the Ethereum network can be prioritized for execution based on the gas fees paid by traders. Generally, the higher the gas fee bid for a transaction, the earlier it's executed in the next block, which gives it precedence over transactions with lower fees. However, this reliance on gas fees as an indicator of execution priority is not entirely reliable due to alternative methods that also ensure a transaction's prompt execution. For instance, Flashbots, launched on November 23, 2020, offers a novel approach with its

MEV-geth for Ethereum, enabling transactions to achieve priority without the need for high gas fees. Through an off-chain auction mechanism, traders can bid for their transactions' execution priority, where miners receive private compensation, and as a result, transactions can secure a leading position in the next block—even at zero gas fees. For example, Lehar and Parlour (2023) indicates that by October 2021, a significant portion of Ethereum blocks bypassed traditional gas fee prioritization, highlighting transactions with no gas fees at the forefront.

For our analysis, we utilize Etherscan, an Ethereum blockchain explorer that provides extensive data on transactions, blocks, and network activity. This tool helps us determine the specific position of each transaction within a block. To systematically categorize transactions based on their execution priority, we analyze the position distribution of mints, burns, and swaps across blocks. Transactions are considered to occupy a top position if their index is below the median of this distribution, set at 80 (noting that indexing starts at 0). This classification allows us to examine the order flows of transactions with different execution priorities, marked as either "top" or "bottom," to explore if higher-priority transactions are indeed more informed.

We estimate the VAR model based on the variables as in Equation (7) but decomposing each order flow variable ($swap(k)$, $mint(k)$ and $burn(k)$) into the corresponding top ($swap^{top}(k)$, $mint(k)^{top}$ and $burn(k)^{top}$) and bottom ($swap^{bottom}(k)$, $mint(k)^{bottom}$ and $burn(k)^{bottom}$) order flows.

[Insert Table 7 approximately here]

Table 7 presents the estimation results of the corresponding CIRFs at $n = 30$ minutes horizon. Both top and bottom swap transactions have positive and significant permanent price impact with transactions from the bottom of the distribution having somewhat higher price impact. This is in contrast with Capponi, Jia, and Yu (2022) results from Uniswap V2 that use high gas fee ordering, which indeed ensured the priority of execution before the introduction of Flashbots MEV-geth.

Net flow of top positioned mint orders within *best* price range has negative significant price impact in DEX(5) pool while net flow of top positioned burn orders has positive significant price impact. Interestingly, top positioned best burn orders have positive and significant price impact also in DEX(30) (unlike the aggregate $burn(30)^{best}$ order flow in Table 4). Top positioned burns in *away* range of the current price have negative and significant at 5% level price impacts (in both pools) indicating active repositioning when price is expected to move away from the liquidity position. This is consistent with the hypothesis that active informed LPs are competing for priority of execution for their orders in an attempt to minimize adverse selection costs or reposition stale liquidity orders.

3.3.3 Strategies of active LPs

In this section, we examine whether an individual liquidity provider's strategy to combine different order types conveys information about future price changes. We consider three different classifications. The first is whether a particular liquidity provider follows a pure vs mixed order strategy. We define pure LPs as those who only submit liquidity orders (mints or burns). In contrast, mixed LPs are defined as those who combine liquidity provision with aggressive trading using swap orders. The intuition behind this definition is that traders combining different order types are more sophisticated and likely to pay more attention to information acquisition than purely passive LPs. The second classification differentiates active LPs who reposition their liquidity based on the state of the market from passive LPs. The third classification differentiates active LPs based on the frequency of their liquidity updates. LPs who actively submit liquidity updates are those who actively utilize the additional tools provided in Uniswap V3 functionality. We start by classifying LPs into pure vs mixed categories, using their wallet ids. We denote by *mixed* those orders that are submitted by a wallet that submitted at least one swap as well as at least one liquidity order (mint or burn) during our sample period. We classify swap orders as *onlyswap* if the wallet submitting it only submits swap orders throughout the sample. Similarly, liquidity orders coming from wallets specializing only on liquidity provision are classified as *onlylp*.

In order to classify wallets as those who engage in repositioning liquidity, we verify if following a burn order, the liquidity provider (wallet) has made a subsequent mint order within (including) 2 minutes. In this case we classify this wallet as *repo*. Wallets that have not submitted any repositioning order bundles are classified as *other*.

Analogously, we classify wallets into frequent ($highfr$) and infrequent ($lowfr$) LPs. Wallets with the number of liquidity position updates (mints and burns) in the upper quartile of the distribution in the sample (which is 4) are classified as frequent ($highfr$). Otherwise, the wallet and all its liquidity orders are classified as infrequent.

[Insert Table 8 approximately here]

Panel A of Table 8 provides price impact estimates for *mixed* versus *onlyswap* and *onlylp* order flow. Both type of swaps (*mixed* and *onlyswap*) exhibit positive and significant price impact in DEX(5) and DEX(30). The results for liquidity order flows support our hypothesis that the orders submitted by mixed type wallets are more likely to convey information – their mint best order flow has negative price impact while burn best order flow has positive price impact in DEX(5). Interestingly, we see that burn order flow away from the price coming from mixed wallets has negative and significant effect. This predictability suggests that traders observing the price moving away from the current price tend to burn this liquidity and execute aggressive swap orders in the direction of price movement.

Panel B of Table 8 provides the results on price impact of providers who engage in active liquidity repositioning. The results suggest that repositioning of liquidity in DEX(5) close to the current price conveys information (active liquidity management). Active liquidity management conveys information only in DEX(5), which supports hypothesis that in low fee pool LPs should be more competitive and active to avoid impermanent loss. Order flow that is burned away from the current price is informative not due to liquidity repositioning strategy. Price impacts of liquidity order flows in DEX(30) are all insignificant suggesting that in high fee pool incentives for active liquidity management are smaller and not driven by informational reasons.

Panel C of Table 8 provides the estimation results for frequent versus infrequent liquidity wallets. The results reveal that, in general, frequency of liquidity updates does not translate into higher information content. In DEX(5), both mint and burn order flows close to the current price have significant price impacts at 10% level regardless whether or not submitted by the frequent or infrequent liquidity wallets. The only exception here are burn orders submitted away from the current price – more active wallets with frequent liquidity updates tend to forecast future price changes in an opposite direction to more passive LPs.

3.4 Information and arbitrage trading

In the previous sections we have found that swaps, mints and burns have persistent price impact on the DEX. An alternative explanation to our hypothesis of information of DEX markets is that they are populated primarily by arbitrageurs that trade in response to the price difference between exchanges. To rule out this possibility, we condition our order flow analysis based on the price difference between exchanges. In particular, we test if the price impact of orders is significant predominantly around arbitrage deviations and whether information conveyed by those orders reflects purely publicly observed price differences across the markets.

We define the price difference between the DEX and the CEX market as $pd = prc^{DEX} - prc^{CEX}$ and the percentage price difference as $ppd = 100 \times pd/prc^{CEX}$. Table 9 summarizes the results. Panel A reports the statistics when the price difference is calculated based on DEX(5) price. The price difference is small on average: its absolute value is about 3.1 USDC. The average percentage price difference is 0.005 per cent and the average of its absolute value is 0.108 per cent. The price difference can, however, be substantially large and can reach up to 564.7 USDC or 28.60 per cent. The price differences on DEX(30) pool (see Panel B) is about 1.5 times larger on average although its extreme values are comparable to the ones on DEX(5).

[Insert Table 9 approximately here]

Given presence of substantial price differences and arbitrage opportunities, a question is whether the order flows play a stabilizing role in the market. For example, in response to a positive price difference ($prc^{DEX} > prc^{CEX}$), stabilizing order flows are buy orders in CEX and sell orders in DEX. Conversely, conditional on a negative price difference, stabilizing order flows are sell orders in CEX and buy orders in DEX. For an arbitrage opportunity, we require that the absolute value of *ppd* be at least 50 basis points. To test this, we identify 17,503 instances of arbitrage opportunities, which occurred 3% of the total time, when using the DEX(5) price. When using the DEX(30) price, we identify 8,473 instances of arbitrage opportunities, which occurred 1.4% of the total time. We then condition price difference and order flow in period 1 and consider the following six cases of (i) $pd_t > 0, swap_{t+1} < 0$, (ii) $pd_t > 0, market_{t+1} > 0$, (iii) $pd_t > 0, swap_{t+1} < 0, market_{t+1} > 0$, (iv) $pd_t < 0, swap_{t+1} > 0$, (v) $pd_t < 0, market_{t+1} < 0$, (vi) $pd_t < 0, swap_{t+1} > 0, market_{t+1} < 0$. Figure 5 investigates the speed at which order flows correct arbitrage opportunities.

[Insert Figure 5 approximately here]

Panel A documents the results using the 0.05% ETH-USDC pool. On the left, we consider cases (i) to (iii), which are stabilizing order flows in response to a positive price difference. The results show that DEX markets have a stronger stabilizing effect on the price at a horizon of 10 minutes. Case (i), which is conditioning on stabilizing order flow on the DEX market, achieves similar price convergence to case (iii) when it is conditioned on stabilizing order flow on both markets. Turning to cases (iv), (v) and (vi), we find that convergence based on stabilizing order flows on both markets matter. Case (vi) generates the most convergence in prices across exchanges, suggesting both order flows matter for stabilization. Panel B considers the 0.3% pool. As before, we find that convergence of peg prices is stronger conditional on DEX order flow when the price difference is positive, however convergence is similar when considering stabilizing order flows in response to a negative price difference.

In order to estimate and test for stabilizing effect of trades in both markets we use the price difference as an additional explanatory variable in our VAR analysis in equation (6). The explanatory variables in our VAR include the order flow (buy and sell) of both

CEX and DEX markets, as well as the price difference between DEX and CEX markets.

$$Y_t = [swap^{sell},\ swap^{buy},\ newliq^{ask,best},\ newliq^{bid,best},$$
$$market^{sell},\ market^{buy},\ limit^{ask,best},\ limit^{bid,best},\ \ pd],$$

where $newliq$ is the new net liquidity provided in the corresponding DEX pool and defined as $newliq = mint - burn$. In line with our results documenting price convergence, we note order flows have stabilizing properties on the price difference in Table 10.

[Insert Table 10 approximately here]

Panel A of Table 10 presents estimates of the effect of a 1 USDC Million order flow CEX buy shock on the price difference. Based on the price difference between DEX(30) and CEX, a sell shock on the CEX has a cumulative effect of increasing the price difference by 27 USDC, while a buy shock on the CEX decreases the price difference by approximately 59 USDC. Similar to the CEX estimates, DEX buy orders have a larger effect on the price difference. For example, in the DEX(30) pool, a 1 USDC Million buy shock increases the price difference by 63 USDC, and a sell shock decreases the price difference by 60 USDC. These are quantitatively larger effects, which suggests that DEX order flow has larger cumulative price impact on the difference between DEX and CEX markets. The asymmetry matches our results based on Figure 5: DEX buy orders have more stabilizing effects on the price difference than DEX sell orders. We find new liquidity of DEX markets have insignificant effects on the price difference between markets. However, a new limit order at the best ask price on the CEX has positive effects on the price difference. A 1 million USDC shock to new liquidity on the CEX leads to an increase in the price difference of approximately 135 USDC.

Having established the fact that orders in the CEX and DEX market makes stabilizing effects on price difference we turn to answering the question if orders covey information beyond exploitation or arbitrage.

We identify arbitrage opportunities when the absolute price difference is at least 50 basis points (0.5%) or greater. We classify an order flow as "*highpd*" ("*lowpd*") if its absolute values of *ppd* is equal to or greater (less) than 50 basis points. We run the following specification in Equation (6) where

$$\begin{aligned} Y_t = [& swap^{sell,highpd},\ swap^{sell,lowpd},\ swap^{buy,highpd},\ swap^{buy,lowpd}, \\ & newliq^{ask,best,highpd},\ newliq^{ask,best,lowpd},\ newliq^{bid,best,highpd},\ newliq^{bid,best,lowpd}, \\ & market^{sell,highpd},\ market^{sell,lowpd},\ market^{buy,highpd},\ market^{buy,lowpd}, \\ & limit^{ask,best,highpd},\ limit^{ask,best,lowpd},\ limit^{bid,best,highpd},\ limit^{bid,best,lowpd},\ ret]. \end{aligned}$$

Panel B of Table 10 summarizes the results. We find that for the CEX market, there are quantitatively larger coefficients for the CEX market conditioned on a high price difference. For example, based on the price difference between DEX(5) and CEX, CEX buy shocks have a price impact of approximately 0.50 per cent 30 minutes after the shock during periods of mispricing, however this decreases to 0.11 per cent when CEX and DEX prices are aligned. Moreover, long-term price impacts for sell orders conditional on high price difference are not significant. This shows that arbitrage trades in the CEX move prices substantially more as compared to non-arbitrage trades but not always result in permanent price move (for example, if the arbitrage appeared due to a liquidity shock, see Foucault, Kozhan, and Tham (2017)).

We find that swaps of sell orders in the DEX(30) market have quantitatively larger price impacts when the price difference between exchanges is below the median. A DEX(30) sell shock has a cumulative price impact of -0.18 percent after 30 minutes for a small price difference. In contrast, the cumulative price impact is -0.09 percent, conditioned on a high price difference. For DEX(30) buy swaps and DEX(5) swaps, the price impact is quantitatively similar when conditioned on the price difference.

More importantly, non-arbitrage trades (those conditioned on low price difference) have a significant long-term price impacts in both markets. This means that trades in both CEX and DEX markets convey information different from the one reflected in the price difference between the two markets.

4 Conclusion

In this paper, we investigate the coexistence of DEXs like Uniswap V3 and traditional limit order book exchanges such as Binance. We address the question of whether DEXs have more information for the price discovery process compared to traditional markets.

Our findings indicate that price discovery happens in both markets, with more permanent price impact on DEX. Informed traders may find decentralized markets more attractive due to the fixed gas fee associated with trading on these platforms, allowing them to pool with larger uninformed traders and minimize the price impact of their trades.

Our main contribution is to explore the role of liquidity provision in addition to market orders. Uniswap V3 concentrated liquidity provision facilitates transmission of information in prices via submissions and cancellations of mints and burns in specific tick ranges. This feature simulates the functions of a limit-order book, and allows LPs to actively re-position liquidity. We reveal evidence of liquidity re-positioning, with net mints close to current market price contains valuable information about future returns.

In addition, we exploit blockchain transaction level-data to show heterogeneity in the price impact of liquidity orders based on transaction size, the execution priority within the block, and whether wallets conduct both swap and liquidity re-positioning transactions. Informed LPs typically post larger transaction size, have higher priority of execution within a block, and are more likely to conduct swap transactions as well. These findings suggest that LPs with more price impact are strategic and vie for priority execution of their transactions.

Finally, we address an alternative explanation for the observed informed trading on DEX; arbitrageurs are trading to exploit price differences between centralized and decentralized markets. Our analysis shows that permanent price impact remains robust to periods of small price differences, suggesting that factors other than arbitrage opportunities contribute to the observed information effects.

In conclusion, our findings show that DEXs can serve as preferred trading venues for informed traders. We note the importance of the liquidity distribution for price discovery. Our research contributes to the broader discussion on the potential of decentralized markets to replace traditional limit order book infrastructure.

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Figures

Figure 1: **Liquidity distribution.**
This figure displays an example of liquidity distribution centered around the current market price for ETH/USDC 0.5%. The x axis shows the relative distance in ticks from the current market price, scaled to 0. The upper panel shows the amount of liquidity deposited within each tick range separately for each token, with values for ETH shown on the right axis and values for USDC on the left axis. Liquidity deposited for tick ranges above the current tick contains only ETH, and corresponds to the ask side of the LOB (selling ETH for USDC). Liquidity deposited for tick ranges below the current tick contains only USDC, and corresponds to the bid side of LOB (buying ETH with USDC). The lower panel of the figure shows the same liquidity distribution with all ETH values converted to USDC.

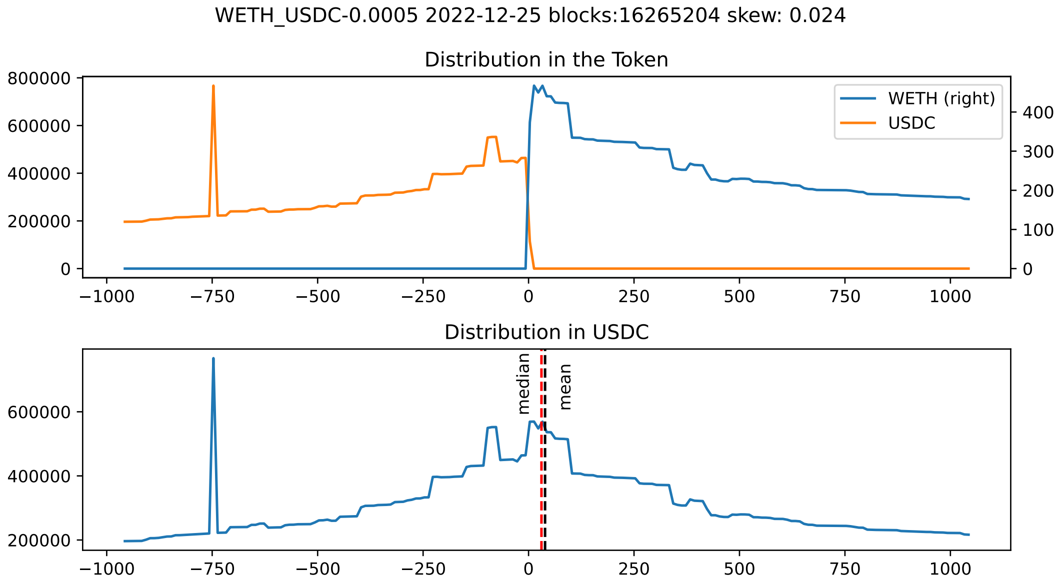
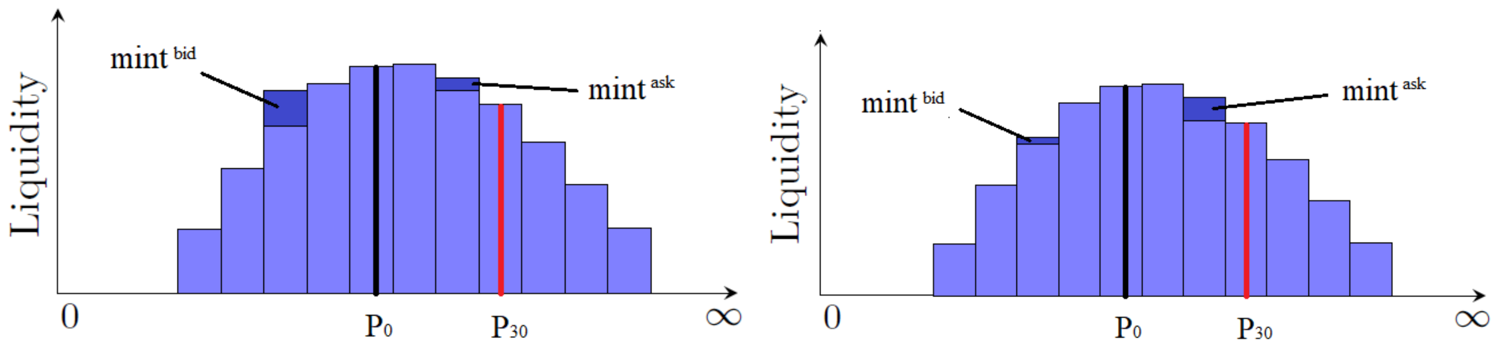


Figure 2: **Mint and Burn order price impacts.**
This figure displays the effects of mint and burn liquidity orders on prices. The current price is denoted by P_0, and the "long-run" price is given by P_{30}. We denote the bid side of the book when liquidity is minted or burned at a price less than the market price. We denote the ask side of the book when liquidity is minted or burned at a price greater than the market price. We consider four hypotheses of the price impact of mints and burns respectively. Panel (a) considers the price impact of mints. Net positive mints on the bid (ask) side can have negative (positive) price impact. These cases are denoted by the left and right schematics of panel (a). Panel (b) considers the price impact of burns. Net positive burns on the bid (ask) side can have negative (positive) price impact. These cases are denoted by the left and right schematics of panel (b). .

Panel A: Price impact of Mint orders: negative (left) and positive(right)



Panel B: Price impact of burn orders: negative (left) and positive(right)

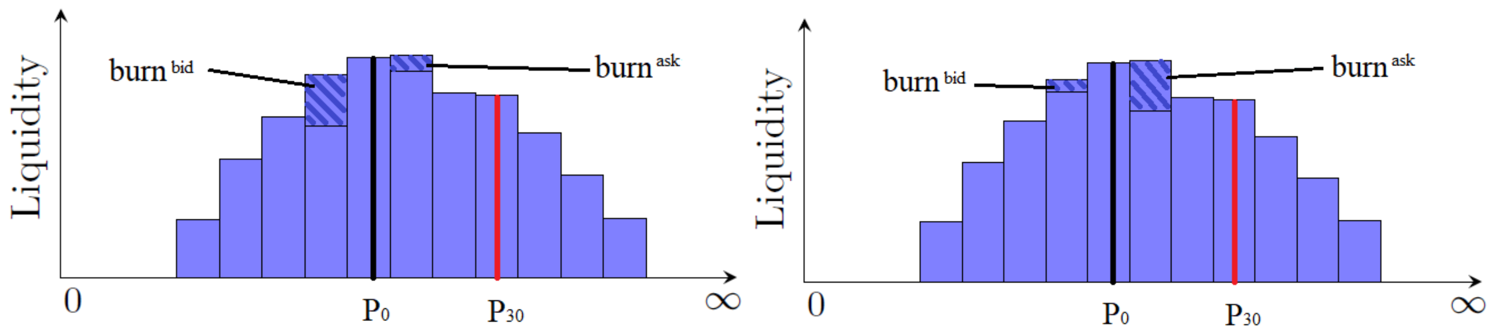
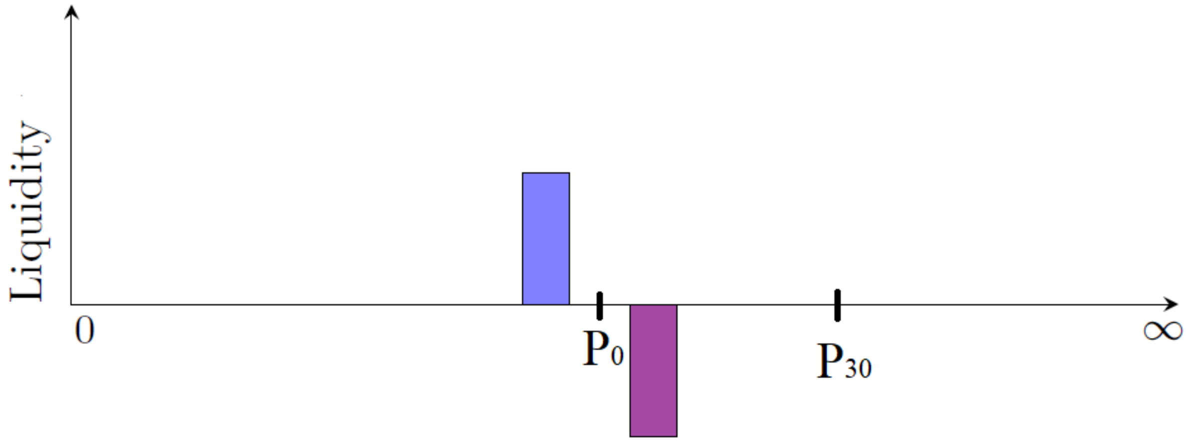


Figure 3: **Aggressive and non-aggressive liquidity price impacts.**
This figure displays the aggressive and non-aggressive strategies LPs can conduct. The current price is denoted by P_0, and the "long-run" price is given by P_{30}. We denote the bid side of the book when liquidity is minted or burned at a price less than the market price. We denote the ask side of the book when liquidity is minted or burned at a price greater than the market price. Liquidity is the minting (burning) of the base currency token if it is posted at the ask (bid). Panel (a) considers aggressive orders placed close to the current price. Positive liquidity posted at bid, and negative liquidity posted at ask, has positive price impact. Panel (b) considers non-aggressive orders placed far away from the current price. Positive liquidity at ask, and negative liquidity at bid, has positive price impact. .

Panel A:Aggressive liquidity



Panel B:Non-aggressive liquidity

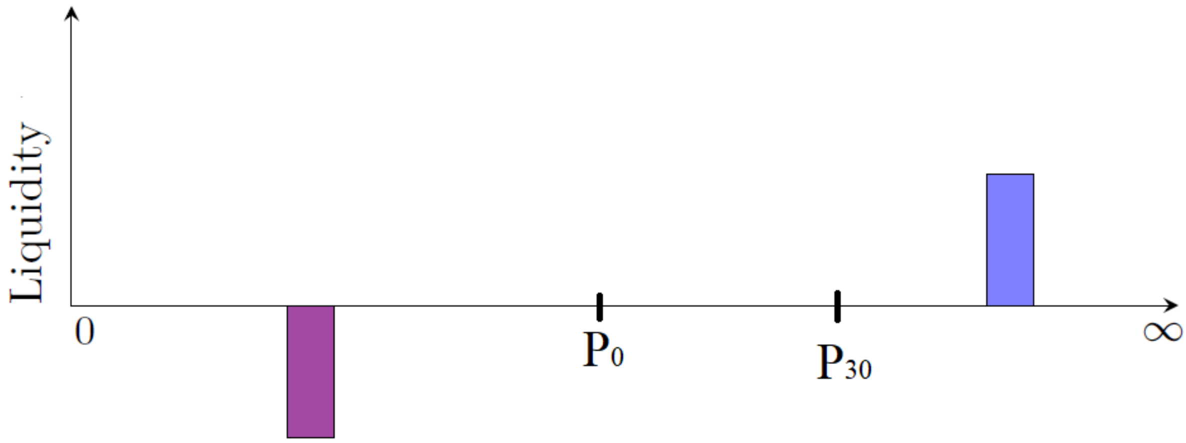
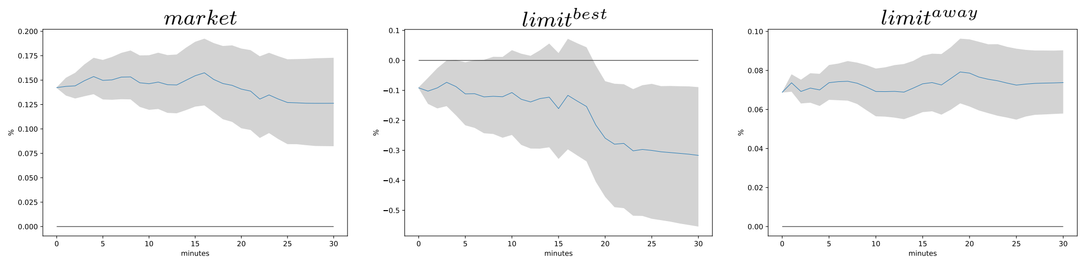


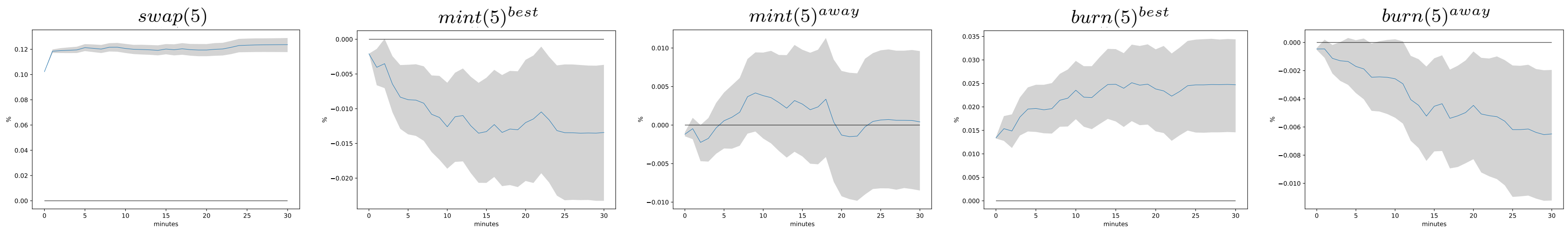
Figure 4: **Cumulative impulse response functions of order flows on returns**

This Figure plots the cumulative impulse response of ETH-USDC returns to a positive shock to order flow in the centralized (Panel A) and the decentralized (Panel b and C) exchanges. The methodology is based on Hasbrouck (1991a). In Panel A, we measure the effect of a 1 million USDC shock to market order flow (*market*), limit order flow posted at the best price (*best*) and away from the best price (*away*). In Panel B (C) we measure the effect of a 1 million USDC shock to swap order flow (*swap*), mint order flow submitted within 5 tick ranges ($mint^{best}$) and outside 5 tick ranges ($mint^{away}$) as well as burn order flow ($burn^{best}$ and $burn^{away}$) on DEX(5) (DEX(30) respectively) pool. The benchmark return is based on bid-ask prices of Binance ETH-USDC. All data is at a minute level. The shaded area represents the range between the 2.5th and 97.5th quantile values, which captures the middle 95% of the data distribution.

Panel A: CIRF of CEX order flow on returns



Panel B: CIRF of DEX(5) order flow on returns



Panel C: CIRF of DEX(30) order flow on returns

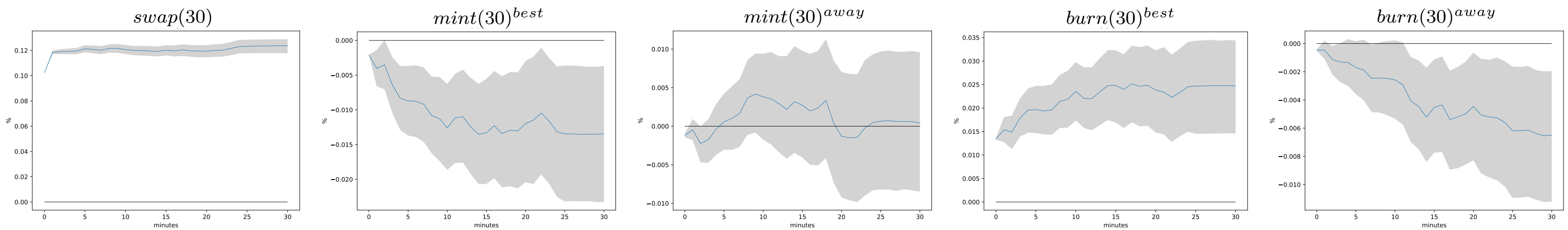
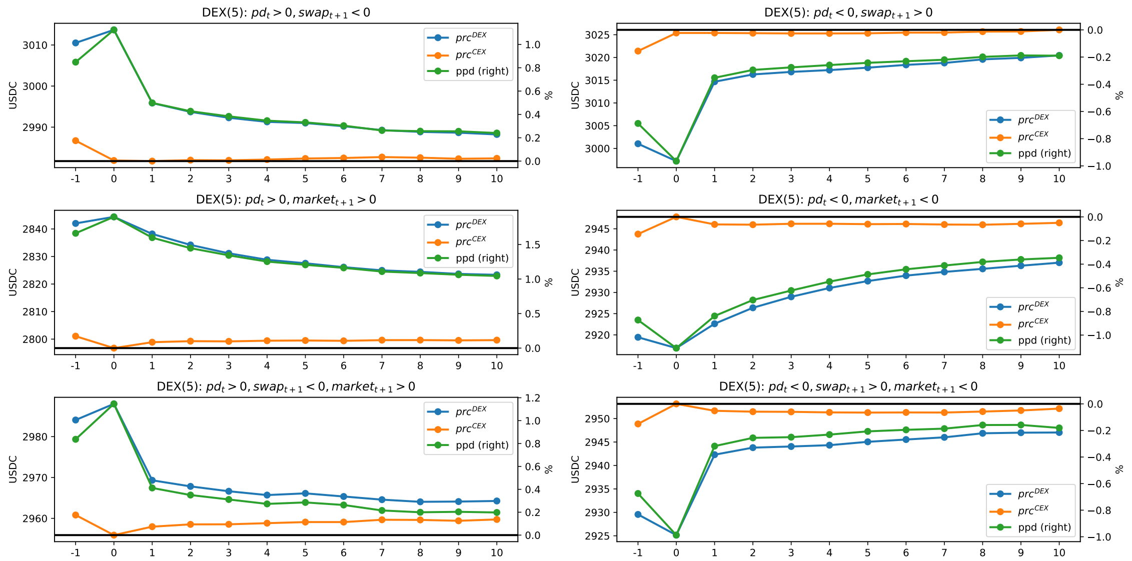


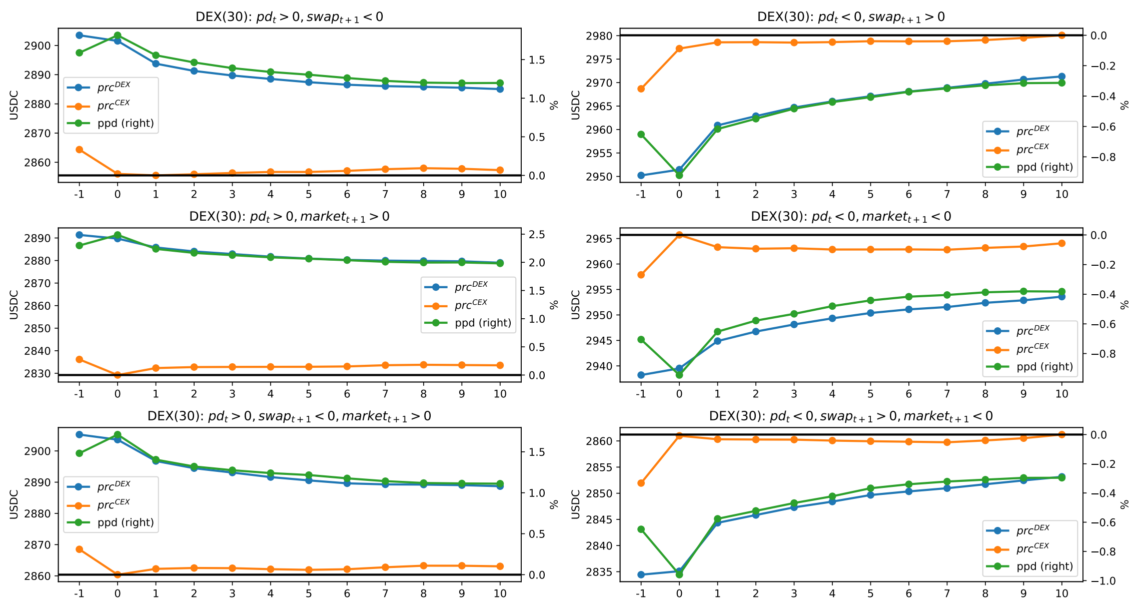
Figure 5: **Arbitrage analysis for WETH-USDC**

This Figure plots the price difference conditional on the sign of order flow for the ETH-USDC pair. We define pd as the price difference between Uniswap ETH-USDC and Binance ETH-USDC price. We condition price difference and order flow in period 1 and consider six cases of (i) $pd_t > 0, swap_{t+1} < 0$, (ii) $pd_t > 0, market_{t+1} > 0$, (iii) $pd_t > 0, swap_{t+1} < 0, markett + 1 > 0$, (iv) $pd_t < 0, swap_{t+1} > 0$, (v) $pd_t < 0, market_{t+1} < 0$, (vi) $pd_t < 0, swap_{t+1} > 0, , market_{t+1} < 0$. We also require that for an arbitrage opportunity, the absolute value of the percentage price difference should be at least 50 basis points. In Panel (a), we conduct the analysis on the DEX(5), and in Panel (b), we conduct the analysis on the DEX(30).

(a) $DEX(5)$



(b) $DEX(30)$



Tables

Table 1: **Distribution of absolute distance from lower and upper tick to current tick**

This table presents summary statistics on the absolute distance of liquidity events (mints and burns) from the current tick in DEX pools. The current tick is derived from the current price. Each liquidity event is associated with a tick range that includes both lower and upper ticks. We calculate the absolute distance from both the lower and upper ticks to the current tick separately. The sample period ranges from 06/05/2021 to 12/07/2022. One tick is equivalent to one basis point of the current price.

	DEX(5)		DEX(30)	
	lower	upper	lower	upper
count	50,845	50,845	92,217	92,217
mean	7,802	4,646	8,076	6,053
SD	81,360	46,725	72,379	44,184
min	0	0	0	0
1%	0	1	5	6
5%	3	3	30	31
10%	7	7	64	66
15%	10	10	114	113
20%	23	22	188	177
25%	53	47	307	285
50%	424	367	1,348	1,279
75%	1,554	1,354	4,205	3,943
max	1,094,907	695,697	1,094,047	695,475

Table 2: **Summary statistics: Order flows, trade sizes and trade frequencies**

This table reports summary statistics of order flows with non-zero values at a one-minute frequency, individual trade sizes at the trade level, and trade frequency per minute for both DEX(5) and DEX(30) pools on Uniswap v3 Ethereum and CEX (Binance) for ETH/USDC pair. *market* is the market order flow in the CEX market, *swap* is the swap order flow from the corresponding DEX pool. We convert ETH amounts to units of USDC. The sample period ranges from 06/05/2021 to 12/07/2022.

Panel A: Order Flows

Pool	variable	count	mean	std	Q1	median	Q3
DEX(5)	$swap(5)^{buy}$	440,474	270,559	596,679	8,046	54,901	292,126
	$swap(5)^{sell}$	457,867	260,452	587,113	9,291	55,455	266,105
DEX(30)	$swap(30)^{buy}$	78,957	364,897	596,957	17,145	184,866	476,399
	$swap(30)^{sell}$	83,313	345,422	589,652	15,100	157,499	441,491
CEX	$market^{buy}$	538,847	21,244	67,310	1,466	6,136	19,297
	$market^{sell}$	538,853	23,144	79,025	1,631	6,745	20,552

Panel B: Individual trade size

Pool	count	mean	std	Q1	median	Q3
DEX(5)	2,297,584	103,738	292,735	2,026	10,722	75,000
DEX(30)	281,884	204,282	372,908	9,480	89,988	263,800
CEX	16,081,076	1,488	5,331	139	499	1,324

Panel C: Trade frequency (per minute)

Pool	nr.minutes	mean	std	Q1	median	Q3
DEX(5)	623,520	3.68	3.17	1.00	3.00	5.00
DEX(30)	623,520	0.45	1.04	0.00	0.00	0.00
CEX	623,520	25.79	47.66	5.00	12.00	28.00

Table 3: **Summary Statistics: Liquidity provision**

This table reports summary statistics of market depth (Panel A), liquidity order flows (Panel B), individual liquidity order sizes (Panel C) and frequency of liquidity orders submissions (Panel D). For DEX, market depth is total liquidity deposited within 2% of the current market price. For CEX, market depth is based on the first best 50 orders on each side. *limit* is the limit order flow of limit orders submitted in the CEX market, $mint(k)$ is the flow of submitted (minted) liquidity in the corresponding DEX(k) pool, $burn(k)$) is the flow of withdrawn (burned) liquidity in the corresponding DEX(k) pool. *bid* and *ask* superscripts indicate buy and sell orders in ETH token respectively. The sample period ranges from 06/05/2021 to 12/07/2022. order flows are in one-minute frequency, with ETH amounts converted to units of USDC. Column count shows number of minutes with non-zero value of the corresponding variable. Column nr.minutes indicate the total number of minutes in the sample.

Panel A: Depth

Pool	variable	count	mean	std	Q1	median	Q3
DEX(5)	*depth*	623,520	8,955,746	6,412,303	3,798,055	7,712,706	12,790,964
DEX(30)	*depth*	623,520	8,627,426	4,016,923	5,491,296	7,868,373	11,352,665
CEX	*depth*	623,520	448,569	211,116	275,103	429,866	597,985

Panel B: Liquidity order flows

Pool	variable	count	mean	std	Q1	median	Q3
DEX(5)	$mint(5)^{ask}$	22,573	2,295,159	7,873,420	6,627	41,624	296,452
	$mint(5)^{bid}$	22,126	1,417,988	4,492,749	5,135	36,717	254,486
	$burn(5)^{ask}$	16,012	3,230,590	9,172,056	17,008	94,069	695,685
	$burn(5)^{bid}$	15,038	2,074,864	5,357,197	17,793	98,892	611,266
DEX(30)	$mint(30)^{ask}$	43,217	532,378	3,545,348	282	5,625	44,334
	$mint(30)^{bid}$	42,623	381,070	2,056,774	221	4,870	41,421
	$burn(30)^{ask}$	25,039	902,611	4,589,663	2,288	20,320	102,665
	$burn(30)^{bid}$	23,890	676,123	2,756,440	2,542	20,766	103,939
CEX	$limit^{ask}$	623,031	18,373	123,576	-26,665	9,235	63,664
	$limit^{bid}$	622,994	20,018	113,044	-21,100	9,777	57,830

Panel C: Individual order size

Pool	variable	count	mean	std	Q1	median	Q3
DEX(5)	mints	27,492	3,026,483	9,061,354	12,389	79,191	504,265
	burns	22,993	3,607,647	9,797,380	25,099	120,000	844,549
DEX(30)	mints	55,095	712,495	4,268,669	133	7,585	70,157
	burns	37,122	1,044,024	5,169,201	2,957	26,529	131,611

Panel D: Order submission frequency

Pool	variable	nr.minutes	mean	std	Q1	median	max
DEX(5)	mints	0.04	0.23	0	0	0	27
	burns	0.04	0.20	0	0	0	7
DEX(30)	mints	0.09	0.36	0	0	0	33
	burns	0.06	0.28	0	0	0	10

Table 4: **CIRF of net orders on returns**

This table reports the cumulative impulse response function (CIRF) of ETH-USDC returns to a buy and sell order flow shock in centralized and decentralized exchanges at horizons of n = 0, 1, 10 and 30 minutes. The methodology is based on Hasbrouck (1991a) with order flow of both exchanges and measures of new liquidity (mints and burns), and the ETH-USDC return. The estimates are the effect of a 1 USDC Million of corresponding order flow on ETH-USDC Return. $market$ is the market order flow in the CEX market, $swap$ is the swap order flow from the corresponding DEX pool, $limit^{best}$ is the limit order flow of limit orders submitted at the best price in the CEX market, $limit^{away}$ is the limit order flow of limit orders submitted away from the best price in the CEX market, $mint^{best}$ ($mint^{away}$) is the flow of minted liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price, $burn^{best}$ ($burn^{away}$) is the flow of burned liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price. The benchmark return is based on bid-ask prices of Binance ETH-USDC. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in one-minute frequency. * denotes significance at a 10 per cent level, ** denotes significance at a 5 per cent level, *** denotes significance at a 1 per cent level.

	$n=0$	$n=1$	$n=10$	$n=30$
Panel A: CEX				
$market$	0.142***	0.144***	0.146***	0.126***
$limit^{best}$	−0.092***	−0.102***	−0.107***	−0.317***
$limit^{away}$	0.069***	0.074***	0.069***	0.074***
Panel B: DEX(5)				
$swap$	0.102***	0.118***	0.121***	0.124***
$mint^{best}$	−0.002***	−0.004***	−0.013***	−0.013***
$mint^{away}$	−0.001***	0.000	0.004	0.000
$burn^{best}$	0.013***	0.015***	0.024***	0.025***
$burn^{away}$	−0.001***	0.000	−0.003*	−0.006***
Panel C: DEX(30)				
$swap$	0.189***	0.208***	0.207***	0.203***
$mint^{best}$	−0.002***	−0.003	0.004	0.010
$mint^{away}$	−0.001***	−0.002	−0.002	−0.007
$burn^{best}$	0.014***	0.015***	0.007	0.002
$burn^{away}$	−0.001***	−0.002	−0.005	0.001

Table 5: **Variance decomposition**

This table reports the forecast error variance decomposition from the Hasbrouck (1991a) VAR in Table 4 at horizons $n = 0$ and 30 minutes. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in one-minute frequency.

	$n = 0$	$n = 30$
Panel A: CEX *order flows*		
$market$	0.71	0.71
$limit^{best}$	0.00	0.01
$limit^{away}$	0.37	0.38
Panel B: DEX(5) *order flows*		
$swap$	9.91	10.03
$mint^{best}$	0.05	0.45
$mint^{away}$	0.00	0.01
$burn^{best}$	0.03	0.04
$burn^{away}$	0.00	0.01
Panel C: DEX(30) *order flows*		
$swap$	14.50	14.47
$mint^{best}$	0.01	0.31
$mint^{away}$	0.00	0.02
$burn^{best}$	0.02	0.02
$burn^{away}$	0.00	0.02

Table 6: **CIRF of net order flows: Size**

This table reports the cumulative impulse response (CIRF) of ETH-USDC returns to a buy and sell order flow shock in decentralized exchanges at 30 minutes horizon. The methodology is based on Hasbrouck (1991a). The estimates are the effect of a 1 USDC Million of corresponding order flow on ETH-USDC Return. $market^{buy}$ ($market^{sell}$) is the market buy (sell) order flow in the CEX market, $swap^{buy}$ ($swap^{sell}$) is the swap buy (sell) order flow from the corresponding DEX pool, $limit^{best}$ is the limit order flow of limit orders submitted at the best price in the CEX market, $limit^{away}$ is the limit order flow of limit orders submitted away from the best price in the CEX market, $mint^{best}$ ($mint^{away}$) is the flow of minted liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price, $burn^{best}$ ($burn^{away}$) is the flow of burned liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price. This table classifies orders based on the size of submitted orders. For $market^{sell}$ and $swap^{sell}$ ($market^{buy}$ and $swap^{buy}$) orders, we classify sell (buy) order flows as large (denoted as $large$) if the sell (buy) order flow exceeds the median size of the distribution of non-zero minute-level sell (buy) order flows, which is 15,661 (14,160) USDC for sell (buy) order flows. For $mint^{best}$ and $mint^{away}$ ($burn^{best}$ and $burn^{away}$), we classify mint (burn) order flows as large (denoted as $large$) if the mint (burn) order flow is greater than the median size of the distribution of transaction-level mint (burn), which is 19,478 (48,810) USDC for mint (burn) orders. The benchmark return is based on bid-ask prices of Binance ETH-USDC. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in one-minute frequency. * denotes significance at a 10 per cent level, ** denotes significance at a 5 per cent level, *** denotes significance at a 1 per cent level.

Variable	CIRF	Variable	CIRF	Variable	CIRF
$market^{large,sell}$	−0.099***	$swap(5)^{large,sell}$	−0.068***	$swap(30)^{large,sell}$	−0.141***
$market^{small,sell}$	−0.362	$swap(5)^{small,sell}$	1.921***	$swap(30)^{small,sell}$	1.246
$market^{large,buy}$	0.138***	$swap(5)^{large,buy}$	0.123***	$swap(30)^{large,buy}$	0.216***
$market^{small,buy}$	0.343	$swap(5)^{small,buy}$	−1.07 ***	$swap(30)^{small,buy}$	−3.649***
$limit^{best}$	−0.331***	$mint(5)^{Large,best}$	−0.014***	$mint(30)^{Large,best}$	0.011
$limit^{away}$	0.074***	$mint(5)^{Small,best}$	6.657	$mint(30)^{Small,best}$	0.911
		$mint(5)^{Large,away}$	0.000	$mint(30)^{Large,away}$	−0.007
		$mint(5)^{Small,away}$	−1.427	$mint(30)^{Small,away}$	−1.135
		$burn(5)^{Large,best}$	0.024***	$burn(30)^{Large,best}$	0.001
		$burn(5)^{Small,best}$	−1.610	$burn(30)^{Small,best}$	−0.549
		$burn(5)^{Large,away}$	−0.007***	$burn(30)^{Large,away}$	0.001
		$burn(5)^{Small,away}$	0.084	$burn(30)^{Small,away}$	0.024

Table 7: **CIRF of net order flows: Priority of execution**

This table reports the cumulative impulse response (CIRF) of ETH-USDC returns to a buy and sell order flow shock in decentralized exchanges at 30 minutes horizon. The methodology is based on Hasbrouck (1991a). The estimates are the effect of a 1 USDC Million of corresponding order flow on ETH-USDC Return. *swap* is the swap order flow from the corresponding DEX pool, $mint^{best}$ ($mint^{away}$) is the flow of minted liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price, $burn^{best}$ ($burn^{away}$) is the flow of burned liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price. We classify a transaction into top (denoted as *top*) if its position index within the block is smaller than the median position of the distribution, which is 80. A transaction is classified as a bottom (denoted as *bottom*) position otherwise. The benchmark return is based on bid-ask prices of Binance ETH-USDC. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in one-minute frequency. * denotes significance at a 10 per cent level, ** denotes significance at a 5 per cent level, *** denotes significance at a 1 per cent level.

Variable	CIRF	Variable	CIRF
$swap(5)^{top}$	0.119***	$swap(30)^{top}$	0.200***
$swap(5)^{bottom}$	0.146***	$swap(30)^{bottom}$	0.222***
$mint(5)^{top,best}$	−0.012**	$mint(30)^{top,best}$	0.003
$mint(5)^{bottom,best}$	−0.015	$mint(30)^{bottom,best}$	0.027
$mint(5)^{top,away}$	0.006	$mint(30)^{top,away}$	0.018
$mint(5)^{bottom,away}$	−0.001	$mint(30)^{bottom,away}$	−0.013
$burn(5)^{top,best}$	0.025***	$burn(30)^{top,best}$	0.031**
$burn(5)^{bottom,best}$	0.027*	$burn(30)^{bottom,best}$	−0.008
$burn(5)^{top,away}$	−0.006**	$burn(30)^{top,away}$	−0.033**
$burn(5)^{bottom,away}$	−0.008***	$burn(30)^{bottom,away}$	0.014

Table 8: **CIRF of net order flows: Combined orders strategies**

This table reports the cumulative impulse response (CIRF) of ETH-USDC returns to a buy and sell order flow shock in decentralized exchanges at 30 minutes horizon. The methodology is based on Hasbrouck (1991a). The estimates are the effect of a 1 USDC Million of corresponding order flow on ETH-USDC Return. *swap* is the swap order flow from the corresponding DEX pool, $mint^{best}$ ($mint^{away}$) is the flow of minted liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price, $burn^{best}$ ($burn^{away}$) is the flow of burned liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price. Panel A classifies wallets into mixed or using only type of orders. We classify LPs submitting the order as using mixed type orders strategy (denoted as *mixed*) if there is a swap and a liquidity order (mint or burn) submitted by the same wallet. Otherwise, a swap order is classified as *onlyswap* and liquidity order is classified as *onlylp*. Panel B classifies orders as repositioning *repo* if a burn order is followed by a mint orders within 2 minutes time coming form the same wallet. Otherwise, it is classified as *other*. Panel C classifies orders by frequency of submission by a wallet. Wallets which update their liquidity more times than the upper quartile of the distribution of the number of liquidity updates in the sample (which is 4) are classified as frequent ($highfr$). Otherwise, the wallet and all its liquidity orders are classified as infrequent ($lowfr$). The benchmark return is based on bid-ask prices of Binance ETH-USDC. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in one-minute frequency. * denotes significance at a 10 per cent level, ** denotes significance at a 5 per cent level, *** denotes significance at a 1 per cent level.

Panel A: Mixed order types vs pure liquidity provision

Variable	CIRF	Variable	CIRF
$swap(5)^{mixed}$	0.109***	$swap(30)^{mixed}$	0.222***
$swap(5)^{onlyswap}$	0.119***	$swap(30)^{onlyswap}$	0.183***
$mint(5)^{mixed,best}$	−0.015***	$mint(30)^{mixed,best}$	0.009
$mint(5)^{onlylp,best}$	0.002	$mint(30)^{onlylp,best}$	0.027
$mint(5)^{mixed,away}$	0.000	$mint(30)^{mixed,away}$	−0.008
$mint(5)^{onlylp,away}$	0.011	$mint(30)^{onlylp,away}$	−0.009
$burn(5)^{mixed,best}$	0.025***	$burn(30)^{mixed,best}$	0.003
$burn(5)^{onlylp,best}$	0.043	$burn(30)^{onlylp,best}$	−0.039
$burn(5)^{mixed,away}$	−0.007***	$burn(30)^{mixed,away}$	0.002
$burn(5)^{onlylp,away}$	0.004	$burn(30)^{onlylp,away}$	−0.004

Panel B: Liquidity repositioning

Variable	CIRF	Variable	CIRF
$swap(5)$	0.124***	$swap(30)$	0.202***
$mint(5)^{repo,best}$	−0.015**	$mint(30)^{repo,best}$	0.015
$mint(5)^{other,best}$	−0.001	$mint(30)^{other,best}$	−0.004
$mint(5)^{repo,away}$	−0.002	$mint(30)^{repo,away}$	−0.007
$mint(5)^{other,away}$	0.001	$mint(30)^{other,away}$	−0.006
$burn(5)^{repo,best}$	0.027***	$burn(30)^{repo,best}$	0.003
$burn(5)^{other,best}$	−0.002	$burn(30)^{other,best}$	−0.015
$burn(5)^{repo,away}$	0.002	$burn(30)^{repo,away}$	0.000
$burn(5)^{other,away}$	−0.008***	$burn(30)^{other,away}$	0.002

Panel C: Frequency of liquidity orders

Variable	CIRF	Variable	CIRF
$swap(5)$	0.124***	$swap(30)$	0.202***
$mint(5)^{highfr,best}$	−0.012**	$mint(30)^{highfr,best}$	0.011
$mint(5)^{lowfr,best}$	−0.057*	$mint(30)^{lowfr,best}$	−0.021
$mint(5)^{highfr,away}$	0.001	$mint(30)^{highfr,away}$	−0.008
$mint(5)^{lowfr,away}$	0.002	$mint(30)^{lowfr,away}$	0.019
$burn(5)^{highfr,best}$	0.023***	$burn(30)^{highfr,best}$	0.001
$burn(5)^{lowfr,best}$	0.057*	$burn(30)^{lowfr,best}$	0.024
$burn(5)^{highfr,away}$	−0.006**	$burn(30)^{highfr,away}$	−0.004
$burn(5)^{lowfr,away}$	0.018	$burn(30)^{lowfr,away}$	0.364

Table 9: **Summary statistics of price difference**

This table reports summary statistics of the price difference between the DEX and WETH/USDC 0.3% on Uniswap v3 Ethereum) and CEX (ETH/USDC pair traded on Binance) exchanges. Panel A (DEX(5) market) summarizes the price differences based on WETH/USDC 0.05% price and Panel B (DEX(30) market) corresponds to the price difference based on WETH/USDC 0.30% price. Price difference is defined as $pd = prc^{DEX} - prc^{CEX}$ while percentage price difference is defined as $ppd = 100 \times pd/prc^{CEX}$. All data are in one-minute frequency, with ETH amounts converted to units of USDC. The sample period ranges from 06/05/2021 to 12/07/2022.

Panel A: DEX(5)

	count	mean	std	min	Q1	median	Q3	max
pd	623,520	0.047	10.433	−398.545	−1.563	−0.048	1.458	564.679
$\|pd\|$	623,520	3.093	9.964	0.000	0.672	1.511	2.825	564.679
ppd	623,520	0.005	0.428	−24.841	−0.056	−0.002	0.053	28.602
$\|ppd\|$	623,520	0.108	0.414	0.000	0.027	0.055	0.092	28.602

Panel B: DEX(30)

in %	count	mean	std	min	Q1	median	Q3	max
pd	623,520	−0.015	10.540	−462.506	−4.582	−0.230	4.062	304.004
$\|pd\|$	623,520	5.516	8.981	0.000	2.027	4.323	7.415	462.506
ppd	623,520	0.004	0.415	−28.389	−0.169	−0.009	0.154	13.993
$\|ppd\|$	623,520	0.189	0.369	0.000	0.079	0.162	0.253	28.389

Table 10: **Order flow and arbitrage trading**

This table examines relationship between price difference across CEX and DEX and the flows of different types of orders. Panel A reports the cumulative impulse response function (CIRF) of the price difference to an order flow shock at horizons of $n = 0$ and 30 minutes. The price difference is measured as the difference in the Uniswap and the Binance ETH-USDC. Panel B reports the CIRF of ETH-USDC returns to a buy and sell order flow shock conditioned on the price difference between the DEX and CEX exchange. The methodology is based on Hasbrouck (1991a) and estimates the effect of a 1 USDC Million of corresponding order flow shock. *market* is the buy or sell market order flow in the CEX market, *swap* is the buy or sell swap order flow from the corresponding DEX pool, *limit* is the limit order flow submitted in the CEX market, *newliq* is the new net liquidity provided in the corresponding DEX pool and defined as $newliq = mint - burn$ with *mint* is the flow of submitted (minted) liquidity and *burn* is the flow of withdrawn (burned) liquidity in the DEX market. The percentage of price difference is defined as $ppp = 100 \times (prc^{DEX} - prc^{CEX})/prc^{CEX}$ where prc^{DEX} is taken from the corresponding DEX pool. Order flows are conditioned on *ppp*, where *highpd* (*lowpd*) represents values 50 bps above (below) of average *ppp*. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in one-minute frequency. *, ** and *** denote significance at 10, 5 and 1 per cent levels respectively.

	DEX(5)		DEX(30)	
	$n = 0$	$n = 30$	$n = 0$	$n = 30$
Panel A: CIRF of order flow on price difference				
$market^{sell}$	2.976***	8.201	3.400***	26.766***
$market^{buy}$	−3.452***	−60.100***	−4.132***	−58.830***
$swap^{sell}$	−0.717***	−7.801***	−1.408***	−59.614***
$swap^{buy}$	1.181***	13.828***	1.180***	62.787***
$limit^{ask,best}$	2.564***	134.784***	4.662***	73.789
$limit^{bid,best}$	−1.372***	−11.196	−0.633***	−24.443
$newliq^{ask,best}$	−0.010***	−1.627*	0.034***	−2.184
$newliq^{bid,best}$	−0.020***	1.979*	−0.121***	−3.484
Panel B: CIRF of order flow on return conditional on price difference				
$market^{sell,highpd}$	−0.272***	−0.172*	−0.226***	−0.066
$market^{sell,lowpd}$	−0.121***	−0.116***	−0.134***	−0.151***
$market^{buy,highpd}$	0.325***	0.502***	0.319***	0.697***
$market^{buy,lowpd}$	0.125***	0.105***	0.144***	0.101***
$swap^{sell,highpd}$	−0.016***	−0.079***	−0.097***	−0.089***
$swap^{sell,lowpd}$	−0.057***	−0.086***	−0.138***	−0.178***
$swap^{buy,highpd}$	0.096***	0.166***	0.203***	0.245***
$swap^{buy,lowpd}$	0.135***	0.158***	0.191***	0.224***
$limit^{ask,best,highpd}$	−0.272***	−0.172*	−0.226***	−0.066
$limit^{ask,best,lowpd}$	−0.121***	−0.116***	−0.134***	−0.151***
$limit^{bid,best,highpd}$	0.325***	0.502***	0.319***	0.697***
$limit^{bid,best,lowpd}$	0.125***	0.105***	0.144***	0.101***
$newliq^{ask,best,highpd}$	−0.016***	−0.079***	−0.097***	−0.089***
$newliq^{ask,best,lowpd}$	−0.057***	−0.086***	−0.138***	−0.178***
$newliq^{buy,best,highpd}$	0.096***	0.166***	0.203***	0.245***
$newliq^{buy,best,lowpd}$	0.135***	0.158***	0.191***	0.224***

Internet Appendix to

"Price Discovery in Cryptocurrencies: Centralized versus Decentralized Markets"

(Not for publication)

A Trading mechanics on Uniswap v3

Compared to Uniswap V2, Uniswap V3 seeks to improve "capital efficiency" of LPs, by allowing them to set specific price ranges for their liquidity positions. When they submit a new liquidity position, they have to specify a price range, $[p_a, p_b]$, where p_a is the minimum price and p_b - the maximum price of token X in units of token Y at which their position is active. The price curve for Uniswap v3 is a modification of $x \cdot y = k$, such that the position is solvent exactly within its price range:[14]

$$(x + \frac{L}{\sqrt{p_b}})(y + L\sqrt{p_a}) = L^2, \tag{8}$$

where L is the (virtual) liquidity within the price range $[p_a, p_b]$; x and y are the quantities of tokens X and Y deposited within this price range. In contrast to Uniswap V2, the amount of tokens deposited in a liquidity position is no longer in 50-50 ratio. In fact, it depends on the position of the price range relative to the current market price, p_M, with larger reserves of X required if the price range is skewed to prices higher than the current price. If the preferred price range is strictly higher than the current price (and excludes it), then liquidity provider only has to deposit X token. Similarly, if the preferred price range is strictly lower than the current price, then liquidity provider only has to deposit Y token.

In Uniswap V3, the space of prices is divided into discrete ticks, i $(i \epsilon Z)$. There can be a tick at every price p that is an integer power of 1.0001, such that the following

14. Source: Uniswap v3 whitepaper available at https://uniswap.org/whitepaper-v3.pdf

relation holds for the price p at tick i:

$$p_i = 1.0001^i. \tag{9}$$

Specifically, this relation implies that each tick is 1 bp (basis point) away from its neighbouring ticks. However, not all ticks can be initialized, but only those that are divisible by a pre-specified tick spacing parameter. For example, USDC/ETH 0.3% pool has a tick spacing of 60. Therefore, only ticks that are divisible by 60 can be initialized for this pool, i.e. (-120, -60, 0, 60, 120...). A tick range can then be defined as $[i, i+l]$,where l is the length of the tick range, equal to tick spacing. One liquidity position of a liquidity provider can cover one or more tick ranges, $[i, i+l]$. The liquidity on each tick range $[i, i+l]$, L_i, is then an aggregation of all liquidity provider positions that are currently active on it. Therefore, aggregate liquidity in a Uniswap V3 pool is no longer constant (as in Uniswap V2), but fragmented across multiple tick ranges.

From Uniswap V3 whitepaper (Adams et al. 2021), we obtain the following relations for x_i, quantity of tokens X locked in the tick range $[i, i+l]$, and y_i, quantity of tokens Y locked in the same tick range:

$$x_i = \frac{L_i}{\sqrt{z_i}} - \frac{L_i}{\sqrt{p_{i+l}}} \tag{10}$$

$$y_i = L_i \cdot (\sqrt{z_i} - \sqrt{p_i}), \tag{11}$$

where $z_i = \begin{cases} p_i \text{ if } p_M \leq p_i \\ p_M \text{ if } p_i < p_M < p_{i+l} \\ p_{i+l} \text{ if } p_{i+l} \leq p_M. \end{cases}$