# Informed Liquidity Provision on Decentralized Exchanges *

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**Abstract**

We study the role of liquidity providers (LPs) in price discovery on decentralized cryptocurrency exchanges. In contrast to traditional limit order markets, where quotes can be revised instantaneously, DEX liquidity providers commit large amounts of capital to liquidity pools and face costly liquidity adjustments. This exposes them to greater adverse selection risk and generates strong incentives to acquire private information. Consistent with this prediction, we find that liquidity provision in the ETH-USDC low-fee pool close to the prevailing price has a permanent price impact, reflecting informed behavior of DEX LPs. We document heterogeneity across LPs, with larger orders, higher execution priority, narrower intervals, and sophisticated providers exhibiting greater informativeness.

Keywords: Price discovery, order flow, decentralized finance

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# 1 Introduction

One of the central functions of financial markets is price discovery—the incorporation of new and dispersed information into asset prices through the interaction of traders and liquidity providers (LPs). In the cryptocurrency ecosystem, this process takes place across two distinct market structures: centralized exchanges (CEXs), which operate traditional limit order books (LOBs), and decentralized exchanges (DEXs), which rely on smart contracts and automated market maker (AMM) protocols. These venues differ in execution speed, transparency, trading costs, and security, features that shape the behavior of informed traders and their choice of where to trade (Lehar and Parlour, 2025).

In Uniswap V2, the dominant AMM design until recently, LPs placed their capital uniformly across all prices. This made liquidity provision largely passive, allowing arbitrageurs to extract rents (Capponi and Jia, 2025) and leaving price discovery to aggressive (swap) traders (Capponi, Jia, and Yu, 2025), similar to traditional markets where market makers primarily absorb order flow (Glosten and Milgrom, 1985; Kyle, 1985). Uniswap V3, launched on Ethereum blockchain in May 2021, altered this design by enabling LPs to concentrate liquidity in chosen price ranges and fee tiers,[1] thereby bringing their role closer to that of limit order traders in LOBs, who are known to contribute to price discovery (e.g., Brogaard, Hendershott, and Riordan, 2019).

Yet despite these similarities, AMM liquidity provision differs from limit order markets in at least three important ways. First, unlike limit orders that can be canceled at any time, deposited liquidity is locked in the AMM pool until actively withdrawn by a liquidity provider - for at least the duration of one block.[2] Second, each liquidity deposit and withdrawal requires paying transaction costs ("gas fees"), making active liquidity management inherently costly.[3] Third, because gas fees make small transactions uneconomical, DEX trades tend to be substantially larger — up to ten times the size of

1. Both features enhance flexibility and capital efficiency by allowing LPs to tailor the scope and profitability of their positions.

2. The average block duration on Ethereum is 12 seconds. While it is technically possible to mint and burn liquidity within the same block — a practice known as just-in-time" (JIT) liquidity — such transactions are rare in our sample.

3. By contrast, submitting or canceling a limit order on a CEX is costless, as on traditional exchanges.

CEX trades — meaning DEXs naturally attract infrequent but large-sized trades.

Taken together, these three structural features imply that DEX liquidity providers have considerably more ”skin in the game” than their CEX counterparts. Their capital is locked, each adjustment is costly, and they face larger trades on average — meaning that a poorly positioned LP on a DEX bears significant adverse selection losses. This stands in sharp contrast to CEX market makers, who can costlessly cancel and repost quotes in response to incoming order flow. Facing these higher stakes, rational DEX liquidity providers have strong incentives to acquire private information about future price movements and to position their liquidity accordingly. These differences in market structure leave open the question of whether LPs in Uniswap V3 behave as informed participants. Understanding this matters not only for DeFi but also more broadly, as it highlights how market design shapes information aggregation.

This paper examines whether LPs in Uniswap V3 actively contribute to price discovery alongside swap traders. Using transaction-level data from the ETH/USDC pair, the most liquid and actively traded on Uniswap V3, we construct detailed measures of liquidity using the tick-level distribution of deposits (mints) and withdrawals (burns) and estimate the price impacts. This approach allows us to test whether liquidity supply in DEXs is purely passive or whether LPs behave strategically in ways that transmit information to prices.

We find that the actions of LPs in decentralized markets reveal information about future returns. Orders placed close to the current price on the decentralized exchange have a statistically significant and persistent impact on prices. In particular, aggressive burns and mints predict returns in the expected direction, consistent with informed repositioning to mitigate adverse selection costs. In economic terms, a one standard deviation liquidity provision event generates an aggregate price impact up to 30 times larger than that of a comparable swap, suggesting that DEX liquidity provision is a more informative signal per unit than swap activity. Yet as the forecast error variance decomposition reveals, swaps account for a larger share of overall return variation, reflecting their far greater frequency rather than superior informational content per trade.

In contrast, orders placed far from the current price – non-aggressive mints and burns – are generally uninformative and typically have insignificant effects. Limit order flow on the CEX also exhibits statistically significant return predictability, but with the opposite sign to that predicted — net ask-side limit order flow positively rather than negatively forecasts returns — suggesting that CEX liquidity providers are less informed than their DEX counterparts.

We next document that the informativeness of liquidity provision in DEXs is heterogeneous across LPs and across orders with different characteristics. In contrast to traditional limit order books, which do not provide user-level information, we exploit the unique granularity of blockchain data to link informativeness directly to wallet- and balance sheet–level characteristics. This enables us to identify features such as execution priority, repositioning behavior, and LP tick ranges as measures of sophistication, providing a novel way to distinguish informed from uninformed liquidity providers. Large orders, those with high execution priority, narrow price ranges, and submissions from sophisticated wallets display predictive content. By contrast, many liquidity events—especially those placed far from the current price or in high-fee pools—appear uninformed or have economically negligible price impacts. These patterns suggest that sophisticated LPs behave strategically, adjusting positions to reduce exposure to adverse selection, while simultaneously repositioning liquidity toward expected prices to earn fees.

Finally, we examine whether LPs rely on public or private information. We condition liquidity provision on tradable price discrepancies between CEX and DEX, defining periods of high and low deviation based on whether the absolute percentage price difference exceeds a threshold that reflects typical transaction costs, including gas fees, slippage, and pool fees. These deviations represent a natural form of public information, since a large share of DEX trading consists of arbitrage activity. We find that much of the informativeness of LPs' orders can be attributed to their reactions to such arbitrage signals, indicating that LPs are active and fast enough to compete with arbitrageurs. At the same time, liquidity orders continue to exert significant price impact even when arbitrage opportunities are absent, consistent with LPs trading on private information or processing more complex public signals. Hence, informed liquidity provision in AMMs is not merely a mechanical response to arbitrage but also contributes independently to price discovery.

These findings have several implications. From a theoretical perspective, they extend the literature on informed liquidity supply in limit order markets (e.g., Bloomfield, O'Hara, and Saar, 2005; Kaniel and Liu, 2006; Goettler, Parlour, and Rajan, 2009; Brogaard, Hendershott, and Riordan, 2019) by providing transparent, position-level evidence from decentralized markets, where liquidity decisions are fully observable on-chain. The closest paper to ours from this literature is Brogaard, Hendershott, and Riordan (2019), who show that price discovery in traditional limit order markets occurs predominantly through limit orders, with HFTs accounting for the bulk of this contribution. Whereas HFTs' informational advantage arises predominantly from their speed and co-location advantages, the mechanism driving informed liquidity provision in our setting is fundamentally different: DEX liquidity providers cannot rely on speed or co-location, since all transactions are settled at the block level. Instead, their informational advantage stems from the large amounts of capital committed to liquidity pools, which generates strong economic incentives to acquire private information about future price movements.

From a market design perspective, our findings highlight how changes in protocol rules, moving from uniform liquidity in Uniswap V2 to concentrated liquidity in Uniswap V3, alter the strategic nature of liquidity provision. From a policy perspective, they show that AMMs represent a viable alternative market structure for price discovery, in which information is aggregated by liquidity providers through capital-at-risk incentives rather than the technological speed and co-location advantages that characterise informed liquidity provision in traditional markets. This distinction matters for the sustainability of liquidity provision, the distribution of rents between informed and uninformed participants, and the assessment of decentralized exchanges relative to traditional trading venues.

**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, 2023).

The early literature on DEXs examines the role of LPs and their coexistence with centralized LOBs (Lehar and Parlour, 2025; Aoyagi and Ito, 2025); the determinants of liquidity provision (Caparros, Chaudhary, and Klein, 2023; Fang, 2024; Lehar, Parlour, and Zoican, 2022; Neuder et al., 2021); empirical differences between DEX and CEX markets (Barbon and Ranaldo, 2025; Han, Huang, and Zhong, 2021; Capponi, Jia, and Yu, 2025; Foley, O'Neill, and Putniņš, 2023; Alexander et al., 2023; Heimbach, Wang, and Wattenhofer, 2021); the role of arbitrage and front-running (Daian et al., 2019; Wang et al., 2022; Capponi and Jia, 2025); and the theoretical foundations of AMM functions and informed trading (Hasbrouck, Rivera, and Saleh, 2022, 2025; Park, 2023; Angeris and Chitra, 2020; Angeris et al., 2021; Angeris, Chitra, and Evans, 2022; Cartea, Drissi, and Monga, 2024; Cartea et al., 2023; Aoyagi, 2020; Huang, Rostova, and Song, 2024).

Within this literature, our paper is closest to studies of market efficiency in Uniswap V3, such as Barbon and Ranaldo (2025), who compare trading costs across DEX and CEX markets and show that concentrated liquidity provision in Uniswap V3 improves efficiency and reduces costs, allowing DEXs to compete directly with CEXs. We also relate to work on price discovery in DEX markets, such as Capponi, Jia, and Yu (2025), who show that trades with higher gas fees carry greater informational content because they increase the likelihood of execution in the next block and incentivize miners through higher tips, and Han, Huang, and Zhong (2021), who argue that price differences between Binance and Uniswap predict order flow. Our main innovation in this context is to consider the relative contributions of swap and liquidity orders to price discovery. In doing so, we contribute to an understanding of the incentives for informed trading in DEX markets. Most closely related on the theory side, Routledge, Shen, and Zetlin-Jones (2025) develop an adverse-selection framework for AMM liquidity provision analogous to Glosten and Milgrom (1985). Their model is set in a Uniswap V2 environment where LPs cannot choose a targeted price interval, and shows that LPs who also trade directionally via swaps are more informed than pure liquidity providers. In Uniswap V3, LPs can instead manage adverse-selection costs directly through the choice of price range and position size, without relying on swap trading. Our empirical results provide direct evidence for this mechanism.

A second focus is on understanding the determinants of liquidity provision (Lehar and Parlour, 2025; Capponi and Jia, 2025; Foley, O'Neill, and Putniņš, 2023). Prior work documents that liquidity provision depends on factors such as adverse selection risk, with pool balances related to the underlying volatility of the pair and the share of informed trading. Turning to whether LPs are passive or active, Fang (2024) show that while LPs are profitable, capital is often misallocated because passive LPs do not reallocate in line with adverse selection risk. Caparros, Chaudhary, and Klein (2023) demonstrate that blockchain scaling solutions such as Polygon and Arbitrum facilitate more active liquidity provision and trade repositioning, while Lehar, Parlour, and Zoican (2022) compare low- and high-fee pools on Uniswap v3, finding that low-fee pools typically attract institutional LPs who rebalance more often, whereas retail LPs tend to concentrate in high-fee pools. We contribute to this literature by studying the information set of LPs. We find that LPs strategically rebalance in response to information about future returns, and that net liquidity posted close to the market price has a permanent impact, consistent with the role 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. Section 3 develops our main research hypotheses, which test whether liquidity provision and withdrawal on decentralized exchanges contribute to price discovery. In Section 4, we conduct our empirical analysis of market order flow and liquidity provision. Section 5 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, paying a pre-specified pool fee, e.g., 0.05% or 0.30%, to LPs. 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 keep custody of their assets. However, execution on DEX is costly and not immediate. 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 (or pool) fees that traders pay to LPs both on CEX and DEX.[4]

Importantly, AMM liquidity provision differs from traditional limit order markets in at least three ways. First, unlike limit orders that can be revised or canceled at any time, liquidity providers are essentially "locking" their capital in the pool when they deposit ("mint") liquidity. The capital is locked for at least the duration of one block, which corresponds on average to 12 seconds on Ethereum. Second, similar to traders, liquidity providers also have to pay gas fees for every mint or burn transaction, making liquidity mints and burns inherently costly. Third, liquidity providers on DEX face a different distribution of expected trade sizes: DEX trades tend to be substantially larger — up to ten times the size of CEX trades - because gas fees make small transactions uneconomical.

Taken together, these three differences imply that DEX liquidity providers have considerably larger exposure to adverse selection than their CEX counterparts: their capital

4. Lehar and Parlour (2025) provide a detailed introduction to decentralized exchanges. Barbon and Ranaldo (2025) compare transaction costs on CEX and DEX, highlighting that the major difference in execution costs on DEX arises due to the existence of high gas fees.

is locked, each adjustment is costly, and they face larger trades on average. In contrast, CEX market makers can costlessly cancel and repost quotes in response to incoming order flow and CEX trades are on average smaller. Facing these higher stakes, rational DEX liquidity providers have strong incentives to acquire private information about future price movements.

On aggregate, decentralized exchanges account for between 6% and 10% of total monthly spot trading volume across both CEX and DEX venues during our sample period, from May 2021 to July 2022.[5] In our further analysis, we concentrate on the largest CEX, Binance, and the largest DEX, Uniswap v3.

## 2.2 Trading Mechanics on Uniswap

### 2.2.1 Liquidity Provision

Uniswap V3 was released in May 2021, implementing two main changes relative to its previous version, Uniswap V2.[6] To understand these innovations, it is helpful to begin with the mechanics of Uniswap V2.

In Uniswap V2, LPs deposit equal values of two tokens into a liquidity pool, and trading is designed to keep the constant product pricing rule (called bonding curve) $x \cdot y = k$, where $x$ and $y$ are the quantities of the two tokens in the pool. Importantly, LPs are not allowed to restrict the price range over which their liquidity was active—liquidity was automatically distributed over the entire price range $[0, \infty]$. Figure 1 illustrates this liquidity distribution. Panel A shows the Uniswap V2 case, where liquidity is uniformly distributed across all prices. This implies that most capital is idle for trades far from the current market price, leading to low capital efficiency.

[Insert Figure 1 approximately here]

In Uniswap V2, when a user executes a swap, the trade is routed through the pool's reserves, and the execution price is determined by the relative quantities of the two tokens.

5. Reference 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.

6. For detailed discussion of Uniswap V2, see Lehar and Parlour (2025), Capponi and Jia (2025), and Park (2023).

Specifically, the reserves must continue to satisfy the constant product rule $x \cdot y = k$ after the trade, which means the execution price is the marginal rate of substitution along this curve. As a result, the price of a trade increases with its size—larger trades incur more price slippage by moving further along the bonding curve.

The first key innovation of Uniswap V3 is the introduction of concentrated liquidity, which allows LPs to set specific price ranges for their liquidity positions. Panel B of Figure 1 shows how this changes the shape of the liquidity distribution: liquidity is no longer spread uniformly, but instead concentrated within a finite interval $[p_a, p_b]$. This aims to improve capital efficiency, as LPs can earn more trading fees with less capital deployed.

When an LP opens a new position in Uniswap V3, they specify a price range $[p_a, p_b]$, where $p_a$ is the minimum price and $p_b$ is the maximum price of token $X$ (the base token) in units of token $Y$ (the quote token) at which the position is active. In contrast to Uniswap V2, this allows LPs to concentrate their liquidity where they expect trading to occur.

The pricing function in Uniswap V3 is a generalization of the constant product formula, ensuring that the relationship between the two quantities holds within the specified price range:[7]

$$\left(x + \frac{L}{\sqrt{p_b}}\right)(y + L\sqrt{p_a}) = L^2, \tag{1}$$

where $x$ and $y$ are the amounts of tokens $X$ and $Y$ deposited, and $L$ is the virtual liquidity of the position. Virtual liquidity governs effective depth within the active range: a higher $L$ implies deeper liquidity and a smaller price impact per unit of trade, while a lower $L$ produces steeper price responses to the same trade size.[8]

This pricing function not only determines how liquidity is allocated, but also governs how trades execute in the protocol. When a user executes a swap in Uniswap V3, the trade

7. Source: Uniswap V3 whitepaper available at https://uniswap.org/whitepaper-v3.pdf

8. This expression reduces to the standard Uniswap V2 constant product formula $x \cdot y = k$ when the price range is unrestricted. In the limit as $p_a \to 0$ and $p_b \to \infty$, the LP's position is active across all prices. Then, $\lim_{p_a \to 0} L\sqrt{p_a} = 0$ and $\lim_{p_b \to \infty} \frac{L}{\sqrt{p_b}} = 0$, so Equation (1) simplifies to $x \cdot y = L^2$. This matches the Uniswap V2 constant product rule, where liquidity is uniformly distributed over $[0, \infty]$ and trades move along a fixed curve with $k = L^2$.

is routed through the active tick range that contains the current price. The execution price of the trade is determined by the marginal rate implied by the current pool reserves, following the same pricing logic as Uniswap V2 but applied locally within the active tick range . Specifically, if a user swaps $\Delta x$ units of token $X$ (e.g., ETH) for token $Y$ (e.g., USDC), the output amount $\Delta y$ is computed so that the updated reserves $(x+\Delta x, y-\Delta y)$ still satisfy equation (1). This ensures that the constant-curve invariant is preserved. Since prices move continuously along the bonding curve during the trade, the effective execution price is the average price over the path of the swap. In practice, this results in slippage: larger trades receive worse prices as they deplete more liquidity within the specified price range.

To implement concentrated liquidity, Uniswap V3 divides the price space into discrete tick intervals. Each tick range $i$ maintains a total liquidity level $L_i$, which aggregates the virtual liquidity $L$ from all LP positions active in that range. The liquidity distribution in Panel B of Figure 1 is built up from these tick-level contributions. This structure allows multiple LPs to deposit liquidity at different prices, resulting in a richer and more flexible liquidity profile than Uniswap V2. We provide more details on tick spacing in Section 2.2.2.

The amount of tokens deposited in a Uniswap V3 position is no longer in a fixed 50-50 ratio, as in Uniswap V2. Instead, it depends on the location of the price range relative to the current market price $p_M$. If the range lies strictly above $p_M$, only token $X$ needs to be deposited (corresponding to the ask side). If the range lies strictly below $p_M$, only token $Y$ is required (corresponding to the bid side). When the range contains $p_M$, both tokens must be deposited, with proportions depending on the position of $p_M$ within the range.

The second key innovation in Uniswap V3 is the introduction of variable fee tiers. Liquidity pools can be created with one of four fee rates: 0.01%, 0.05%, 0.3%, or 1%. Hence, the same token pair may be traded across multiple pools. For example, the most liquid pair—USDC/ETH—is actively traded in both the 0.05% and 0.3% fee pools. Lehar, Parlour, and Zoican (2022) show that fragmentation across low- and high-fee pools is driven by economies of scale. Low-fee pools are primarily used by large, i.e., professional, LPs who can afford to frequently update positions despite fixed gas costs. In contrast, smaller, i.e., retail, LPs prefer to passively provide liquidity in higher-fee pools where rebalancing is less frequent.

Together, concentrated liquidity and variable fees make Uniswap V3 significantly more flexible and capital-efficient than its predecessor. However, these benefits come at a cost of more frequent monitoring required from LPs, which also creates new strategic behaviors in liquidity provision.

### 2.2.2 Tick Spacing

In Uniswap V3, prices are not continuous but are discretized into fixed increments called ticks. Each tick is indexed by an integer $i \in \mathbb{Z}$, and the price corresponding to tick $i$ is given by:

$$p_i = 1.0001^i. \tag{2}$$

This exponential mapping implies that each tick represents approximately a 1 basis point price increment, since $1.0001 \approx 1 + 0.01\%$. As $i$ increases, prices rise slightly faster than linearly in tick space.

Importantly, the discrete tick structure also provides a mapping between tick intervals and price ranges. If an LP selects a lower tick $i$ and an upper tick $i + l$, this corresponds to a price range $[p_a, p_b] = [p_i, p_{i+l}]$ with $p_i = 1.0001^i$ and $p_{i+l} = 1.0001^{i+l}$. This mapping connects the tick-based notation used throughout this section with the continuous price interval $[p_a, p_b]$ introduced earlier in the discussion of virtual liquidity.

Not all ticks can be used for liquidity provision. Each Uniswap v3 pool specifies a tick spacing parameter, which restricts the set of valid (initializable) ticks. Only ticks divisible by this spacing can be used to define a price range. For example, in the USDC/ETH 0.3% fee pool, the tick spacing is 60, meaning that valid ticks include −120, −60, 0, 60, 120, and so on. In the USDC/ETH 0.05% pool, the tick spacing is narrower, equal to 10, allowing for more granular price levels spaced about 10 basis points apart.

LPs select a lower tick $i$ and an upper tick $i + l$ to define a price range $[i, i + l]$ over which they allocate liquidity. The length of the tick range, $l$, must be a multiple of the pool's tick spacing. A single LP position can cover one or more such tick ranges. The total liquidity on tick range $[i, i+l]$, denoted $L_i$, aggregates all active LP positions overlapping that range. As a result, the aggregate liquidity distribution across the pool becomes fragmented and uneven, in contrast to Uniswap V2 where liquidity was uniformly distributed across all prices.

According to the Uniswap v3 whitepaper (Adams et al., 2021), the amounts of tokens locked within a given tick range $[i, i+l]$ are given by:[9]

$$x_i = \frac{L_i}{\sqrt{z_i}} - \frac{L_i}{\sqrt{p_{i+l}}} \tag{3}$$

$$y_i = L_i \cdot (\sqrt{z_i} - \sqrt{p_i}) \tag{4}$$

where $x_i$ and $y_i$ denote the quantities of tokens $X$ and $Y$ (the base and quote assets, respectively) deposited within the tick range. The intermediate price $z_i$ depends on the current market price $p_M$ and adjusts based on the position of $p_M$ relative to the tick range:

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

This definition ensures that the token amounts vary depending on whether the tick range lies entirely above, entirely below, or contains the current price.

Figure 2 displays an example of the liquidity distribution around the current market price for the ETH/USDC 0.05% pool, referred to here as DEX(5). The actual Uniswap v3 pool is denominated as USDC/ETH 0.05%, where USDC is the base token ($X$), quoted in units of ETH ($Y$). For ease of interpretation, we reverse this convention in our analysis: ETH is treated as the base token ($X$), and USDC as the quote token ($Y$). Under this notation, liquidity provided in ETH corresponds to the ask side (i.e., LPs are willing to

9. See also Lehar, Parlour, and Zoican (2022) and Caparros, Chaudhary, and Klein (2023) for further details and numerical examples.

sell ETH for USDC), while liquidity provided in USDC corresponds to the bid side (i.e., LPs are willing to buy ETH with USDC).

[Insert Figure 2 approximately here]

The figure corresponds to block 16,265,204 on December 25, 2022. The horizontal axis shows the distance from the current tick, which corresponds to the discrete tick index $i$ such that the tick price $p_i = 1.0001^i$ is the largest tick price less than or equal to the current market price $p_M$. We normalize tick 0 to align with this current tick. In this pool, the tick spacing is set to 10, meaning that only every tenth tick (e.g., $-20$, $-10$, 0, 10, 20) can be initialized and used for liquidity provision. A tick range is defined as $[i, i + 10]$, and each liquidity position is distributed across one or more of these 10-tick intervals.

Liquidity is expressed in millions of USDC on both sides of the book to allow consistent measurement of bid- and ask-side depth. Tick ranges below the current price correspond to the bid side of the limit order book (LOB), — that is, LP positions denominated entirely in USDC, standing ready to purchase ETH as the price declines (akin to buy limit orders for ETH). Tick ranges above the current price correspond to the ask side. LP positions on the ask side are denominated entirely in ETH, standing ready to sell ETH as the price increases (akin to sell limit orders for ETH). Expressing both sides in USDC units allows us to directly compare relative liquidity and track changes across price movements in a common numeraire.

## 2.3 DEX Data

Our sample of DEX data consists of the two most liquid pools on Uniswap V3: ETH/USDC 0.05% (denoted DEX(5)) and ETH/USDC 0.3% (DEX(30)). The sample period runs from May 6, 2021, the launch date of Uniswap V3, until July 12, 2022. We end the sample in mid-2022 because our benchmark CEX, Binance, delisted the ETH-USDC trading pair in late 2022.

We focus on the ETH/USDC pair because it is the most actively traded pair on

Uniswap V3 and exhibits by far the highest level of LP activity during our sample period. Based on our sample, the average LP in the ETH/USDC pools submits 330 liquidity events (mints and burns) per day, compared to 75 in the second most liquid pool in our data (ETH/BTC). This concentration of LP activity makes ETH/USDC the natural choice for studying active, informed liquidity provision. Within this pair, we include both the low-fee DEX(5) and the high-fee DEX(30) pool to capture the full cross-section of LP behavior: DEX(5) attracts predominantly professional and institutional LPs who rebalance their positions more frequently (Lehar, Parlour, and Zoican, 2022), while DEX(30) serves as a comparison group of more passive retail LPs. If informed repositioning drives our results, we expect stronger effects in DEX(5) than in DEX(30), which is precisely what we find.

We obtain trade data for the DEX(5) and DEX(30) pools via the Subgraph API.[10] The trade data includes the pool address, fee tier, block number, token amounts swapped, and the pool price after each transaction. Using these data, we compute the ETH buy (sell) volume in USDC for each block, denoted as buy (sell) order flow, $swap_{(k)}^{buy}$ ($swap_{(k)}^{sell}$), where $k = 5$ for the 0.05% pool and $k = 30$ for the 0.3% pool. Net swap flow within each block is defined as:

$$swap_{(k)} = swap_{(k)}^{buy} - swap_{(k)}^{sell}. \tag{5}$$

Liquidity data, sourced via the Kaiko API, includes all liquidity events (mints and burns).[11] Each event record contains the pool address, fee tier, block number, token pair, wallet ID, amount minted or burned, and the corresponding tick range.

We use liquidity events to construct the net mints of liquidity on the ask side (token $X$) and the bid side (token $Y$), denoted $mint_{(k)}$. Specifically, we define $mint_{(k)}$ as the difference between $mint_{(k)}^{ask}$ and $mint_{(k)}^{bid}$ for each block, for $k = 5, 30$:

$$mint_{(k)} = mint_{(k)}^{ask} - mint_{(k)}^{bid}. \tag{6}$$

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

11. https://docs.kaiko.com/rest-api/data-feeds/level-1-and-level-2-data/level-2-tick-level/mints-and-burns

For each mint of $[x_p; y_p]$ posted on a price range $[p_a, p_b]$, we compute

$$mint^{ask}_{(k)} = x_p \cdot p_M, \tag{7}$$

$$mint^{bid}_{(k)} = y_p, \tag{8}$$

where $p_M$ is the current market price of ETH in USDC. If there are multiple mints in a block, we sum $mint^{ask}_{(k)}$ and $mint^{bid}_{(k)}$ across all mints before computing $mint_{(k)}$ as in (1).

By design, in Uniswap V2 LPs must supply both tokens in equal value proportions across the full price range, i.e. they cannot choose the specific price range on which their liquidity position is active. Because liquidity provision is symmetric and passive by construction, LP minting and burning decisions carry no directional information about LPs' price expectations in Uniswap V2. In contrast, Uniswap V3 allows LPs to concentrate liquidity within chosen price ranges, so $mint_{(k)}$ can take positive or negative values. A positive value indicates that LPs have minted more of token $X$ (ask side) than token $Y$ (bid side), akin to more sell limit orders being placed than buy limit orders in a traditional LOB. This asymmetry is unique to the V3 framework and provides a source of information about LPs' expectations regarding future price direction.

Following the same logic, we define the net burn per block as

$$burn_{(k)} = burn^{ask}_{(k)} - burn^{bid}_{(k)}. \tag{9}$$

For each burn of $[x_p; y_p]$ on a price range $[p_a, p_b]$, we compute

$$burn^{ask}_{(k)} = x_p \cdot p_M, \tag{10}$$

$$burn^{bid}_{(k)} = y_p, \tag{11}$$

where $p_M$ is the current market price of ETH in USDC. A positive value of $burn_{(k)}$ indicates that more token $X$ (ask-side liquidity) has been withdrawn than token $Y$ (bid-side), akin to ask-side order cancellations in traditional markets.

Since activity near the current price may impact price discovery more directly, we decompose net liquidity into "best" (close to the current price) and "away" (far from the current price) ranges:

$$mint^{b}_{(k)} = mint^{b,ask}_{(k)} - mint^{b,bid}_{(k)}, \tag{12}$$

$$mint^{a}_{(k)} = mint^{a,ask}_{(k)} - mint^{a,bid}_{(k)}. \tag{13}$$

We define the "best" price sub-range as the five tick ranges around the current tick (i.e., $[-5, 5]$). Each tick range consists of multiple individual ticks, and the width of each tick range is determined by the pool's tick spacing. In the DEX(5) pool, the tick spacing is 10, so five tick ranges correspond to 50 ticks. In the DEX(30) pool, the tick spacing is 60, so five tick ranges correspond to 300 ticks. These thresholds match the 25th percentile of the distribution of absolute distances between liquidity positions and the current tick, as reported in Table 1. Thus, this sub-range captures the quarter of all events closest to the current market price.

Specifically, for each mint or burn event on a tick range $[i_a, i_b]$, we compute the absolute distance from both the lower tick $i_a$ and the upper tick $i_b$ to the current tick $i_M$. Table 1 reports the distribution of these distances separately for the DEX(5) and DEX(30) pools. As noted, the lower quartile corresponds to approximately 50 ticks in DEX(5) and 300 ticks in DEX(30), equivalent to 5 tick ranges in each pool.

Some liquidity positions span both "best" and "away" regions, so we disaggregate the total liquidity accordingly. For each mint on a price range $[p_a, p_b]$, we first compute the total position liquidity $L_p$ using Equations (3) and (4).[12] We then use the same equations to split the ETH and USDC token amounts across the relevant sub-ranges. For example, to calculate $mint^{b,ask}_{(k)}$ in DEX(5), we compute the amount of token $X$ (ETH) minted within the five tick ranges above the current tick — i.e., tick intervals $[0, 10]$, $[10, 20]$, ..., $[40, 50]$ —which span approximately 50 basis points above the current price $p_M$:

$$mint^{b,ask}_{(k)} = x_p[0; 50] \cdot p_M \tag{14}$$

12. See Caparros, Chaudhary, and Klein (2023), Appendix D, for a worked example.

where $x_p[0;50]$ is computed using Equation (3), setting $p_i = p_M$ and $p_{i+l} = p_M + 50\text{bps}$. We similarly compute the liquidity deposited above this range as:

$$mint_{(k)}^{a,ask} = x_p[50;\infty] \cdot p_M \tag{15}$$

Applying the same method to token $Y$ yields:

$$mint_{(k)}^{b,bid} = y_p[-50;0], \tag{16}$$

$$mint_{(k)}^{a,bid} = y_p[-\infty;-50], \tag{17}$$

The same disaggregation is performed for burn events.

## 2.4 CEX Data

Our sample of CEX data consists of the ETH–USDC pair traded on Binance over the same sample period as the DEX pools, from May 6, 2021 to July 12, 2022. We obtain Binance tick-level data from CryptoTick, a subsidiary of CoinAPI, and resample the data to the block level using DEX block timestamps.

We define the block-level market order flow in the CEX market as:

$$market = market^{buy} - market^{sell}, \tag{18}$$

where $market^{buy}$ and $market^{sell}$ represent the volume of buy and sell market orders per each Ethereum block, respectively.

We construct the end-of-block mid-price series using limit order book snapshots from CryptoTick. The mid-price is calculated as the average of the best bid and best ask prevailing at or just before the timestamp of each Ethereum block. Log returns are then computed as the difference in log mid-prices:

$$ret = \log(p_t) - \log(p_{t-1}). \tag{19}$$

We define depth as the aggregate volume of buy (bid) and sell (ask) limit orders resting in the order book across price levels. In our data, depth is measured from the top 50 levels of the Binance order book snapshots, spanning approximately 0.50%–1% on either side of the mid-price.

Changes in depth therefore capture the net effect of limit order submissions and cancellations within these levels. Since our data do not separately identify submissions and cancellations, we approximate the net liquidity added to the ask (bid) side during each block as the change in depth on the ask (bid) side, adjusted for executed market orders:

$$limit^{ask} = \Delta depth^{ask} + market^{buy}, \tag{20}$$

$$limit^{bid} = \Delta depth^{bid} + market^{sell}, \tag{21}$$

$$limit = limit^{ask} - limit^{bid}. \tag{22}$$

Appendix A provides detailed definitions of all variables used in the analysis, along with their data sources. This includes block-level measures of swap flows, disaggregated mint and burn activity by price range on Uniswap V3, and approximated market and limit order flows on Binance.

## 2.5 Summary Statistics

Table 2 presents summary statistics for trade and liquidity flows across the DEX(5), DEX(30), and Binance CEX markets. All flows are measured at the Ethereum block level and expressed in USDC. The table is divided into three panels.

[Insert Table 2 approximately here]

Panel A summarizes the distribution of net trade order flows on each venue. The average block-level net order flow is close to zero across all platforms, indicating balanced trading activity between buy and sell orders. However, the standard deviation of the net trade order flows (which is an indication of the average trade size) differs substantially:

the highest is on DEX(30), roughly \$464,298, followed by DEX(5) with a standard deviation of \$321,763, and the CEX (Binance) exhibits a much smaller standard deviation of \$47,213. This difference reflects the cost structure of each platform: due to gas fees, DEXs are better suited for infrequent but large trades, whereas CEXs facilitate smaller, more frequent transactions. Indeed, the CEX platform is the most active in terms of the number of trades; there are 1,585,597 block intervals with at least one market order traded during that interval. For DEX(5), there are 1,294,246 blocks with at least one swap order executed. In contrast, DEX(30) is the least active in terms of the number of trades (only 223,011 blocks with an executed trade).

Panel B reports statistics on liquidity provision activity. For DEX pools, this includes mint and burn events both near the current price (within five tick ranges) and away from it. In DEX(5), liquidity flows are substantially larger: average net mints near the price ($mint^b_{(5)}$) exceed \$780,000, and average net burns ($burn^b_{(5)}$) are even larger at over \$1.5 million. In comparison, DEX(30) exhibits consistently smaller average net mints and burns near the current price: \$123,877 and \$232,370, respectively. This pattern is also true for the standard deviations of net mints and burns. This is consistent with findings in Lehar, Parlour, and Zoican (2022) that low-fee pools attract larger and more active LPs, while high-fee pools cater more to smaller passive LPs.

Mints occur more frequently than burns in both pools. However, when burns do occur, they tend to be larger in size (as reflected in their standard deviations). This asymmetry suggests that LPs more actively deposit liquidity but withdraw strategically in response to adverse market conditions.

The CEX limit order flow proxy, *limit*, shows much smaller standard deviation—around \$175,990—but occurs nearly every block, indicating continuous and fine-grained liquidity provision. Although our data do not permit identification of individual order submissions and cancellations, the high frequency aligns with the microstructure of traditional order books.

Panel C reports mid-price returns at three horizons — 1, 10, and 60 blocks — computed as log differences in mid-prices. Given Ethereum's average block time of 12 seconds, these horizons correspond to approximately 12 seconds, 2 minutes, and 12 minutes respectively. As expected, return dispersion increases with horizon, ranging from a standard deviation of 0.07% over 1 block to 0.52% over 60 blocks. Median returns are zero at all horizons, indicating no directional bias.

Overall, these statistics reveal that DEXs and CEXs serve different trading roles. DEXs concentrate on larger, less frequent trades and liquidity updates, while CEXs operate at a higher frequency with smaller volumes. The data also suggest that liquidity behavior on DEXs is both strategic and heterogeneously distributed across fee tiers.

# 3 Research Hypotheses

The introduction of concentrated liquidity in Uniswap V3 transforms liquidity provision from a passive into a potentially strategic activity. In this section, we develop a set of hypotheses to test whether LPs use their positions to act on information about future price movements. These behaviors may arise either from attempts to reduce adverse selection costs, such as impermanent loss, or from the need to remove stale liquidity that no longer earns trading fees. We distinguish between different mechanisms through which LPs may contribute to price discovery: the timing and placement of their deposits and withdrawals (mints and burns), the location of those orders relative to the current price, and wallet- or order-level characteristics that may reveal informational advantage. The hypotheses are grouped as follows: **H1** tests for the information content of overall liquidity orders; **H2** investigates how price impact varies with the proximity of liquidity orders to the current price; and **H3** explores whether informativeness varies across wallets and order types.

In earlier versions of AMMs, such as Uniswap V2, LPs were designed to be passive participants, with no control over the price at which they transact or the fees they earn in return for liquidity provision. It is, therefore, natural to expect that LP behavior contained little information. The concentrated liquidity design of Uniswap V3 fundamentally alters the LP's role: rather than passively providing liquidity, LPs must actively manage their positions to ensure capital remains within the active tick range and continues to earn fees. In particular, LPs can now target specific price ranges, allowing them to optimally reposition their liquidity in response to new information—whether public or private—to maximize expected profits.

When LPs add liquidity to a pool, they are exposed to impermanent loss—the risk that the value of their allocated assets changes from the time of deposit. If this price change is driven by fundamental information, it may become permanent, resulting in adverse selection costs for LPs. LPs have several tools at their disposal to manage this risk. First, they can concentrate their liquidity within pre-specified intervals around particular price levels, known as price ranges. Narrower price ranges reduce exposure to price movements outside the selected interval, but also limit fee earnings, since LPs are only rewarded when trades occur within their active range. Second, when LPs anticipate a permanent price change, they can burn their existing positions and/or reposition their liquidity closer to the new expected price level.

Routledge, Shen, and Zetlin-Jones (2025) provide an adverse-selection framework for AMM liquidity provision whose structure is analogous to Glosten and Milgrom (1985). An LP who chooses virtual liquidity $L$ over price range $[p_a, p_b]$ earns expected profit:

$$\Pi(L,\, p_a,\, p_b) \;=\; \pi\, \mathcal{F}(L,\, p_a,\, p_b) \;-\; (1-\pi)\, \mathcal{A}(L,\, p_a,\, p_b), \tag{23}$$

where $\pi$ is the fraction of uninformed liquidity takers, $\mathcal{F} > 0$ is the fee income earned from those traders, and $\mathcal{A} \geq 0$ is the adverse-selection loss when an informed taker pushes the price from $p_M$ to $p^*$. Using the Uniswap V3 pricing rule (Equation 1), the adverse-selection term is:

$$\mathcal{A}(L,\, p_a,\, p_b) \;=\; \frac{L}{\sqrt{p_M}}\, \mathbb{E}\Big[\Big(\sqrt{p^*} - \sqrt{p_M}\Big)^2 \cdot \mathbf{1}_{p^* \in [p_a,\, p_b]}\Big]. \tag{24}$$

Unlike a traditional market maker who can widen the bid–ask spread to screen informed traders, the AMM bonding curve is fixed by protocol. The LP's only instrument for managing adverse-selection risk is therefore the *quantity* deposited on each side of the current price, specifically the choice of $L$ and $[p_a, p_b]$. Because these choices are observable in transaction data as mints and burns, they encode the LP's directional view and should have predictive power over subsequent price movements.

Further, from Table 2, mint sizes on DEXs are significantly larger than those of limit orders on CEXs, with standard deviations of \$7,360,373 for $mint^b_{(5)}$ versus \$175,990 for *limit*. With large amounts of capital locked in liquidity pools, DEX liquidity providers face strong incentives to acquire private information and actively monitor public releases to minimize their adverse selection losses. Their exposure to adverse selection is compounded by the larger expected trade sizes documented in Section 2.5. In contrast, CEX liquidity providers operate at a considerably smaller scale — both in terms of limit order size and expected trade size — and can quickly and costlessly revise their quotes in response to incoming informed order flow.

Overall, CEX liquidity providers have weaker incentives to acquire private information and more closely resemble the classical uninformed market maker who learns from order flow, as in Glosten and Milgrom (1985). DEX liquidity providers, by contrast, are effectively endogenously informed: the scale of their capital commitment generates strong incentives to actively acquire information about future price movements in order to mitigate adverse selection losses.

This reasoning suggests that sophisticated LPs either acquire private information or respond quickly to public information. actively adjusting their positions to maximise fee income and limit adverse-selection losses. Accordingly, we expect that LPs' mint and burn activity contributes to price discovery on DEXs. Our first hypothesis is:

> **H1**: *Mint and burn activity on DEXs contains predictive information about future price movements.*

If LPs correctly anticipate future price changes and strategically use this information to increase expected profit or avoid risks, the direction of future price movements should be reflected in the composition of mint and burn activity. To rationalize the sign of this predictive relationship, we interpret how net minting or burning of liquidity relates to subsequent price direction.

Figure 3 illustrates four possible states that relate net minted and burned liquidity to future price changes. In all four scenarios, the long-term price, $p^*$, is assumed to be higher than the current price, $p_0$. A positive net mint, $mint_{(k)}$, corresponds to a larger amount of liquidity added above the current price (ask) relative to liquidity added below the current price (bid), as illustrated on the right side of Panel A. We define a positive net mint as having a ”positive price impact” when an increase in liquidity submitted above the current price positively predicts future returns. Importantly, we use the term “price impact” to refer to the return-predictive content of liquidity adjustments rather than their immediate effect on transaction prices. In contrast, a negative net mint corresponds to a larger amount of liquidity added to the bid side relative to the ask side, as illustrated on the left side of Panel A. We refer to the scenario where a negative net mint predicts a future price increase as a “negative price impact” of a net mint.[13]

Panel B shows similar scenarios for net burns. A positive net burn (right side of Panel B), corresponds to greater wothdrawal of liquidity above the current price (on the ask side) relative to below it (on the bid side). In this case, a positive (negative) price impact arises when this net removal of ask-side liquidity positively (negatively) predicts future returns. Conversely, a net burn on the bid side (left side of Panel B) has a positive (negative) price impact if it is negatively (positively) related to subsequent returns.

[Insert Figure 3 approximately here]

An informed LP can adopt several strategies to utilize information about future price changes. For example, if the LP expects the base currency token $X$ to appreciate permanently, posting liquidity at or just above the current price (i.e., near the ask) would be irrational, as it exposes the LP to impermanent loss from adverse selection. Instead, it is more rational to post liquidity at or close to the best bid, corresponding to a “buy low”

13. Similarly, a positive net mint could have a “negative price impact” if it predicts a future price decrease. By “negative price impact”, we refer here to the negative relation between net liquidity minted and subsequent returns.

strategy similar to submitting a limit buy order in traditional markets. Although such a strategy carries a low probability of execution, it avoids losses from longer-term adverse price movements while potentially earning fees from short-term reversals (it earns liquidity fees only if the token price depreciates temporarily before appreciating permanently).

Conversely, when the LP expects the token to depreciate in the long run, liquidity provision near the ask carries little adverse selection risk. Overall, since it is rational to post at or close to the best bid when the base token $X$ is expected to appreciate, and to post at or close to the best ask when $X$ is expected to depreciate, we expect a negative relation between net liquidity minted close to the current price (denoted $mint^b$) and subsequent returns. In terms of equation (24), a bid-side position lies outside the indicator for any upward informed move ($p^* > p_M$ falls outside $[p_a, p_M]$), so $\mathcal{A} = 0$ while fees $\mathcal{F}$ are still earned from uninformed reversals into the range. Panel A of Figure 4 visualizes this strategic behavior and its expected price impact.

[Insert Figure 4 approximately here]

A similar logic applies to liquidity withdrawal strategies. In response to a permanent expected appreciation in the base currency, rational LPs may burn liquidity on the ask side to avoid being "picked off" and minimize adverse selection risk. Burning ask-side liquidity directly reduces $L$ above $p_M$ in equation (24), lowering $\mathcal{A}$ from incoming informed buyers. This strategy implies a positive price impact of burn activity placed close to the current price (denoted $burn^b$). This behavior is also illustrated in Panel A of Figure 4.

> **H2a** (Risk-avoidance): *Mint orders placed close to the current price have negative price impacts, and burn orders close to the current price have positive price impacts.*

Another strategy of an informed LP is to post liquidity orders at prices away from the current price in anticipation of future price movements. For example, if the LP expects the price to increase by 20 basis points, they may mint new liquidity around that anticipated future price range. Once the price rises, this liquidity will start earning trading fees. In contrast, it would be irrational to mint on the bid side, since that liquidity would remain far from the active trading range and fail to generate fees. As a result, we expect mint orders placed away from the current price to occur more frequently on the ask side than the bid side in case of expected price appreciation. This leads to a positive price impact of mint orders placed away from the current price—denoted as $mint^a$ orders. Panel B of Figure 4 visualizes this strategy and its corresponding price impact.

Similarly, if LPs expect the price to appreciate and currently have liquidity posted on the bid side away from the current price, those orders will be further away from the active price range and are unlikely to be executed. Maintaining such stale orders incurs opportunity costs without generating fees. Therefore, it is optimal to burn liquidity on the bid side posted away from the current price. In contrast, it would not be optimal to burn ask-side liquidity, as this is now closer to the expected trading range and likely to earn fees. As a result, we expect to observe more burns placed away from the current price on the bid side than the ask side when price is expected to permanently appreciate.

Since "price impact" refers to the return-predictive content of these liquidity adjustments, net burns on the bid side away from the current price are expected to precede positive returns (as illustrated in Panel B of Figure 4). Conversely, net liquidity burned on the ask side away from the current price is expected to precede negative returns. Overall, this implies a negative relation between net liquidity burned away from the current price, denoted $burn^a$, and future returns.

> **H2b**: (Liquidity repositioning) *Mint orders placed away from the current price have positive price impacts, while burn orders away from the current price have negative price impacts.*

Our final set of hypotheses concerns heterogeneity across LPs. It is reasonable to assume that not all LPs are equally active — some remain passive. A key question is which characteristics differentiate informed LPs from uninformed ones. One approach is to condition on order submission strategies, either at the wallet level (by grouping all transactions from a single address) or based on order-level characteristics such as size or execution priority.

We hypothesize that larger orders tend to have greater price impact. LPs who deposit large amounts of liquidity face higher exposure to adverse selection and are therefore more likely to be informed. For example, Capponi, Jia, and Yu (2025) show that in Uniswap V2, high-fee DEX trade flows are significantly more informative than low-fee flows. A similar logic applies to LP strategies: informed LPs have incentives to expedite execution of their mint or burn transactions. As a result, we expect that liquidity submissions with higher execution priority (e.g., those placed earlier within a block) will exhibit stronger price impacts. We also expect that liquidity orders associated with a narrower liquidity range (concentrated liquidity) to have a greater price impact. While the liquidity orders posted on a narrow range limits LP's exposure to adverse selection risk, it also reduces its potential profit. Hence, for that liquidity order to be profitable (in excess of gas fee), the LP has to be rather precise in their forecast of future price. We expect this effect to be more pronounced in the low-fee pool.

> **H3a** (Order-level characterization): *Price impact of liquidity orders is increasing in order size, priority of execution, and the degree of liquidity concentration.*

We also hypothesize that the sophistication and activity of wallets are key indicators of informed liquidity provision. For example, an LP who alternates between supplying passive liquidity and executing aggressive swaps is more likely to process market information actively. Likewise, LPs who frequently reposition by minting and burning liquidity in response to price movements are likely to be more sophisticated. Because frequent updates incur gas and opportunity costs, wallets that regularly adjust their positions are likely to do so only when they possess informational advantages. We therefore use the frequency of liquidity updates as an additional proxy for sophistication.

> **H3b** (Wallet-level characterization): *Price impact of liquidity orders is increasing with the degree of sophistication of LPs posting the orders.*

# 4 Empirical Analysis

## 4.1 Baseline Estimation

We begin our analysis by estimating a VAR that includes measures of trading activity on both DEX and CEX, alongside benchmark CEX returns. This specification follows prior work on the price informativeness of order flow, including Capponi, Jia, and Yu (2025).

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

where the vector of endogenous variables is defined as:

$$\begin{aligned} Y_t =& [swap_{(30)}, swap_{(5)}, mint^a_{(30)}, mint^b_{(30)}, burn^a_{(30)}, burn^b_{(30)}, mint^a_{(5)}, mint^b_{(5)}, burn^a_{(5)}, \\ & burn^b_{(5)}, market, limit, ret]. \end{aligned} \tag{26}$$

The first six variables capture DEX swap flows and liquidity provision (mints and burns) on both the low-fee (DEX(5)) and high-fee (DEX(30)) Uniswap V3 pools. The next two variables are market and limit order flows on Binance (CEX), and the final variable is the benchmark return, computed from Binance mid-prices.

We impose a recursive structure on the system through the following identifying assumptions:

1. **Block-time pre-determination.** We order DEX variables (swaps, mints, burns) ahead of CEX market and limit order flows. Ethereum blocks are produced approximately every 12 seconds, and once a transaction is submitted to the mempool its content is fixed. DEX activity within a block is therefore committed before any Binance order flow in that same period, so the ordering reflects genuine temporal precedence rather than an arbitrary normalisation.

2. **Market orders affect limit orders contemporaneously, but not vice versa.** This ordering captures the intuition that market order flow may trigger immediate

liquidity adjustments in the order book, while changes in limit order flow typically affect market orders with a delay.

3. **CEX order flow can impact returns contemporaneously.** Following the structural VAR identification strategy of Hasbrouck (1991a), we allow CEX market and limit order flows to contemporaneously affect returns. In contrast, we assume that returns affect order flow with a delay. Because our return measure is derived from CEX mid-prices, we assume no contemporaneous mechanical relationship between DEX activity and CEX returns, as DEX prices cannot mechanically affect CEX returns.

To assess the statistical significance of the estimated impulse responses, we compute cumulative impulse response functions (CIRFs) and construct empirical confidence bands using the Wild bootstrap method. Specifically, we generate 1,000 CIRF realizations by resampling residuals using a Rademacher distribution and reconstructing synthetic datasets from the estimated model. In each iteration, we re-estimate the VAR and calculate CIRFs. The confidence intervals are then formed using percentiles from the empirical distribution of bootstrapped CIRFs.[14]

[Insert Table 3 approximately here]

Table 3 reports the CIRFs of DEX and CEX order flow variables on ETH-USDC returns at horizons $n = 0$, 1, 10, and 60 blocks.[15] The table presents results separately for the low-fee DEX(5) pool (Panel A), the high-fee DEX(30) pool (Panel B), and the centralized exchange (Panel C). Each coefficient represents the return impact (in percentage points) of a 1 standard deviation of net order flow shock.

We begin with a swap activity on DEX. We find that net swaps have a positive and statistically significant effect on prices in both pools. For DEX(5), the return increases by 2.3 basis points 60 blocks after a 1 standard deviation shock to a net buy order.

14. This procedure is implemented using the VAR Toolbox developed by Ambrogio Cesa-Bianchi. See https://sites.google.com/site/ambropo/MatlabCodes?authuser=0.

15. One Ethereum block corresponds to approximately 12 seconds during our sample period. So, 10 blocks correspond to 120 seconds or 2 minutes, and 60 blocks correspond to 12 minutes.

For DEX(30), the corresponding effect is 3.8 basis points. These results confirm that DEX trading activity contributes to price discovery, consistent with Capponi, Jia, and Yu (2025).[16]

Turning to liquidity provision, we find strong evidence in support of **H1** in the low-fee pool: mint and burn orders contain predictive information about future returns. In DEX(5), a one standard deviation increase in $mint^b$—net liquidity deposited within 5 tick ranges (or 0.5%) of the current price—predicts a negative price impact of 9.6 basis points. Conversely, a one standard deviation increase in $burn^b$ predicts a positive price impact of 11.9 basis points. These signs are consistent with **H2a**, which posits that informed LPs mint more liquidity close to the current ask (bid) price when they anticipate return declines (increases). Further, informed LPs withdraw liquidity close to the current ask (bid) price when they anticipate return increases (decreases). It is worth mentioning that while the coefficients are about three times larger than those for swaps, the standard deviations of net mint and burn orders are more than ten times larger than the standard deviations of swap orders (see Table 2). In economic terms, this implies that a one standard deviation liquidity provision event has an aggregate price impact up to 30 times larger than that of a comparable swap. This finding is consistent with our earlier argument that DEX liquidity providers — unlike their CEX counterparts — deploy sufficiently large amounts of capital to justify acquiring private information.

In contrast, we find no statistically significant price response to $mint^a$ or $burn^a$ activity in DEX(5) at a 60-block horizon, suggesting that LPs do not reposition liquidity away from the current price in a return-predictive manner. This provides no support for hypothesis **H2b** in the DEX(5) pool. The DEX(30) pool exhibits limited evidence of informed liquidity provision. Only $mint^a_{(30)}$ has a statistically significant effect, with a one standard deviation increase in net mint flow leading to a negative price impact of 0.5 basis points. However, this effect is small in magnitude and its sign is inconsistent with the prediction of **H2b**, making it difficult to interpret as evidence of anticipatory LP behavior.

16. Table B1 in the Internet Appendix documents the CIRFs for 1 million USDC shocks to net order flows.

These patterns are consistent with the view that informed liquidity provision is concentrated in DEX(5), which features smaller tick spacing and receives the bulk of initial trade flow due to lower transaction costs. Because orders are routed first to DEX(5), LPs in this pool have stronger incentives to actively manage positions. Infrequent execution in DEX(30), by contrast, leads to more passive LP behavior. A complementary explanation stems directly from the fee structure. In the low-fee pool, fee income per unit of liquidity is six times smaller than in DEX(30). To remain profitable, LPs in DEX(5) must therefore achieve a correspondingly lower adverse-selection cost, since they cannot rely on fee income alone to offset impermanent loss. This forces active repositioning, as LPs must withdraw liquidity from the side where informed order flow is expected and shift it to the other side before prices move against them. LPs in DEX(30), by contrast, earn sufficient fee income to remain profitable with less frequent position management. The stronger incentive to actively manage positions in DEX(5) is reflected in the larger and more significant price impacts of $mint^b$ and $burn^b$ relative to DEX(30). Our explanation is consistent with evidence from Lehar, Parlour, and Zoican (2022), who find that professional LPs dominate low-fee pools, while retail LPs tend to provide liquidity more passively in high-fee environments.

For the CEX market, we find that a one standard deviation shock to market order flow leads to a 1.1 basis point increase in returns after 60 blocks, about half the effect of DEX swap orders. Limit order flow also has statistically significant impact on returns of similar magnitude (1.1 basis points over the same horizon). The sign of this effect, however, is surprising. By analogy with mints close the current price, one would expect net ask-side limit order flow (within 0.5% - 1% of the mid-price) to negatively predict returns, as it signals an informed expectation of price declines. The positive sign we find instead suggests that CEX limit orders are less informationally driven than DEX mints. In terms of economic significance, the price impact of CEX limit order flow is considerably smaller in aggregate than that of DEX mints: the coefficients are approximately ten times smaller, and the standard deviation of CEX limit order flow is around 40 times smaller than that of $mint^b_{(5)}$. Taken together, these findings are consistent with our earlier argument that

DEX liquidity providers deploy far greater capital and therefore have stronger incentives to acquire and trade on private information.

Figure 5 presents the CIRFs for each type of order flow.

[Insert Figure 5 approximately here]

**Robustness of VAR Ordering.** To assess the robustness of our identifying assumptions, Appendix C presents additional analysis using three alternative recursive orderings of the VAR system. These variants relax aspects of the baseline structure, including contemporaneous effects between DEX and CEX order flows, and between market and limit orders on centralized exchanges. The first alternative ordering allows DEX activity to contemporaneously affect CEX market and limit orders. The second removes this link but permits CEX limit orders to affect market orders contemporaneously. The third combines both, allowing DEX orders to affect CEX orders and limit orders to affect market orders.

The results are consistent across specifications and reinforce our baseline findings. Liquidity deposits and withdrawals on decentralized exchanges—particularly in the low-fee DEX(5) pool—play a significant role in price discovery. We find robust evidence that LPs mint and burn liquidity on DEX in ways that reflect expectations about future price movements, consistent with hypotheses **H1** and **H2a**.

**Variance Decomposition.** While we find evidence that LPs adjust their positions in response to new information and that their liquidity management contains predictive content for returns, the impulse responses alone do not reveal the overall contribution of each order type to price discovery.

To address this, we complement our analysis with the forecast error variance decomposition introduced by Hasbrouck (1991b). This method weights the cumulative impulse responses by the variance of shocks to each order type, allowing us to estimate the proportion of return variation attributable to each source of order flow. The results are presented in Table 4.

[Insert Table 4 approximately here]

We find that swap orders in the DEX(5) and DEX(30) pools contribute a combined 7.4% to return variation, while market orders on the CEX account for only 1.0%. The lower contribution of CEX market orders reflects the fact that, although they occur more frequently, their average (non-zero) trade size is smaller, so their aggregate contribution is smaller than that of DEX swaps.

Mint and burn activity in the DEX pools contributes approximately 1.5% of return variation in total, with the majority explained by mint orders close to the current price. While informative, their overall contribution is smaller than that of DEX swaps. Overall, our findings suggest that DEX liquidity provision is a more informative signal *per unit* than swap activity. However, swaps account for a larger share of overall return variation, reflecting their far greater frequency rather than superior informational content per trade.

Limit order flow in the CEX accounts for 2.2% of return variation. However, as discussed previously, the sign on *limit* in Table 3 is contrary to what one would expect by analogy with DEX mints. In general, forecast error variance decomposition captures the total contribution of a variable to return variation regardless of its direction, so a variable can account for a substantial share of variance while carrying little or no directional information about future price movements.

Overall, the results from variance decomposition reinforce the view that DEX liquidity activity contributes to price discovery, particularly in the low-fee pool where informed LPs have greater incentives to reposition actively. This is consistent with the higher activity and informativeness observed in DEX(5) relative to DEX(30), and supports hypotheses **H1** and **H2a**.

## 4.2 Heterogeneity in Liquidity Orders: Order- and Wallet-level Classifications

In this section, we test hypotheses **H3a** and **H3b** on the determinants of price impact of LP activity. We explore in more detail how strategic behavior varies across LPs in the

DEX market. First, we classify liquidity orders by order-level characteristics such as size, execution priority and, liquidity concentration (**H3a**). Second, we examine wallet-level characteristics that proxy for LP sophistication, including whether a wallet engages in both swaps and liquidity provision, or frequently repositions its liquidity (**H3b**).

### 4.2.1 Order-level classification

We begin by testing whether the informativeness of liquidity orders depends on their size. Traders and LPs submitting large orders generally have greater incentives to gather and act on information. We classify a liquidity order as *large* if its size exceeds the median of the corresponding order size distribution in our sample. We then estimate a VAR as in Equation (25), replacing each DEX liquidity variable with its large and small counterparts:

$$\begin{aligned} Y_t =&[swap_{(30)}, swap_{(5)}, mint^{a,small}_{(30)}, mint^{b,small}_{(30)}, burn^{a,small}_{(30)}, burn^{b,small}_{(30)}, mint^{a,small}_{(5)}, mint^{b,small}_{(5)}, \\ & burn^{a,small}_{(5)}, burn^{b,small}_{(5)}, mint^{a,large}_{(30)}, mint^{b,large}_{(30)}, burn^{a,large}_{(30)}, burn^{b,large}_{(30)}, mint^{a,large}_{(5)}, mint^{b,large}_{(5)}, \\ & burn^{a,large}_{(5)}, burn^{b,large}_{(5)}, market, limit, ret]. \end{aligned} \tag{27}$$

[Insert Table 5 approximately here]

**Order size.** The results broadly support **H3a**: large mint and burn orders in DEX(5) have statistically significant long-term price effects, whereas small orders do not. As before, DEX(30) liquidity activity is not informative. Although $mint^{a,large}_{(30)}$ shows a weakly significant (5%) negative effect, the economic magnitude of the price impact (0.7 basis points) is more than ten times smaller than the price impacts in DEX(5) and its sign is opposite to what would be expected under **H2b**.

The finding that large orders are more informative than small ones is consistent with Glosten (1994), who show that informed traders place large orders to maximize profits from private information. Large informative orders on DEXs contrast with the "stealth trading" patterns observed in traditional markets (Barclay and Werner, 1993; Chakravarty, 2001), where informed traders tend to break up orders to avoid detection and minimize price impact. The transparency of blockchain and the constant-product pricing function eliminate the benefits of order splitting (Park, 2023), implying that informed traders should consistently favor large orders when trading on DEXs.

**Execution priority.** We next test whether informed LPs actively expedite the execution of their liquidity orders by securing early placement within a block. While in principle Ethereum transactions with higher gas fees are executed first, the introduction of Flashbots MEV-geth in late 2020 decoupled gas price from execution priority. Through off-chain auctions, traders can obtain top-of-block execution even with low or zero gas fees (Lehar and Parlour, 2023). This means that gas fees no longer provide a reliable signal of execution priority, making transaction order within the block a more accurate measure of whether LPs secure early execution.

To assess priority, we use Etherscan data to retrieve the index of each transaction within its block.[17] We classify transactions as *top* if their index is below the sample median (index $\leq 81$), and *bottom* otherwise.[18] Using this classification, we estimate a VAR including swap, mint, and burn orders based on their position within a given block:

$$\begin{aligned} Y_t =[&swap^{bot}_{(30)}, swap^{bot}_{(5)}, mint^{a,bot}_{(30)}, mint^{b,bot}_{(30)}, burn^{a,bot}_{(30)}, burn^{b,bot}_{(30)}, mint^{a,bot}_{(5)}, mint^{b,bot}_{(5)}, burn^{a,bot}_{(5)}, \\ &burn^{b,bot}_{(5)}, swap^{top}_{(30)}, swap^{top}_{(5)}, mint^{a,top}_{(30)}, mint^{b,top}_{(30)}, burn^{a,top}_{(30)}, burn^{b,top}_{(30)}, mint^{a,top}_{(5)}, mint^{b,top}_{(5)}, \\ &burn^{a,top}_{(5)}, burn^{b,top}_{(5)}, market, limit, ret]. \end{aligned} \tag{28}$$

Panel B of Table 5 presents the CIRFs for this estimation. In both DEX pools, swap orders exhibit significant price impacts regardless of execution position, with slightly larger impacts from top-positioned swaps. This confirms earlier findings from Uniswap V2 in Capponi, Jia, and Yu (2025), where high gas fee (and thus early) orders were more informative.

In DEX(5), top-positioned mints close to the current price ($mint^{b,top}_{(5)}$) have negative price impacts, while burns ($burn^{b,top}_{(5)}$) have positive price impacts, consistent with risk-mitigating strategies. Bottom-positioned mints and burns show similar effects, although

17. https://docs.etherscan.io/etherscan-v2

18. Ethereum blocks typically contain several hundred transactions. We classify the top half based on the empirical distribution, and robustness checks using the top quartile or decile yield similar results.

the magnitude of their price impacts is about 15 times smaller. Mints and burns placed away from the current price in DEX(5) remain uninformative, regardless of their execution position. These results indicate that execution priority is economically important in DEX(5), as the price impacts of top-positioned orders are much larger than those of bottom-positioned ones.

In contrast, we find stronger evidence of strategic positioning in DEX(30). Top-positioned mints near the current price ($mint^{b,top}_{(30)}$) are associated with negative price impacts, while top burns ($burn^{b,top}_{(30)}$) have positive price impacts—both significant at the 5% level. These results are consistent with anticipatory repositioning to reduce adverse selection and support **H2a**. Although additional significant effects appear in DEX(30), such as $mint^{a,bot}_{(30)}$ and $burn^{a,top}_{(30)}$ (negative at the 5% level) and $burn^{a,bot}_{(30)}$ (positive at the 10% level), their magnitudes are small and remain below those observed in DEX(5).

Overall, these results suggest that informed LPs selectively expedite their minting and burning activity, particularly in less active pools such as DEX(30), either to reduce exposure to price risk or to enhance fee earnings. The substantially larger price impact of top-positioned relative to bottom-positioned orders also supports the view that the causal ordering from DEX activity to prices reflects informed positioning rather than a common information shock. There are, however, important limitations to this analysis. Although our sample ends in July 2022, just-in-time (JIT) liquidity provision, in which LPs mint and burn liquidity within the same block to minimize exposure while collecting fees, may confound our estimates (Capponi, Jia, and Zhu, 2023). Simultaneous mint and burn behavior could obscure the predictive content of top-positioned orders. Evidence from Wan and Adams (2022), however, indicates that during our sample period only approximately 0–1 percent of total Uniswap V3 liquidity was provided by JIT LPs.

**Liquidity concentration.** We finally test whether the choice of liquidity interval range (liquidity concentration) carries information about future price changes. We classify a liquidity order as wide (*wid*) if the width of the corresponding liquidity interval exceeds the upper quartile of the empirical distribution of interval ranges. This corresponds to

2,740 ticks for DEX(5) and 7,020 for DEX(30). Otherwise, we classify it as narrow (*nar*). We then estimate a VAR as in Equation (25), replacing each DEX liquidity variable with its wide and narrow counterparts:

$$
\begin{aligned}
Y_t =& [swap_{(30)}, swap_{(5)}, mint^{a,nar}_{(30)}, mint^{b,nar}_{(30)}, burn^{a,nar}_{(30)}, burn^{b,nar}_{(30)}, mint^{a,nar}_{(5)}, mint^{b,nar}_{(5)}, burn^{a,nar}_{(5)}, \\
& burn^{b,nar}_{(5)}, mint^{a,wid}_{(30)}, mint^{b,wid}_{(30)}, burn^{a,wid}_{(30)}, burn^{b,wid}_{(30)}, mint^{a,wid}_{(5)}, mint^{b,wid}_{(5)}, burn^{a,wid}_{(5)}, burn^{b,wid}_{(5)}, \\
& market, limit, ret]. \qquad (29)
\end{aligned}
$$

Panel C of Table 5 reports the CIRFs at $n = 60$ blocks. The results are also broadly consistent with predictions of **H3a**: mint and burn orders posted on narrow intervals in DEX(5) have statistically significant long-term price effects, while the orders associated with wide intervals do not. While the price impacts of $burn^{b,wid}_{(5)}$, $burn^{a,wid}_{(5)}$ and $burn^{a,wid}_{(30)}$ are significant (al least at the 10% level), the economic magnitudes are small.

### 4.2.2 Wallet-level Classification

We now examine whether liquidity placement strategies of sophisticated investors convey information about future price changes, as predicted by Hypothesis **H3**. We consider three wallet-level classifications to proxy for investor sophistication: (i) pure vs mixed liquidity provision, (ii) liquidity repositioning, and (iii) frequency of updates.

**Mixed vs. pure provision.** We first classify wallets as those that engage in mixed liquidity provision, *mix*, if they participated in both liquidity provision and swap trading within our sample period. In contrast, we classify wallets that engage in pure liquidity provision as *pure*. The reasoning behind our classification is that wallets executing mixed strategies are more likely to belong to sophisticated investors who closely monitor price-relevant information. Routledge, Shen, and Zetlin-Jones (2025) show theoretically that LPs who also trade as swappers can use their directional positions to actively rebalance and offset adverse-selection exposure, making them more informed than pure liquidity providers. We estimate the VAR model based on Equation (25), using the following variables:

$$
\begin{aligned}
Y_t = [&swap^{pure}_{(30)}, swap^{pure}_{(5)}, mint^{a,pure}_{(30)}, mint^{b,pure}_{(30)}, burn^{a,pure}_{(30)}, burn^{b,pure}_{(30)}, mint^{a,pure}_{(5)}, mint^{b,pure}_{(5)}, \\
&burn^{a,pure}_{(5)}, burn^{b,pure}_{(5)}, swap^{mix}_{(30)}, swap^{mix}_{(5)}, mint^{a,mix}_{(30)}, mint^{b,mix}_{(30)}, burn^{a,mix}_{(30)}, burn^{b,mix}_{(30)}, \\
&mint^{a,mix}_{(5)}, mint^{b,mix}_{(5)}, burn^{a,mix}_{(5)}, burn^{b,mix}_{(5)}, market, limit, ret]. \qquad (30)
\end{aligned}
$$

Panel A of Table 6 shows that swap orders from both *mix* and *pure* wallets have a significant price impact in both DEX(5) and DEX(30). However, for mints, price informativeness is more concentrated among *mix* wallets in DEX(5): $mint^{b,mix}_{(5)}$ is significant, while $mint^{b,pure}_{(5)}$ is not. Both $burn^{b,mix}_{(5)}$ and $burn^{b,pure}_{(5)}$ are significant, with the former exhibiting a larger coefficient. Our findings suggest that LPs who combine trading and liquidity provision tend to submit aggressive mints close to the current price in anticipation of price changes, contributing to price discovery. This is consistent with Routledge, Shen, and Zetlin-Jones (2025), who show that LPs who also trade as swappers can use their directional positions to offset adverse-selection exposure and are consequently more informed than pure liquidity providers. At the same time, some pure LPs, who only provide liquidity, appear to react more strongly to adverse selection risk by withdrawing liquidity when facing unfavorable price movements. In DEX(30), all of the *mix* liquidity order flows have insignificant price impacts. While $mint^{a,pure}_{(30)}$ and $burn^{b,pure}_{(30)}$ display significant coefficients at the 5% level, their magnitudes are almost 10 times smaller than those from DEX(5). This result is consistent with earlier evidence that more strategic behavior is concentrated in DEX(5).

[Insert Table 6 approximately here]

**Repositioning behavior.** Our second proxy for sophistication is the repositioning behavior of LPs. A wallet is classified as engaging in repositioning, *repo*, if it has at least one burn followed by a mint within two minutes (equivalent to 10 next blocks). Other wallets are labeled *other*. We estimate the VAR model based on Equation (25) and the following variables:

$$
\begin{aligned}
Y_t = [&swap_{(30)}, swap_{(5)}, mint^{a,other}_{(30)}, mint^{b,other}_{(30)}, burn^{a,other}_{(30)}, burn^{b,other}_{(30)}, mint^{a,other}_{(5)}, mint^{b,other}_{(5)}, \\
&burn^{a,other}_{(5)}, burn^{b,other}_{(5)}, mint^{a,repo}_{(30)}, mint^{b,repo}_{(30)}, burn^{a,repo}_{(30)}, burn^{b,repo}_{(30)}, mint^{a,repo}_{(5)}, mint^{b,repo}_{(5)},
\end{aligned}
$$

$$burn^{a,repo}_{(5)}, burn^{b,repo}_{(5)}, market, limit, ret]. \quad (31)$$

Panel B of Table 6 shows that both *repo* and *other* wallets in DEX(5) contribute to price discovery. $mint^{b,repo}_{(5)}$ and $burn^{b,repo}_{(5)}$ are significant, as are their *other* counterparts. The magnitude of coefficients for *other* wallets is about twice as small as that of *repo* wallets. These findings suggest that repositioning behavior helps avoiding adverse selection; yet, minting or burning liquidity on a more permanent basis by *other* wallets appears to be also informative. In DEX(30), $mint^{a,repo}_{(30)}$ and $burn^{b,other}_{(30)}$ are weakly significant but their economic magnitude is small. These results provide limited support for repositioning-based hypotheses in wider-spread pools, because these pools are mostly used by passive liquidity providers, consistent with findings in Lehar, Parlour, and Zoican (2022).

**Update frequency.** We finally examine the frequency of liquidity orders. LPs in the top quartile of mint and burn activity—more than four updates—are classified as *high-frequency* ($hfr$); all others are classified as *low-frequency* ($lfr$). We estimate the VAR model using the following specification:

$$\begin{aligned} Y_t =&[swap_{(30)}, swap_{(5)}, mint^{a,lfr}_{(30)}, mint^{b,lfr}_{(30)}, burn^{a,lfr}_{(30)}, burn^{b,lfr}_{(30)}, mint^{a,lfr}_{(5)}, mint^{b,lfr}_{(5)}, burn^{a,lfr}_{(5)},\\ &burn^{b,lfr}_{(5)}, mint^{a,hfr}_{(30)}, mint^{b,hfr}_{(30)}, burn^{a,hfr}_{(30)}, burn^{b,hfr}_{(30)}, mint^{a,hfr}_{(5)}, mint^{b,hfr}_{(5)}, burn^{a,hfr}_{(5)}, burn^{b,hfr}_{(5)},\\ &market, limit, ret]. \end{aligned} \quad (32)$$

Panel C of Table 6 shows that in DEX(5), both $mint^{b,hfr}_{(5)}$ and $burn^{b,hfr}_{(5)}$ are highly significant (1% level), while the corresponding $lfr$ orders are only weakly significant (10%). These results indicate that more active LPs are also more likely to be informed. We observe only limited informativeness in DEX(30), though $burn^{a,lfr}_{(30)}$ is surprisingly relatively large and significant at the 5%, most likely driven by an infrequent number of burns further away from the current price submitted by low-frequency investors.

Taken together, these results suggest that informed liquidity provision is concentrated in DEX(5), particularly among wallets that combine swaps with liquidity provision, engage in both permanent and repositioning-based mints or burns, and submit liquidity orders more frequently. In contrast, DEX(30) shows weaker evidence of informativeness across all wallet types.

## 4.3 Information and Arbitrage Trading

In the previous sections, we showed that liquidity provision in DEX conveys information and contributes to the price discovery process. Our primary hypothesis is that LPs either possess private information or have a superior ability to process public information. However, LPs may also condition their liquidity provision decisions on publicly observable signals, such as the price difference between DEX and CEX. For instance, to mitigate adverse selection risk and avoid being picked off by informed arbitrageurs, LPs may strategically reposition liquidity around these price gaps. While this is a form of strategic (and rational) behavior, it does not require knowledge of private information. If LPs are sufficiently fast in updating their position when such arbitrage deviations arise, their orders may exert price impact despite being based on public information.

To differentiate between private and public signals, we examine whether the information content of liquidity provision differs during periods of publicly observable price differences across markets. Specifically, we test whether the price impact of DEX orders is concentrated during periods of high price deviation (hpd), defined as when the absolute CEX–DEX price difference exceeds the transaction-cost threshold for profitable arbitrage, relative to periods of low price deviation (lpd), when such deviations are too small to exploit.

Due to gas fees, exchange fees, and deterministic price impacts, not all arbitrage opportunities between CEX and DEX are economically exploitable. Moreover, price deviations may not fully revert due to these frictions. Therefore, before analyzing price impacts, we first characterize the distribution of arbitrage deviations and the dynamics of price reversals in DEX 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 $ppd = 100 \times pd/prc^{CEX}$. Panels A and B of Table 7 report summary statistics for $ppd$ and its absolute value $|ppd|$, accordingly. For DEX(5) pool, the average percentage price difference is small, with a mean of 0.004 per cent, and the mean of its absolute value of 0.106 per cent. However, deviations can occasionally be large, reaching up to 27.06 per cent. The average absolute price difference is about 1.8 times larger for the DEX(30) pool, although the extreme values are of similar magnitude.

[Insert Table 7 approximately here]

Figure 6 plots the average dynamics of price differences between DEX and CEX markets, conditional on the next incoming swap/market order that exploits (i.e., trades in the direction of) the arbitrage opportunity. We consider the following six cases: (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) $pd_t < 0$, $swap_{t+1} > 0$, $market_{t+1} < 0$.

[Insert Figure 6 approximately here]

Panel A presents the results for the DEX(5) pool. The left-hand plots correspond to cases (i)–(iii), where stabilizing order flow follows a positive price difference. We find that DEX order flow alone, as in case (i), generates price convergence comparable to that in case (iii), where both DEX and CEX order flows act in the stabilizing direction. For cases (iv)–(vi), which involve negative price differences, convergence is more pronounced when either DEX alone or both markets respond. This suggests that DEX order flow plays a central role in restoring price parity.

Panel B considers the DEX(30) pool. As before, stabilizing DEX flow in response to a price difference leads to strong price convergence.

Next, we assess whether orders convey information beyond the exploitation of arbitrage opportunities. For an arbitrage to be economically viable, the absolute percentage price deviation ($|ppd|$) must exceed transaction costs. We estimate these costs using the median values of gas fees, pool fees, and slippage across the sample. Gas fees are computed at the transaction level and converted from ETH to USDC using contemporaneous

ETH prices. Pool fees correspond to the fee tier of each pool (5 basis points for DEX(5) and 30 basis points for DEX(30)). Slippage is measured at the trade level as the difference between the execution price and the pre-trade price implied by pool reserves. The execution price is calculated using the relative token amounts exchanged in the swap, while the pre-trade price is based on the reserve ratio immediately prior to the transaction.

For DEX(5), the median gas fee is approximately 30.29 basis points, and the median combined cost of pool fees and slippage is 5.17 basis points, yielding a total transaction cost of 35.46 basis points. For DEX(30), gas costs are lower at 5.25 basis points, while the combined cost of pool fees and slippage is higher at 31.34 basis points, resulting in a total of 36.59 basis points. Based on these estimates, we round to a common cutoff of 36 basis points to define the threshold at which price deviations become sufficiently large to incentivize arbitrage. Orders submitted when $|ppd|$ exceeds or equals this threshold are classified as high price deviation ($hpd$) periods; those below the threshold are designated as low price deviation ($lpd$) periods. Based on this classification, we identify 110,225 $hpd$ blocks in DEX(5) and 142,788 in DEX(30), where price deviations are large enough to incentivize arbitrage. These account for approximately 4% and 5.2% of the sample, respectively.

Panel C of Table 7 reports the cumulative impulse response function (CIRF) estimates from a VAR model, where the variable vector is defined in Equation (33). The specification includes DEX swaps, aggressive and non-aggressive mints ($mint^b$ and $mint^a$), and aggressive and non-aggressive burns ($burn^b$ and $burn^a$), split by $hpd$ and $lpd$ classifications. CEX order flow shocks (market and limit orders) and the CEX return are included as controls. The model specification is given by:

$$
\begin{aligned}
Y_t = [&swap^{lpd}_{(30)}, swap^{lpd}_{(5)}, mint^{a,lpd}_{(30)}, mint^{b,lpd}_{(30)}, burn^{a,lpd}_{(30)}, burn^{b,lpd}_{(30)}, mint^{a,lpd}_{(5)}, mint^{b,lpd}_{(5)}, burn^{a,lpd}_{(5)}, \\
&burn^{b,lpd}_{(5)}, swap^{hpd}_{(30)}, swap^{hpd}_{(5)}, mint^{a,hpd}_{(30)}, mint^{b,hpd}_{(30)}, burn^{a,hpd}_{(30)}, burn^{b,hpd}_{(30)}, mint^{a,hpd}_{(5)}, mint^{b,hpd}_{(5)}, \\
&burn^{a,hpd}_{(5)}, burn^{b,hpd}_{(5)}, market, limit, ret]. 
\end{aligned} \tag{33}
$$

We find that non-arbitrage swaps, classified as $lpd$, have significant and persistent price impacts in both DEX(5) and DEX(30). For instance, $swap^{lpd}_{(5)}$ has a CIRF of 2.2 basis points while $swap^{hpd}_{(5)}$ has a CIRF of 8.0 basis points. On DEX(30), $swap^{lpd}_{(30)}$ has higher price impact than $swap^{hpd}_{(5)}$ (4.1 basis points versus 3.1 basis points). This suggests that when the CEX and DEX prices are misaligned, swaps contribute more strongly to price discovery on DEX(5).

In contrast, liquidity orders (mints and burns) exhibit more heterogeneous patterns. On DEX(5), aggressive mint orders placed close to the current price during *hpd* periods ($mint^{b,hpd}_{(5)}$) have a large negative price impact of $-40.9$ basis points, while the same order type during *lpd* periods has five times smaller, but statistically more significant effect ($-8.9$ basis points). Similarly, burns close to the current price in *hpd* periods ($burn^{b,hpd}_{(5)}$) have a large positive impact of 46.2 basis points, consistent with liquidity withdrawal in response to observable arbitrage signals. Again, the same order type during *lpd* periods has a smaller, but statistically more significant effect (12.0). The price impacts of liquidity orders on DEX(30) are much smaller and barely significant.

Overall, these results suggest that LPs condition their behavior on both private and public signals. While both *lpd* and *hpd* orders exhibit statistically significant price effects, the magnitude is typically larger during *hpd* periods, indicating that a substantial portion of information transmission reflects benchmarking against CEX prices, for example minting near the best bid and burning near the best ask when the CEX price exceeds the DEX price. At the same time, the significance of $mint^{b,lpd}_{(5)}$ and $burn^{b,lpd}_{(5)}$ in the absence of exploitable arbitrage opportunities indicates that LP-driven price discovery is not a mechanical artifact of CEX–DEX mispricings; LPs either possess private information or process public signals more rapidly than we observe at block-level frequency.

# 5 Conclusion

In this paper, we study the role of LPs in price discovery on the Uniswap V3 platform. Using data on the ETH/USDC market from both centralized (Binance) and decentralized (Uniswap) exchanges, we estimate the long-term price impacts of trades and liquidity orders across both venues. Contrary to the common perception of LPs as passive, we show that liquidity orders play a significant role in the price discovery process.

Uniswap V3's concentrated liquidity design allows LPs to control the price range over which their liquidity is active, enabling strategic behavior similar to that observed in limit order books. We formulate and test hypotheses linking LP actions to information transmission, focusing on whether informed LPs manage positions through risk avoidance and strategic repositioning of liquidity. Consistent with this behavior, we find that mint and burn activity placed close to the current price contains predictive information about future returns.

Using transaction-level blockchain data, we examine heterogeneity in the price impact of liquidity provision. LPs are generally more informed in the low-fee pool, while liquidity orders in the high-fee pool contribute little to price discovery. We document several order-level characteristics that influence the informativeness of liquidity flows, including order size, execution priority, and the width of LPs' liquidity positions. In particular, mints and burns that are larger in size, executed at the top of a block, or placed within narrower price intervals exhibit larger and more significant long-term price impacts. We also find that orders submitted by more sophisticated LPs—characterized by wallets that combine liquidity provision with swaps, actively reposition liquidity relative to the current price, or submit orders more frequently—are more likely to be informed.

We then test whether the information set of informed LPs is based solely on cross-exchange price differences between CEX and DEX markets. While we find stronger effects when price deviations are high, liquidity orders also have a significant price impact in periods of small deviations with no tradeable arbitrage opportunities. Overall, our findings suggest that arbitrage deviations are not the only source of LPs' information, and that LPs use both private signals and public benchmarks, such as CEX prices, to guide their strategies and reposition liquidity.

In conclusion, our results demonstrate that decentralized exchanges can support informed trading and meaningful price discovery. The ability of LPs to strategically allocate and reposition liquidity plays a central role in this process. These findings highlight the informational value of liquidity provision and suggest that decentralized exchanges represent a viable and competitive alternative to centralized trading venues based on limit order books.

# References


**Adams, Hayden, Noah Zinsmeister, Moody Salem, River Keefer, and Dan Robinson.** 2021. "Uniswap v3 whitepaper." *Tech. rep., Uniswap, https://uniswap.org/whitepaper-v3.pdf.*

**Alexander, Carol, Xi Chen, Jun Deng, and Qi Fu.** 2023. "Market Efficiency Improvements from Technical Developments of Decentralized Crypto Exchanges." *Available at SSRN 4495589.*

**Angeris, Guillermo, and Tarun Chitra.** 2020. "Improved price oracles: Constant function market makers." In *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies,* 80–91.

**Angeris, Guillermo, Tarun Chitra, and Alex Evans.** 2022. "When does the tail wag the dog? Curvature and market making."

**Angeris, Guillermo, Hsien-Tang Kao, Rei Chiang, Charlie Noyes, and Tarun Chitra.** 2021. "An analysis of Uniswap markets."

**Aoyagi, Jun.** 2020. "Liquidity provision by automated market makers." *Working paper, Hong Kong University of Science and Technology.*

**Aoyagi, Jun, and Yuki Ito.** 2025. "Coexisting exchange platforms: Limit order books and automated market makers." *Journal of Political Economy Microeconomics* 3 (3): 000–000.

**Barbon, Andrea, and Angelo Ranaldo.** 2025. "On The Quality Of Cryptocurrency Markets: Centralized Versus Decentralized Exchanges." *Management Science,* forthcoming.

**Barclay, M., and J. Werner.** 1993. "Stealth Trading and Volatility: Which Trades Move Prices." *Journal of Financial Economics* 34 (3): 281–305.

**Bloomfield, Robert, Maureen O'Hara, and Gideon Saar.** 2005. "The "make or take" decision in an electronic market: Evidence on the evolution of liquidity." *Journal of Financial Economics* 75 (1): 165–199.

**Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan.** 2019. "Price discovery without trading: Evidence from limit orders." *Journal of Finance* 74 (4): 1621–1658.

**Caparros, Basile, Amit Chaudhary, and Olga Klein.** 2023. "Blockchain Scaling and Liquidity Concentration on Decentralized Exchanges." *Working Paper, Warwick Business School.*

**Capponi, Agostino, and Ruizhe Jia.** 2025. "Liquidity Provision on Blockchain-Based Decentralized Exchanges." Advance access published July 14, 2025, *Review of Financial Studies,* https://doi.org/10.1093/rfs/hhaf046.

**Capponi, Agostino, Ruizhe Jia, and Shihao Yu.** 2025. "Price discovery on decentralized exchanges." *Available at SSRN 4236993.*

**Capponi, Agostino, Ruizhe Jia, and Brian Zhu.** 2023. "The paradox of just-in-time liquidity in decentralized exchanges: More providers can sometimes mean less liquidity." *arXiv preprint arXiv:2311.18164.*

**Cartea, Álvaro, Fayçal Drissi, and Marcello Monga.** 2024. "Decentralised finance and automated market making: Predictable loss and optimal liquidity provision." *Working paper, Oxford-Man Institute of Quantitative Finance.*

**Cartea, Álvaro, Fayçal Drissi, Leandro Sánchez-Betancourt, David Siska, and Lukasz Szpruch.** 2023. "Automated Market Makers Designs Beyond Constant Functions." *Available at SSRN 4459177.*

**Chakravarty, S.** 2001. "Stealth Trading: Which Traders' Trades Move Stock Prices." *Journal of Financial Economics* 61 (2): 289–307.

**Daian, Philip, Steven Goldfeder, Tyler Kell, Yunqi Li, Xueyuan Zhao, Iddo Bentov, Lorenz Breidenbach, and Ari Juels.** 2019. "Flash boys 2.0: Frontrunning, transaction reordering, and consensus instability in decentralized exchanges." *arXiv preprint arXiv:1904.05234.*

**Fang, Chuck.** 2024. "Learning Financial Innovations: Experience from Automated Market Makers." *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper.*

**Foley, Sean, Peter O'Neill, and Tālis J Putniņš.** 2023. "A Better Market Design? Applying 'Automated Market Makers' to Traditional Financial Markets." *Working Paper, Macquarie University.*

**Glosten, L., and P. Milgrom.** 1985. "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders." *Journal of Financial Economics* 14 (1): 71–100.

**Glosten, Lawrence R.** 1994. "Is the electronic open limit order book inevitable?" *The Journal of Finance* 49 (4): 1127–1161.

**Goettler, Ronald L, Christine A Parlour, and Uday Rajan.** 2009. "Informed traders and limit order markets." *Journal of Financial Economics* 93 (1): 67–87.

**Han, Jianlei, Shiyang Huang, and Zhuo Zhong.** 2021. "Trust in DeFi: an empirical study of the decentralized exchange." *Working Paper, Macquarie University.*

**Hasbrouck, Joel.** 1991a. "Measuring the information content of stock trades." *Journal of Finance* 46 (1): 179–207.

———. 1991b. "The summary informativeness of stock trades: An econometric analysis." *Review of Financial Studies* 4 (3): 571–595.

**Hasbrouck, Joel, Thomas J Rivera, and Fahad Saleh.** 2022. "The need for fees at a DEX: How increases in fees can increase DEX trading volume." *Working paper, Wake Forest University.*

———. 2025. "An economic model of a decentralized exchange with concentrated liquidity." *Management Science.*

**Heimbach, Lioba, Ye Wang, and Roger Wattenhofer.** 2021. "Behavior of liquidity providers in decentralized exchanges." *arXiv preprint arXiv:2105.13822.*

**Huang, Wenqian, Natalia Rostova, and Zhaogang Song.** 2024. "Decentralized Exchanges for Near-Money Assets."

**John, Kose, Leonid Kogan, and Fahad Saleh.** 2023. "Smart contracts and decentralized finance." *Annual Review of Financial Economics* 15 (1): 523–542.

**Kaniel, Ron, and Hong Liu.** 2006. "So what orders do informed traders use?" *Journal of Business* 79 (4): 1867–1913.

**Kyle, Albert S.** 1985. "Continuous auctions and insider trading." *Econometrica* 53:1315–1335.

**Lehar, Alfred, and Christine A Parlour.** 2023. "Battle of the Bots: Flash loans, Miner Extractable Value and Efficient Settlement." *Working paper, Haas School of Business, UC Berkeley.*

———. 2025. "Decentralized Exchange: The Uniswap Automated Market Maker." *Journal of Finance* 80 (1): 321–374.

**Lehar, Alfred, Christine A Parlour, and Marius Zoican.** 2022. "Liquidity Fragmentation on Decentralized Exchanges." *Working paper, University of Calgary and University of California, Berkeley.*

**Neuder, Michael, Rithvik Rao, Daniel J Moroz, and David C Parkes.** 2021. "Strategic liquidity provision in uniswap v3." *arXiv preprint arXiv:2106.12033.*

**Park, Andreas.** 2023. "The conceptual flaws of decentralized automated market making." *Management Science* 69 (11): 6731–6751.

**Routledge, Bryan R, Yikang Shen, and Ariel Zetlin-Jones.** 2025. "Automated Exchange Economies."

**Schär, Fabian.** 2021. "Decentralized finance: On blockchain-and smart contract-based financial markets." *FRB of St. Louis Review.*

**Wan, Xin, and Austin Adams.** 2022. "Just-in-time liquidity on the uniswap protocol." *Available at SSRN 4382303.*

**Wang, Ye, Yan Chen, Haotian Wu, Liyi Zhou, Shuiguang Deng, and Roger Wattenhofer.** 2022. "Cyclic arbitrage in decentralized exchanges." In *Companion Proceedings of the Web Conference 2022,* 12–19.

# Figures

**Figure 1: Liquidity Distribution in Uniswap V2 vs V3.**

Panel A of this figure displays the uniform liquidity distribution on the entire price range on Uniswap v2. Panel B illustrates the fragmentation of liquidity, $L$, across multiple tick ranges between $p_a$ and $p_b$ on Uniswap v3. Liquidity within each tick range remains constant and represents an aggregation of all LP positions active on this tick range.

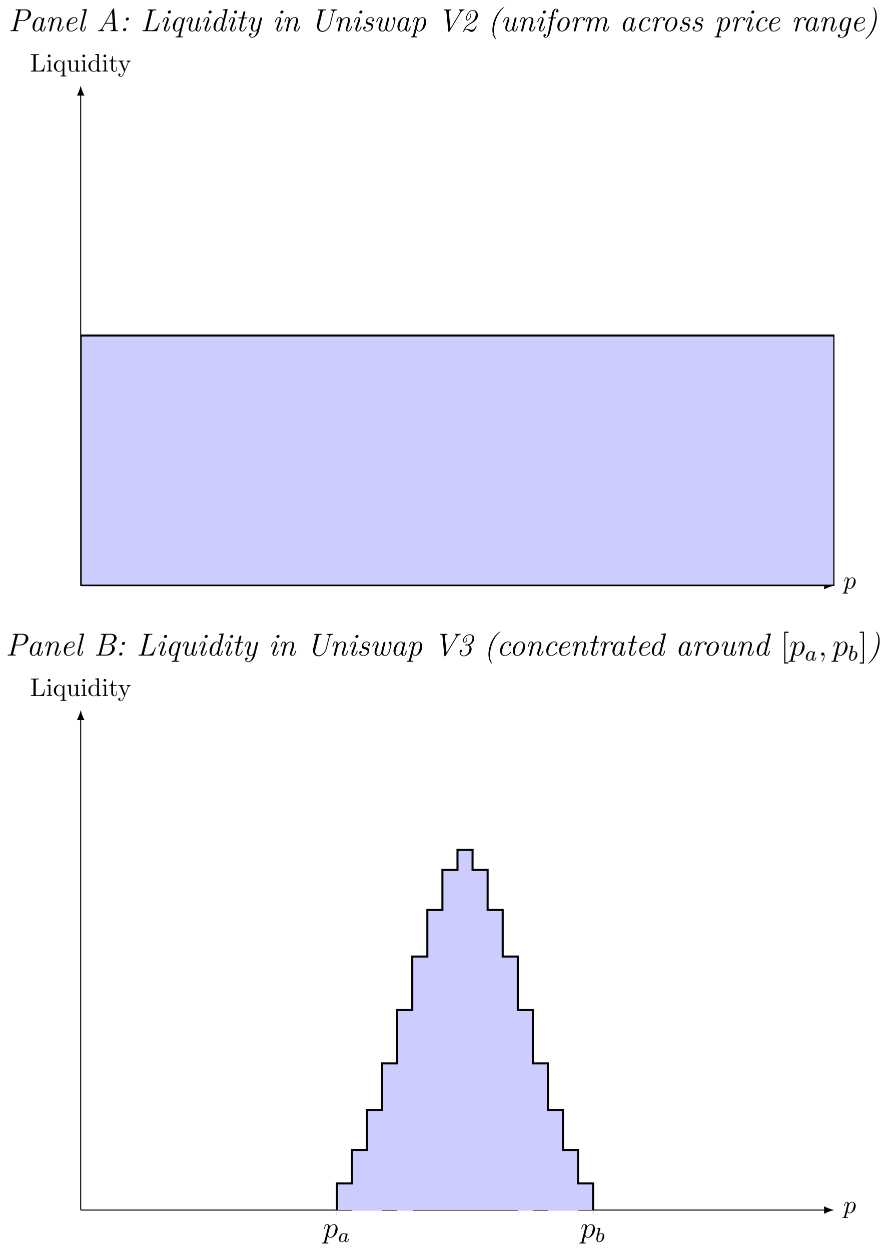
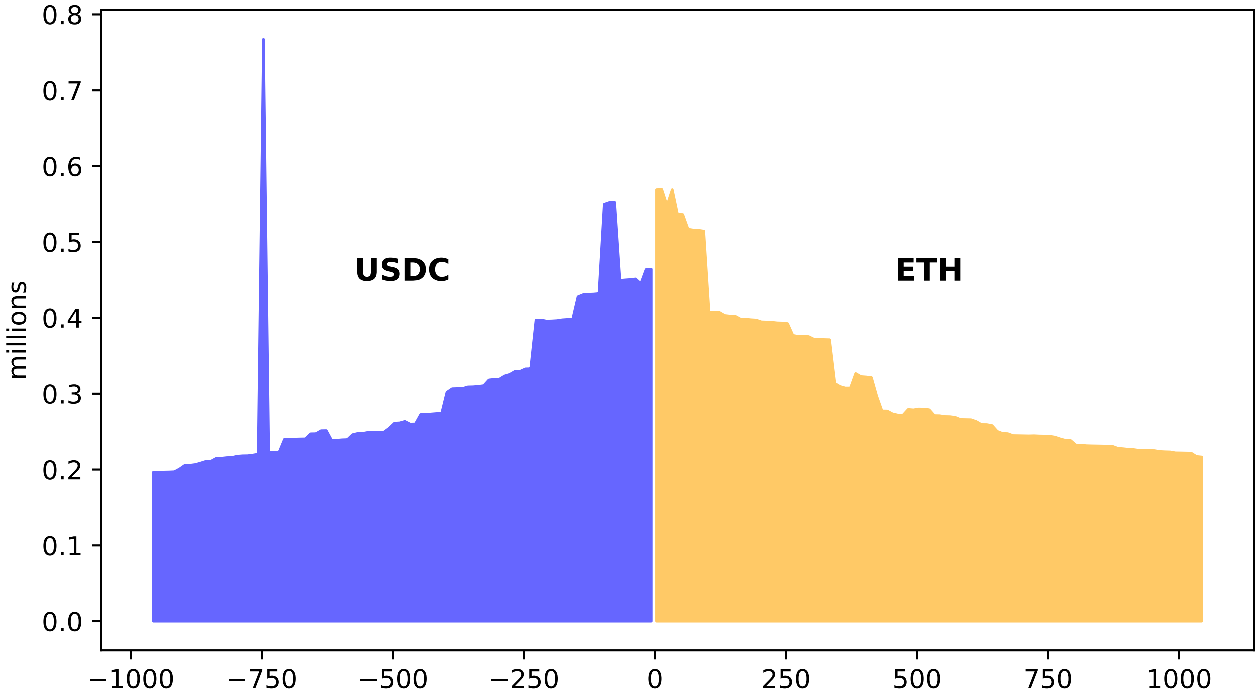


**Figure 2: Liquidity distribution.**

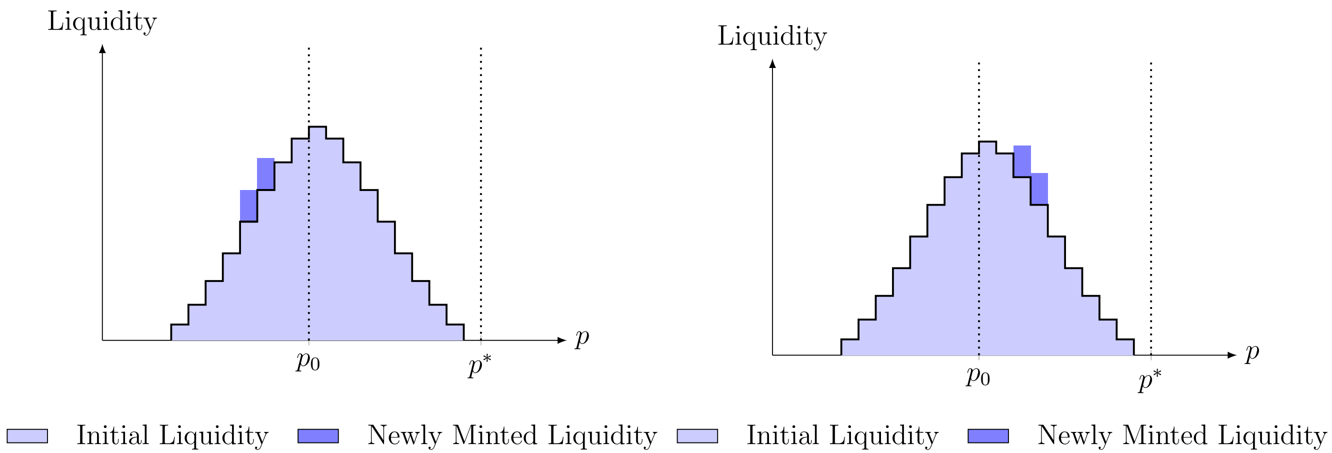
This figure displays the tick-level distribution of liquidity around the current market price for the ETH-USDC 0.05% Uniswap V3 pool, observed at block 16,265,204 on December 25, 2022. The horizontal axis measures tick distance from the prevailing pool price (denoted as tick 0), where each tick represents a discrete price interval in log base $\sqrt{1.0001}$ units. The pool has a fixed tick spacing of 10, which means that LPs can only provide liquidity at every 10th tick. This spacing implies price intervals of approximately 0.1% (10 basis points), determining the granularity of allowable liquidity placements. Ticks to the left of zero represent liquidity *below* the current market price. These correspond to *buy limit orders for ETH* (i.e., LPs are willing to purchase ETH by selling USDC). Conversely, ticks to the right of zero represent liquidity *above* the market price and correspond to *sell limit orders for ETH* (i.e., LPs are willing to sell ETH in exchange for USDC). Liquidity in each tick is expressed in USDC millions on both sides of the book.



## **Figure 3: Mint and Burn order price impacts.**

This figure illustrates four possible states relating net minted and burned liquidity to future price changes. The current price is denoted by $p_0$, and the long-run price by $p^*$. The bid side refers to mints/burns below the market price; the ask side refers to mints/burns above the market price. Panel (a) shows possible price impacts of mint orders. A positive net mint, $mint_{(k)}$, corresponds to a larger amount of liquidity added above the current price (ask) relative to liquidity added below the current price (bid), as illustrated on the right side of Panel (a). We refer to the scenario where a positive (negative) net mint predicts a future price increase (decrease) as a "positive price impact" of a net mint. A negative net mint corresponds to a larger amount of liquidity added on the bid side, relative to the ask side, as illustrated on the left side of Panel (a). We refer to the scenario where a negative net mint predicts a future price increase (or, similarly, if a positive net mint predicts a future price decrease) as a "negative price impact" of a net mint. Panel (b) shows possible price impacts of burn orders. A positive net burn corresponds to a higher burn volume on the ask side relative to the bid side, as illustrated on the right side of Panel (b). A negative net burn corresponds to a higher burn volume on the bid side relative to the ask side, as illustrated on the left side of Panel (b). In this case, a positive (negative) price impact of burned liquidity refers to scenarios where more liquidity withdrawn above (below) the current price predicts a future price increase. These schematics are illustrative and do not distinguish between aggressive and passive orders.

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



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

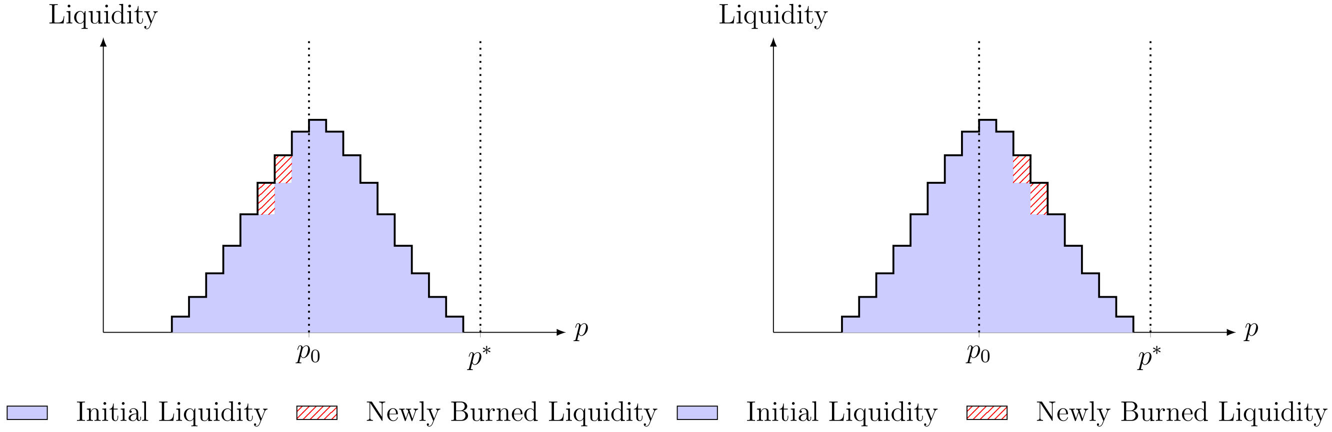
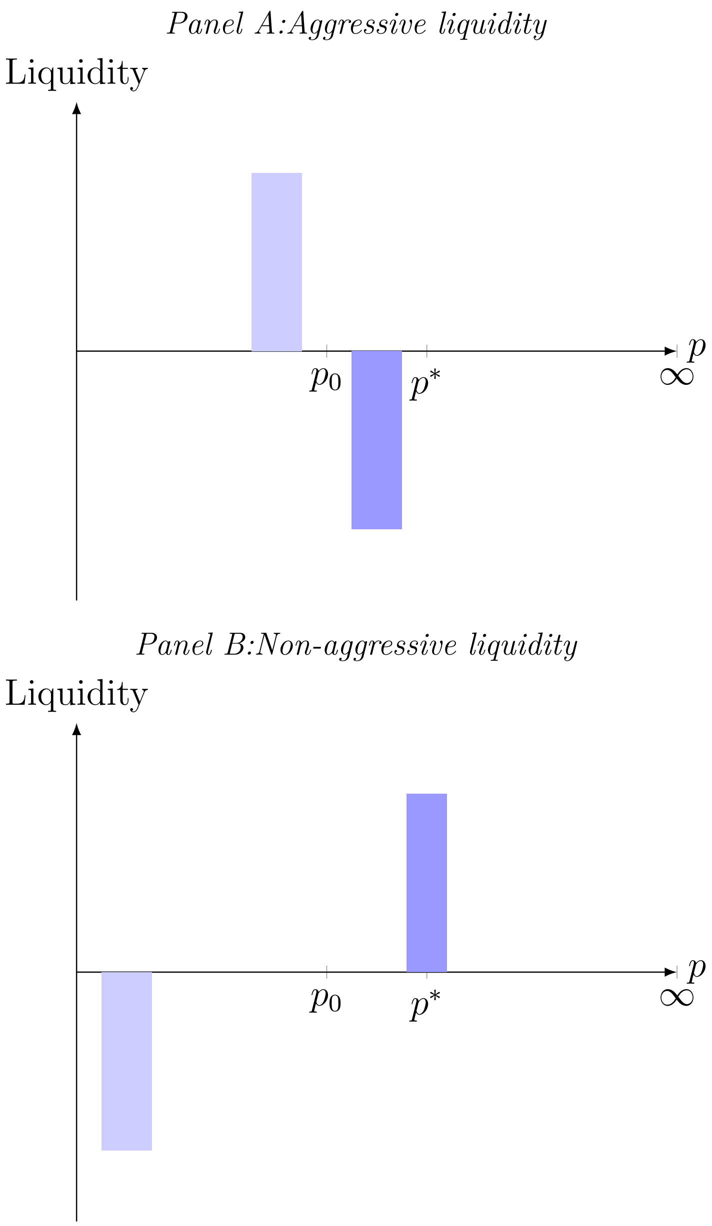


**Figure 4: Aggressive and non-aggressive liquidity price impacts.**

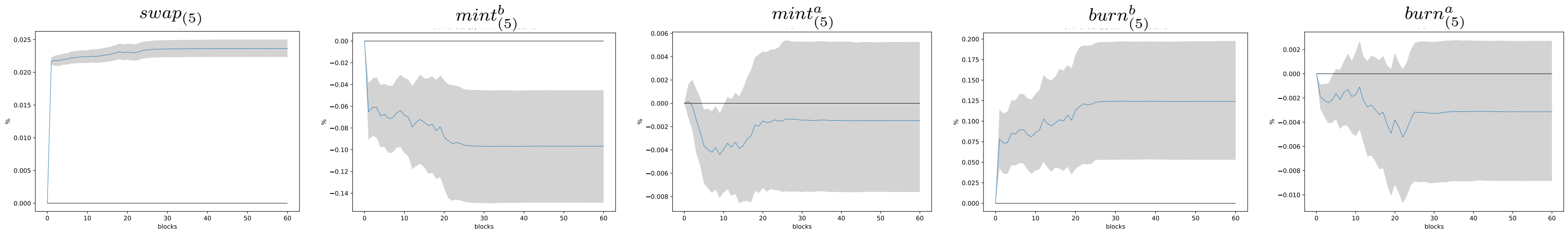
This figure displays aggressive and non-aggressive liquidity adjustment strategies of LPs. The current price is denoted by $p_0$, and the "long-run" price by $p^*$. The bid side refers to mints/burns below the current price; the ask side refers to mints/burns above the current price. The Y-axis, "Liquidity", shows net minting (burning) of liquidity by LPs. Panel (a) illustrates two aggressive liquidity strategies: 1) net minting liquidity on the bid side close to the current price, i.e., $mint^b < 0$ and 2) net burning liquidity on the ask side close to the current price, i.e., $burn^b > 0$. According to H2a, we expect a negative relation between net minting liquidity on the bid side close to the current price and subsequent returns, i.e., mints placed close to the current price have negative price impacts. We further expect a positive relation between net burning liquidity on the ask side close to the current price and subsequent returns. Panel (b) illustrates two non-aggressive liquidity strategies: 1) net minting liquidity on the ask side further away from the current price, i.e., $mint^a > 0$ and 2) net burning liquidity on the bid side further away from the current price, i.e., $burn^a < 0$. According to H2b, we expect a positive relation between net minting liquidity on the ask side away from the current price and subsequent returns, i.e., mints placed away from the current price have positive price impacts. We further expect a negative relation between net burning liquidity on the bid side away from the current price and subsequent returns, i.e., burn orders away from the current price have negative price impacts.



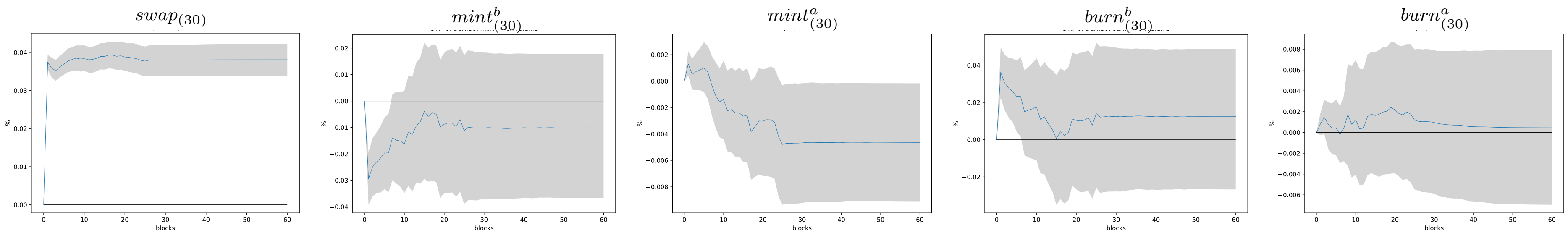
## Figure 5: Cumulative impulse response functions of order flows on returns

This figure plots the cumulative impulse response of ETH-USDC returns to a positive shock to order flow on DEX (Panels A and B) and on CEX (Panel C). The methodology is based on Hasbrouck (1991a). In Panels A and B, we measure the effect of 1 standard deviation of net order flow shock to swap orders (*swap*), aggressive and non-aggressive mints ($mint^b$ and $mint^a$), aggressive and non-aggressive burns ($burn^b$ and $burn^a$) for DEX(5) and DEX(30) pools, respectively. In Panel C, we measure the effect of a 1 standard deviation of net order flow shock to market order flow (*market*) and limit order flow (*limit*). The benchmark return is computed from Binance mid-prices of ETH-USDC. Appendix A provides detailed definitions of all variables used in the analysis. The sample period runs from 06/05/2021 to 12/07/2022. All data are in block frequency. The shaded area represents the range between the 2.5th and 97.5th quantile values, which captures the middle 95% of the data distribution.

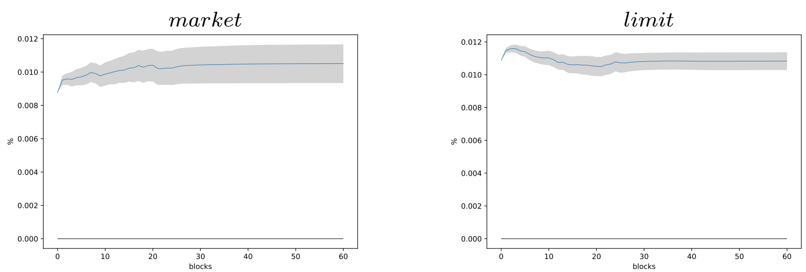
*Panel A: CIRF of DEX(5) orders on returns*




*Panel B: CIRF of DEX(30) orders on returns*



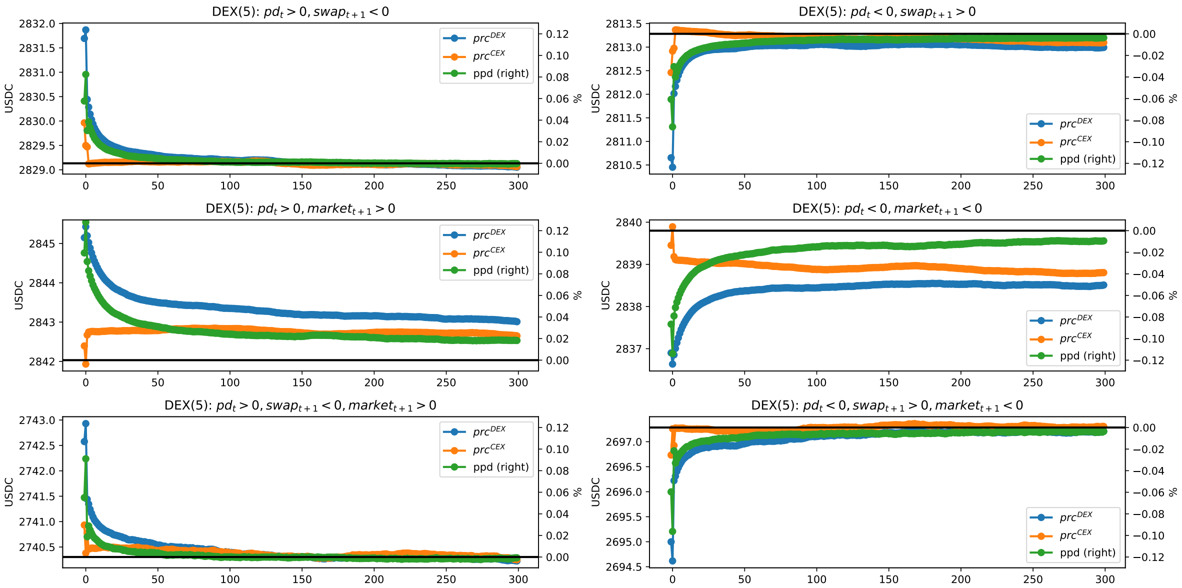

*Panel C: CIRF of CEX order flow on returns*



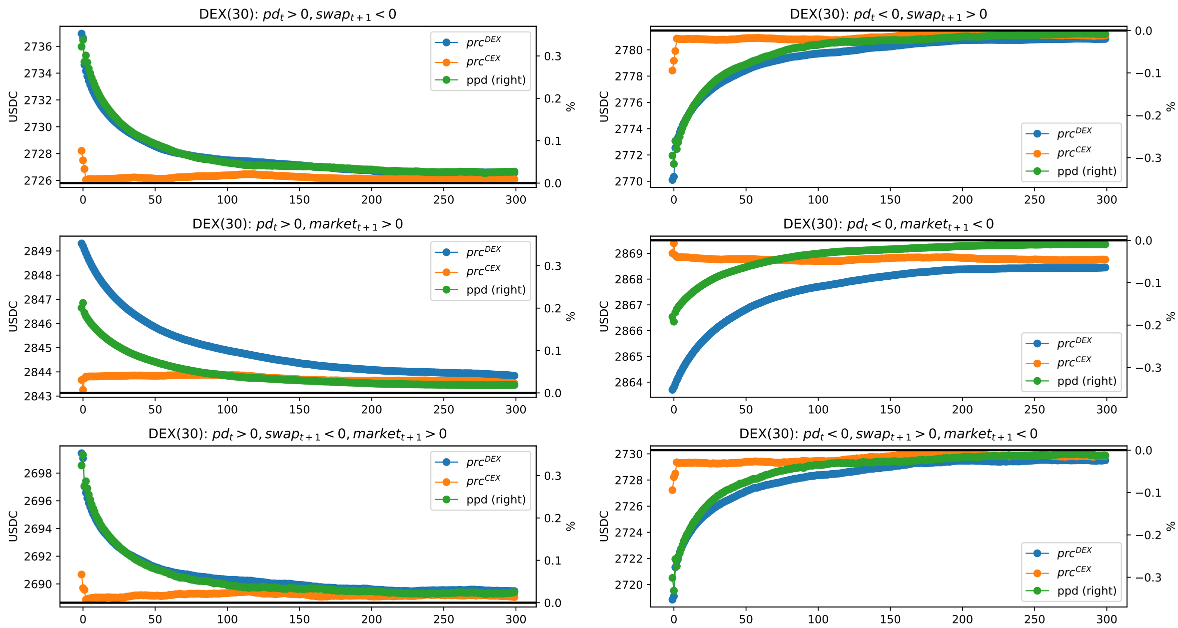
## Figure 6: Arbitrage deviations and price convergence

This figure plots the average dynamics of the price difference between Uniswap and Binance ETH-USDC prices, conditional on the sign of the next incoming swap/market order that exploits the arbitrage opportunity. We define the price difference as $pd_t = prc_t^{DEX} - prc_t^{CEX}$ and consider six conditioning cases: (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) $pd_t < 0$, $swap_{t+1} > 0$, $market_{t+1} < 0$. These conditions identify cases where either DEX, or CEX, or both platforms respond to arbitrage deviations. Panel A displays dynamics for the DEX(5) pool, and Panel B for the DEX(30) pool. The x-axis is measured in blocks, and the y-axis represents the average price difference.

*Panel A: DEX(5)*




*Panel B: DEX(30)*



# Tables

### Table 1: Distribution of 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

This table reports summary statistics for trades and liquidity flows with non-zero values at the block level for both DEX(5) and DEX(30) pools on Uniswap v3 Ethereum, as well as the CEX Binance for the ETH/USDC pair. *market* is the block-level net market order flow in the CEX, defined as buy minus sell volume. $swap_{(k)}$ is the block-level net swap flow on the corresponding DEX(k) pool, defined as ETH buy minus sell volume (in USDC). *limit* is the block-level net limit order flow on the CEX, proxied by changes in depth adjusted for executed market orders. $mint^b_{(k)}$ and $burn^b_{(k)}$ denote mint and burn flows near the current price (within five tick ranges), while $mint^a_{(k)}$ and $burn^a_{(k)}$ are flows away from the current price. All amounts are converted to USDC. Returns are computed from log mid-prices over 1, 10, and 60 blocks and are in percentage points. Column count presents the number of block intervals with at least one order of the corresponding type. Appendix A provides detailed definitions of all variables used in the analysis. The sample period is from 06/05/2021 to 12/07/2022.

*Panel A: Trade orders*

| Variable | count | mean | std | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|---|---|
| *market* | 1,585,597 | -646 | 47,213 | -22,003 | -2,209 | -15 | 1,911 | 20,002 |
| $swap_{(5)}$ | 1,294,246 | -145 | 321,763 | -403,434 | -27,185 | -295 | 21,736 | 412,498 |
| $swap_{(30)}$ | 223,011 | -57 | 464,298 | -613,402 | -118,373 | -377 | 120,001 | 617,619 |

*Panel B: Liquidity orders*

| Variable | count | mean | std | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|---|---|
| *limit* | 2,730,640 | -374 | 175,990 | -240,206 | -47,286 | -15 | 45,476 | 240,723 |
| $mint^b_{(5)}$ | 25,155 | 783,748 | 7,360,737 | -3,469,365 | 0 | 1 | 143 | 7,626,490 |
| $mint^a_{(5)}$ | 21,812 | 33,074 | 1,402,734 | -248,198 | -7,273 | 62 | 15,514 | 409,539 |
| $burn^b_{(5)}$ | 12,941 | 1,537,658 | 9,953,216 | -10,494,282 | -911 | 1 | 2,718 | 24,988,820 |
| $burn^a_{(5)}$ | 18,454 | 34,164 | 2,572,021 | -891,150 | -50,541 | 403 | 67,432 | 1,002,886 |
| $mint^b_{(30)}$ | 48,433 | 123,877 | 2,855,405 | -15,445 | -1 | 0 | 10 | 22,718 |
| $mint^a_{(30)}$ | 42,274 | 18,116 | 652,460 | -52,175 | -541 | 0 | 1,313 | 78,552 |
| $burn^b_{(30)}$ | 25,027 | 232,370 | 3,892,722 | -106,283 | -165 | 0 | 119 | 116,991 |
| $burn^a_{(30)}$ | 28,681 | 22,078 | 1,041,103 | -229,567 | -11,020 | 3 | 13,592 | 291,812 |

*Panel C: Returns (log mid-price)*

| Variable | count | mean | std | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|---|---|
| *ret* (1 bl) | 2,753,596 | 0.00 | 0.07 | -0.09 | -0.02 | 0.00 | 0.02 | 0.08 |
| *ret* (10 bl) | 2,753,587 | 0.00 | 0.21 | -0.28 | -0.09 | 0.00 | 0.08 | 0.28 |
| *ret* (60 bl) | 2,753,537 | 0.00 | 0.52 | -0.71 | -0.22 | 0.00 | 0.21 | 0.70 |

## Table 3: CIRF of net orders on returns

This table reports the cumulative impulse response functions (CIRFs) of DEX and CEX order flow variables on ETH-USDC returns at horizons $n = 0$, 1, 10, and 60 blocks. Our methodology is based on Hasbrouck (1991a), with vector of endogenous variables consisting of DEX net swap flows and DEX net liquidity provision (mints and burns), CEX market and limit order flows, and the ETH-USDC return on CEX. The table presents results separately for the low-fee DEX(5) pool (Panel A), the high-fee DEX(30) pool (Panel B), and the centralized exchange (Panel C). Each coefficient represents the return impact (in percentage points) of a 1 standard deviation of net order flow shock. *market* is the net market order flow in the CEX market, *limit* is the net limit order flow in the CEX market, and *swap* is the net swap flow in the corresponding DEX pool. $mint^b$ ($mint^a$) is the net liquidity minted in the corresponding DEX pool within (away from) 5 tick ranges of the current price, and $burn^b$ ($burn^a$) is the net liquidity burned within (away from) 5 tick ranges. The benchmark return is computed from Binance mid-prices of ETH-USDC. Appendix A provides detailed definitions of all variables used in the analysis. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in block 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.

| | $n = 0$ | $n = 1$ | $n = 10$ | $n = 60$ |
|---|---|---|---|---|
| *Panel A:* DEX(5) | | | | |
| *swap* | 0 | 0.022*** | 0.022*** | 0.023*** |
| $mint^b_{(5)}$ | 0 | −0.066*** | −0.066*** | −0.096*** |
| $mint^a_{(5)}$ | 0 | 0.000 | −0.004** | −0.001 |
| $burn^b_{(5)}$ | 0 | 0.080*** | 0.090*** | 0.119*** |
| $burn^a_{(5)}$ | 0 | −0.003*** | −0.003 | −0.003 |
| *Panel B:* DEX(30) | | | | |
| *swap* | 0 | 0.038*** | 0.039*** | 0.038*** |
| $mint^b_{(30)}$ | 0 | −0.029*** | −0.017 | −0.011 |
| $mint^a_{(30)}$ | 0 | 0.001*** | −0.001 | −0.005** |
| $burn^b_{(30)}$ | 0 | 0.035*** | 0.019 | 0.012 |
| $burn^a_{(30)}$ | 0 | 0.001 | 0.001 | 0.000 |
| *Panel C:* CEX | | | | |
| *market* | 0.009*** | 0.010*** | 0.010*** | 0.011*** |
| *limit* | 0.011*** | 0.011*** | 0.011*** | 0.011*** |

## Table 4: Variance decomposition

This table reports the forecast error variance decomposition from the Hasbrouck (1991a) VAR in Table 3 at horizons $n = 1$ and 60 blocks. *market* is the net market order flow in the CEX market, *limit* is the net limit order flow in the CEX market, and *swap* is the net swap flow in the corresponding DEX pool. $mint^b$ ($mint^a$) is the net liquidity minted in the corresponding DEX pool within (away from) 5 tick ranges of the current price, and $burn^b$ ($burn^a$) is the net liquidity burned within (away from) 5 tick ranges. The benchmark return is computed from Binance mid-prices of ETH-USDC. Appendix A provides detailed definitions of all variables used in the analysis. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in block frequency.

| | $n = 1$ | $n = 60$ |
|---|---|---|
| *Panel A:* DEX(5) *orders* | | |
| $swap$ | 4.79 | 4.78 |
| $mint^b$ | 0.94 | 1.03 |
| $mint^a$ | 0.00 | 0.00 |
| $burn^b$ | 0.01 | 0.01 |
| $burn^a$ | 0.00 | 0.00 |
| *Panel B:* DEX(30) *orders* | | |
| $swap$ | 2.61 | 2.62 |
| $mint^b$ | 0.36 | 0.44 |
| $mint^a$ | 0.00 | 0.00 |
| $burn^b$ | 0.01 | 0.01 |
| $burn^a$ | 0.00 | 0.00 |
| *Panel C:* CEX *orders* | | |
| $market$ | 1.04 | 1.04 |
| $limit$ | 2.20 | 2.20 |

## Table 5: CIRF of DEX orders: Order-level classification

This table reports the cumulative impulse response functions (CIRFs) of DEX order flow variables on ETH-USDC returns at a horizon of 60 blocks. We estimate the VAR model in Equation (25), following the methodology of Hasbrouck (1991a). Panel A splits mints and burns by their size. A mint (burn) is classified as large (*large*) if its size exceeds the median of its distribution in the sample; otherwise, it is classified as small. Equation (27) provides the full variable specification. Panel B splits mints and burns by priority of their execution within the block. A mint (burn) is classified as a top-of-block (*top*) if its position index within the block is less than or equal to the sample median of 81; otherwise, it is classified as a bottom-of-block (*bot*). Panel C splits mints and burns by the width of their price range interval. A mint (burn) is associated with a wide interval (*wid*) if the width of its interval is above the upper quartile of the corresponding distribution; otherwise, it is classified as narrrow (*nar*). Equation (29) provides the full variable specification. The benchmark return is computed from Binance mid-prices of ETH-USDC. Each coefficient represents the return impact (in percentage points) of a 1 standard deviation of net order flow shock. Appendix A provides detailed definitions of all variables used in the analysis. The sample period runs from 06/05/2021 to 12/07/2022. All data are in block frequency. * denotes significance at the 10 per cent level, ** at the 5 per cent level, and *** at the 1 per cent level.

| DEX(5) | | | | DEX(30) | | | |
|---|---|---|---|---|---|---|---|
| *Panel A: Order size classification (60-block horizon)* | | | | | | | |
| $swap_{(5)}$ | 0.023*** | | | $swap_{(30)}$ | 0.038*** | | |
| $mint^{b,large}_{(5)}$ | −0.112*** | $mint^{b,small}_{(5)}$ | −0.003 | $mint^{b,large}_{(30)}$ | −0.018 | $mint^{b,small}_{(30)}$ | −0.003 |
| $mint^{a,large}_{(5)}$ | −0.002 | $mint^{a,small}_{(5)}$ | −0.001 | $mint^{a,large}_{(30)}$ | −0.007** | $mint^{a,small}_{(30)}$ | 0.000 |
| $burn^{b,large}_{(5)}$ | 0.139*** | $burn^{b,small}_{(5)}$ | −0.004 | $burn^{b,large}_{(30)}$ | 0.017 | $burn^{b,small}_{(30)}$ | −0.001 |
| $burn^{a,large}_{(5)}$ | −0.003 | $burn^{a,small}_{(5)}$ | 0.003 | $burn^{a,large}_{(30)}$ | 0.000 | $burn^{a,small}_{(30)}$ | 0.000 |
| *Panel B: Order execution priority classification (60-block horizon)* | | | | | | | |
| $swap^{top}_{(5)}$ | 0.028*** | $swap^{bot}_{(5)}$ | 0.011*** | $swap^{top}_{(30)}$ | 0.041*** | $swap^{bot}_{(30)}$ | 0.036*** |
| $mint^{b,top}_{(5)}$ | −0.151*** | $mint^{b,bot}_{(5)}$ | −0.005** | $mint^{b,top}_{(30)}$ | −0.082** | $mint^{b,bot}_{(30)}$ | 0.002 |
| $mint^{a,top}_{(5)}$ | 0.000 | $mint^{a,bot}_{(5)}$ | −0.003 | $mint^{a,top}_{(30)}$ | 0.002 | $mint^{a,bot}_{(30)}$ | −0.006** |
| $burn^{b,top}_{(5)}$ | 0.167*** | $burn^{b,bot}_{(5)}$ | 0.009*** | $burn^{b,top}_{(30)}$ | 0.108** | $burn^{b,bot}_{(30)}$ | −0.002 |
| $burn^{a,top}_{(5)}$ | −0.006 | $burn^{a,bot}_{(5)}$ | −0.002 | $burn^{a,top}_{(30)}$ | −0.019** | $burn^{a,bot}_{(30)}$ | 0.007* |
| *Panel C: Liquidity concentration classification (60-block horizon)* | | | | | | | |
| $swap_{(5)}$ | 0.023*** | | | $swap_{(30)}$ | 0.038*** | | |
| $mint^{b,nar}_{(5)}$ | −0.111*** | $mint^{b,wid}_{(5)}$ | 0.005 | $mint^{b,nar}_{(30)}$ | −0.014 | $mint^{b,wid}_{(30)}$ | 0.004 |
| $mint^{a,nar}_{(5)}$ | −0.002 | $mint^{a,wid}_{(5)}$ | −0.006 | $mint^{a,nar}_{(30)}$ | 0.001 | $mint^{a,wid}_{(30)}$ | −0.014 |
| $burn^{b,nar}_{(5)}$ | 0.138*** | $burn^{b,wid}_{(5)}$ | −0.018*** | $burn^{b,nar}_{(30)}$ | 0.017 | $burn^{b,wid}_{(30)}$ | −0.009 |
| $burn^{a,nar}_{(5)}$ | −0.006 | $burn^{a,wid}_{(5)}$ | −0.011* | $burn^{a,nar}_{(30)}$ | 0.007** | $burn^{a,wid}_{(30)}$ | −0.023** |

## Table 6: CIRF of DEX orders: Wallet-level classification

This table reports the cumulative impulse response functions (CIRFs) of DEX order flow variables on ETH-USDC returns at a horizon of 60 blocks. We estimate the VAR model in Equation (25), following the methodology of Hasbrouck (1991a). Panel A classifies wallets based on the type of their liquidity provision. We classify wallets as those that engage in mixed liquidity provision, *mix*, if they participated in both liquidity provision and swap trading within our sample period. In contrast, we classify wallets that engage in pure liquidity provision as *pure*. The variable vector is defined in Equation (30). Panel B classifies wallets as repositioning, *repo*, if they have at least one burn followed by a mint within two minutes (equivalent to 10 next blocks). Remaining wallets, who mint or burn on a more permanent basis, are labeled *other*. The variable vector is defined in Equation (31). Panel C classifies wallets based on frequency of liquidity provision. Wallets that submit more than four liquidity orders (mints or burns) over the sample period—the upper quartile of the distribution—are classified as high-frequency ($hfr$). All other wallets are classified as low-frequency ($lfr$). The variable vector is defined in Equation (32). The benchmark return is computed from Binance mid-prices of ETH-USDC. Each coefficient represents the return impact (in percentage points) of a 1 standard deviation of net order flow shock. Appendix A provides detailed definitions of all variables used in the analysis. The sample period runs from 06/05/2021 to 12/07/2022. All data are in block frequency. * denotes significance at the 10 per cent level, ** at the 5 per cent level, and *** at the 1 per cent level.

| DEX(5) | | | | DEX(30) | | | |
|---|---|---|---|---|---|---|---|
| *Panel A: Mixed order types vs pure liquidity provision* | | | | | | | |
| $swap^{mix}_{(5)}$ | 0.033*** | $swap^{pure}_{(5)}$ | 0.020*** | $swap^{mix}_{(30)}$ | 0.049*** | $swap^{pure}_{(30)}$ | 0.030*** |
| $mint^{b,mix}_{(5)}$ | −0.107*** | $mint^{b,pure}_{(5)}$ | −0.007 | $mint^{b,mix}_{(30)}$ | −0.016 | $mint^{b,pure}_{(30)}$ | −0.001 |
| $mint^{a,mix}_{(5)}$ | −0.001 | $mint^{a,pure}_{(5)}$ | −0.004 | $mint^{a,mix}_{(30)}$ | −0.001 | $mint^{a,pure}_{(30)}$ | −0.013** |
| $burn^{b,mix}_{(5)}$ | 0.134*** | $burn^{b,pure}_{(5)}$ | 0.020*** | $burn^{b,mix}_{(30)}$ | 0.017 | $burn^{b,pure}_{(30)}$ | −0.015** |
| $burn^{a,mix}_{(5)}$ | −0.003 | $burn^{a,pure}_{(5)}$ | −0.008 | $burn^{a,mix}_{(30)}$ | 0.001 | $burn^{a,pure}_{(30)}$ | 0.000 |
| *Panel B: Liquidity repositioning* | | | | | | | |
| $swap_{(5)}$ | 0.023*** | | | $swap_{(30)}$ | 0.038*** | | |
| $mint^{b,repo}_{(5)}$ | −0.118*** | $mint^{b,other}_{(5)}$ | −0.045** | $mint^{b,repo}_{(30)}$ | −0.041 | $mint^{b,other}_{(30)}$ | 0.004 |
| $mint^{a,repo}_{(5)}$ | −0.006 | $mint^{a,other}_{(5)}$ | 0.000 | $mint^{a,repo}_{(30)}$ | −0.007* | $mint^{a,other}_{(30)}$ | −0.002 |
| $burn^{b,repo}_{(5)}$ | 0.133*** | $burn^{b,other}_{(5)}$ | 0.069** | $burn^{b,repo}_{(30)}$ | 0.047 | $burn^{b,other}_{(30)}$ | −0.012** |
| $burn^{a,repo}_{(5)}$ | 0.004 | $burn^{a,other}_{(5)}$ | −0.007 | $burn^{a,repo}_{(30)}$ | −0.007 | $burn^{a,other}_{(30)}$ | 0.008 |
| *Panel C: Frequency of liquidity orders* | | | | | | | |
| $swap_{(5)}$ | 0.023*** | | | $swap_{(30)}$ | 0.038*** | | |
| $mint^{b,hfr}_{(5)}$ | −0.092*** | $mint^{b,lfr}_{(5)}$ | −0.110* | $mint^{b,hfr}_{(30)}$ | −0.014 | $mint^{b,lfr}_{(30)}$ | 0.008 |
| $mint^{a,hfr}_{(5)}$ | −0.001 | $mint^{a,lfr}_{(5)}$ | 0.003 | $mint^{a,hfr}_{(30)}$ | −0.005* | $mint^{a,lfr}_{(30)}$ | −0.000 |
| $burn^{b,hfr}_{(5)}$ | 0.113*** | $burn^{b,lfr}_{(5)}$ | 0.161* | $burn^{b,hfr}_{(30)}$ | 0.013 | $burn^{b,lfr}_{(30)}$ | −0.029 |
| $burn^{a,hfr}_{(5)}$ | −0.003 | $burn^{a,lfr}_{(5)}$ | −0.002 | $burn^{a,hfr}_{(30)}$ | −0.005 | $burn^{a,lfr}_{(30)}$ | 0.071** |

## Table 7: Arbitrage deviations and CIRF of DEX orders

This table reports the cumulative impulse response function (CIRF) of ETH-USDC returns to order flow shocks on DEX at a 60-block horizon. We estimate the VAR model following the methodology of Hasbrouck (1991a). Panel A reports summary statistics of the percentage price difference between DEX and CEX markets, defined as $ppd = 100 \times (prc^{DEX} - prc^{CEX})/prc^{CEX}$, where $prc^{DEX}$ is the observed DEX pool price. Panel B reports the distribution of the absolute percentage price difference $|ppd|$. Panel C presents CIRF estimates conditional on the magnitude of arbitrage opportunities between DEX and CEX markets. Order flow observations are split by $|ppd|$: orders that are submitted when $|ppd|$ is greater than or equal to 36 basis points are classified as *highpd*, corresponding to deviations large enough to exceed median DEX transaction costs (gas, pool fees, and slippage). Orders below this threshold are classified as *lowpd*. Each coefficient represents the return impact (in percentage points) of a 1 standard deviation of net order flow shock. Appendix A provides detailed definitions of all variables used in the analysis. The sample period spans from 06/05/2021 to 12/07/2022. All data are sampled at the block level. * denotes significance at the 10 per cent level, ** at the 5 per cent level, and *** at the 1 per cent level.

*Panel A: Distribution of ppd*

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| DEX(5) | 2,753,596 | 0.0042 | 0.4250 | -30.82 | -0.0554 | -0.0023 | 0.0515 | 27.06 |
| DEX(30) | 2,753,596 | 0.0028 | 0.4128 | -31.82 | -0.1681 | -0.0096 | 0.1521 | 12.62 |

*Panel B: Distribution of |ppd|*

| | count | mean | std | 50% | 75% | 95% | 99% | max |
|---|---|---|---|---|---|---|---|---|
| DEX(5) | 2,753,596 | 0.1058 | 0.4117 | 0.0535 | 0.0897 | 0.2858 | 0.9759 | 30.82 |
| DEX(30) | 2,753,596 | 0.1874 | 0.3678 | 0.1604 | 0.2513 | 0.3622 | 0.5386 | 31.82 |

*Panel C: CIRF of DEX orders conditional on arbitrage*

| DEX(5) | | DEX(30) | |
|---|---|---|---|
| $swap^{hpd}_{(5)}$ | 0.080*** | $swap^{hpd}_{(30)}$ | 0.031*** |
| $swap^{lpd}_{(5)}$ | 0.022*** | $swap^{lpd}_{(30)}$ | 0.041*** |
| $mint^{b,hpd}_{(5)}$ | −0.409** | $mint^{b,hpd}_{(30)}$ | 0.030* |
| $mint^{b,lpd}_{(5)}$ | −0.089*** | $mint^{b,lpd}_{(30)}$ | −0.029* |
| $mint^{a,hpd}_{(5)}$ | −0.115** | $mint^{a,hpd}_{(30)}$ | −0.003 |
| $mint^{a,lpd}_{(5)}$ | −0.001 | $mint^{a,lpd}_{(30)}$ | −0.004* |
| $burn^{b,hpd}_{(5)}$ | 0.462** | $burn^{b,hpd}_{(30)}$ | −0.018 |
| $burn^{b,lpd}_{(5)}$ | 0.120*** | $burn^{b,lpd}_{(30)}$ | 0.040* |
| $burn^{a,hpd}_{(5)}$ | 0.024 | $burn^{a,hpd}_{(30)}$ | 0.036 |
| $burn^{a,lpd}_{(5)}$ | −0.003 | $burn^{a,lpd}_{(30)}$ | −0.003 |

# Informed Liquidity Provision on Decentralized Exchanges

(Not for publication)

# A Variable Definitions and Data Sources

**Table A1: Variables Definitions**

| Variable | Description | Source |
|---|---|---|
| $swap^{buy}_{(k)}$ | ETH buy volume (in USDC) per block in DEX pool $k$, where $k = 5$ for 0.05% and $k = 30$ for 0.3%. | The Graph |
| $swap^{sell}_{(k)}$ | ETH sell volume (in USDC) per block in DEX pool $k$. | The Graph |
| $swap_{(k)}$ | Net swap flow: $swap^{buy}_{(k)} - swap^{sell}_{(k)}$. | The Graph |
| $mint^{ask}_{(k)}$ | USDC equivalent of token $X$ (ETH) minted: $x_p \cdot p_M$. | Kaiko |
| $mint^{bid}_{(k)}$ | USDC amount of token $Y$ (USDC) minted: $y_p$. | Kaiko |
| $mint_{(k)}$ | Net mint: $mint^{ask}_{(k)} - mint^{bid}_{(k)}$. | Kaiko |
| $burn^{ask}_{(k)}$ | USDC equivalent of token $X$ (ETH) burned: $x_p \cdot p_M$. | Kaiko |
| $burn^{bid}_{(k)}$ | USDC amount of token $Y$ (USDC) burned: $y_p$. | Kaiko |
| $burn_{(k)}$ | Net burn: $burn^{ask}_{(k)} - burn^{bid}_{(k)}$. | Kaiko |
| $mint^{b}_{(k)}$ | Minted liquidity within 5 tick ranges of the current price ("best"): $mint^{b,ask} - mint^{b,bid}$. | Kaiko |
| $mint^{a}_{(k)}$ | Minted liquidity beyond 5 tick ranges ("away"): $mint^{a,ask} - mint^{a,bid}$. | Kaiko |
| $burn^{b}_{(k)}$ | Burned liquidity within 5 tick ranges of the current price: $burn^{b,ask} - burn^{b,bid}$. | Kaiko |
| $burn^{a}_{(k)}$ | Burned liquidity beyond 5 tick ranges: $burn^{a,ask} - burn^{a,bid}$. | Kaiko |
| $market^{buy}$ | Buy market order volume (in USDC) per block on Binance. | CryptoTick / CoinAPI |
| $market^{sell}$ | Sell market order volume (in USDC) per block on Binance. | CryptoTick / CoinAPI |
| $market$ | Net market order flow: $market^{buy} - market^{sell}$. | CryptoTick / CoinAPI |
| $limit^{ask}$ | Net liquidity added to the ask side: $\Delta depth^{ask} + market^{buy}$. | CryptoTick / CoinAPI |
| $limit^{bid}$ | Net liquidity added to the bid side: $\Delta depth^{bid} + market^{sell}$. | CryptoTick / CoinAPI |
| $limit$ | Net limit order flow: $limit^{ask} - limit^{bid}$. | CryptoTick / CoinAPI |
| $ret$ | Log return of mid-price: $\log(p_t) - \log(p_{t-1})$. | CryptoTick / CoinAPI |

# B CIRFs for 1 Million USDC Shock

### Table B1: CIRF of net orders on returns

This table reports the cumulative impulse response functions (CIRFs) of DEX and CEX order flow variables on ETH-USDC returns at horizons $n = 0$, 1, 10, and 60 blocks. Our methodology is based on Hasbrouck (1991a), with vector of endogenous variables consisting of DEX net swap flows and DEX net liquidity provision (mints and burns), CEX market and limit order flows, and the ETH-USDC return on CEX. The table presents results separately the low-fee DEX(5) pool (Panel A), and the high-fee DEX(30) pool (Panel B), and for the centralized exchange (Panel C). Each coefficient represents the return impact (in basis points) of a 1 million USDC net order flow shock. *market* is the net market order flow in the CEX market, *limit* is the net limit order flow in the CEX market, and *swap* is the net swap flow in the corresponding DEX pool. $mint^b$ ($mint^a$) is the net liquidity minted in the corresponding DEX pool within (away from) 5 tick ranges of the current price, and $burn^b$ ($burn^a$) is the net liquidity burned within (away from) 5 tick ranges. The benchmark return is computed from Binance mid-prices of ETH-USDC. Appendix A provides detailed definitions of all variables used in the analysis. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in block 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.

| | $n = 0$ | $n = 1$ | $n = 10$ | $n = 60$ |
|---|---|---|---|---|
| | | *Panel A:* DEX(5) | | |
| *swap* | 0 | 0.068*** | 0.069*** | 0.073*** |
| $mint^b_{(5)}$ | 0 | −0.009*** | −0.009*** | −0.013*** |
| $mint^a_{(5)}$ | 0 | 0.000 | −0.003** | −0.001 |
| $burn^b_{(5)}$ | 0 | 0.008*** | 0.009*** | 0.012*** |
| $burn^a_{(5)}$ | 0 | −0.001*** | −0.001 | −0.001 |
| | | *Panel B:* DEX(30) | | |
| *swap* | 0 | 0.081*** | 0.083*** | 0.082*** |
| $mint^b_{(30)}$ | 0 | −0.010*** | −0.006 | −0.004 |
| $mint^a_{(30)}$ | 0 | 0.002*** | −0.002 | −0.007** |
| $burn^b_{(30)}$ | 0 | 0.009*** | 0.005 | 0.003 |
| $burn^a_{(30)}$ | 0 | 0.001 | 0.001 | 0.000 |
| | | *Panel C:* CEX | | |
| *market* | 0.186*** | 0.202*** | 0.209*** | 0.223*** |
| *limit* | 0.062*** | 0.065*** | 0.063*** | 0.062*** |

## Table B2: CIRF of DEX orders: Order-level classification

This table reports the cumulative impulse response functions (CIRFs) of DEX order flow variables on ETH-USDC returns at a horizon of 60 blocks. We estimate the VAR model in Equation (25), following the methodology of Hasbrouck (1991a). Panel A splits mints and burns by their size. A mint (burn) is classified as large (*large*) if its size exceeds the median of its distribution in the sample; otherwise, it is classified as small. Equation (27) provides the full variable specification. Panel B splits mints and burns by priority of their execution within the block. A mint (burn) is classified as a top-of-block (*top*) if its position index within the block is less than or equal to the sample median of 80; otherwise, it is classified as a bottom-of-block (*bot*). Panel C splits mints and burns by the width of their price range interval. A mint (burn) is associated with a wide interval (*wid*) if the width of its interval is above the upper quartile of the corresponding distribution; otherwise, it is classified as narrrow (*nar*). Equation (29) provides the full variable specification. The benchmark return is computed from Binance mid-prices of ETH-USDC. Appendix A provides detailed definitions of all variables used in the analysis. The sample period runs from 06/05/2021 to 12/07/2022. All data are in block frequency. * denotes significance at the 10 per cent level, ** at the 5 per cent level, and *** at the 1 per cent level.

| DEX(5) | | | | DEX(30) | | | |
|---|---|---|---|---|---|---|---|
| *Panel A: Order size classification (60-block horizon)* | | | | | | | |
| $swap_{(5)}$ | 0.073*** | | | $swap_{(30)}$ | 0.082*** | | |
| $mint^{b,large}_{(5)}$ | −0.013*** | $mint^{b,small}_{(5)}$ | −2.266 | $mint^{b,large}_{(30)}$ | −0.004 | $mint^{b,small}_{(30)}$ | −2.204 |
| $mint^{a,large}_{(5)}$ | −0.001 | $mint^{a,small}_{(5)}$ | −0.170 | $mint^{a,large}_{(30)}$ | −0.007** | $mint^{a,small}_{(30)}$ | 0.188 |
| $burn^{b,large}_{(5)}$ | 0.012*** | $burn^{b,small}_{(5)}$ | −1.009 | $burn^{b,large}_{(30)}$ | 0.003 | $burn^{b,small}_{(30)}$ | −0.149 |
| $burn^{a,large}_{(5)}$ | −0.001 | $burn^{a,small}_{(5)}$ | 0.153 | $burn^{a,large}_{(30)}$ | 0.000 | $burn^{a,small}_{(30)}$ | 0.004 |
| *Panel B: Order execution priority classification (60-block horizon)* | | | | | | | |
| $swap^{top}_{(5)}$ | 0.073*** | $swap^{bot}_{(5)}$ | 0.078*** | $swap^{top}_{(30)}$ | 0.076*** | $swap^{bot}_{(30)}$ | 0.131*** |
| $mint^{b,top}_{(5)}$ | −0.013*** | $mint^{b,bot}_{(5)}$ | −0.014** | $mint^{b,top}_{(30)}$ | −0.016** | $mint^{b,bot}_{(30)}$ | 0.005 |
| $mint^{a,top}_{(5)}$ | 0.000 | $mint^{a,bot}_{(5)}$ | −0.002 | $mint^{a,top}_{(30)}$ | 0.003 | $mint^{a,bot}_{(30)}$ | −0.009** |
| $burn^{b,top}_{(5)}$ | 0.012*** | $burn^{b,bot}_{(5)}$ | 0.020*** | $burn^{b,top}_{(30)}$ | 0.016** | $burn^{b,bot}_{(30)}$ | −0.005 |
| $burn^{a,top}_{(5)}$ | −0.002 | $burn^{a,bot}_{(5)}$ | −0.001 | $burn^{a,top}_{(30)}$ | −0.018** | $burn^{a,bot}_{(30)}$ | 0.007* |
| *Panel C: Liquidity concentration classification (60-block horizon)* | | | | | | | |
| $swap_{(5)}$ | 0.073*** | | | $swap_{(30)}$ | 0.082*** | | |
| $mint^{b,nar}_{(5)}$ | −0.013*** | $mint^{b,wid}_{(5)}$ | 1.606 | $mint^{b,nar}_{(30)}$ | −0.004 | $mint^{b,wid}_{(30)}$ | 0.199 |
| $mint^{a,nar}_{(5)}$ | −0.001 | $mint^{a,wid}_{(5)}$ | −0.008 | $mint^{a,nar}_{(30)}$ | 0.001 | $mint^{a,wid}_{(30)}$ | −0.021 |
| $burn^{b,nar}_{(5)}$ | 0.012*** | $burn^{b,wid}_{(5)}$ | −0.820*** | $burn^{b,nar}_{(30)}$ | 0.004 | $burn^{b,wid}_{(30)}$ | −0.628 |
| $burn^{a,nar}_{(5)}$ | −0.002 | $burn^{a,wid}_{(5)}$ | 0.006* | $burn^{a,nar}_{(30)}$ | 0.007** | $burn^{a,wid}_{(30)}$ | −0.023** |

## Table B3: CIRF of DEX orders: Wallet-level classification

This table reports the cumulative impulse response functions (CIRFs) of DEX order flow variables on ETH-USDC returns at a horizon of 60 blocks. We estimate the VAR model in Equation (25), following the methodology of Hasbrouck (1991a). Panel A classifies wallets based on the type of their liquidity provision. We classify wallets as those that engage in mixed liquidity provision, *mix*, if they combine liquidity provision with swap trading within the same block. In contrast, we classify wallets that engage in pure liquidity provision as *pure*. The variable vector is defined in Equation (30). Panel B classifies wallets as repositioning, *repo*, if they have at least one burn followed by a mint within two minutes (equivalent to 10 next blocks). Remaining wallets, who mint or burn on a more permanent basis, are labeled *other*. The variable vector is defined in Equation (31). Panel C classifies wallets based on frequency of liquidity provision. Wallets that submit more than four liquidity orders (mints or burns) over the sample period—the upper quartile of the distribution—are classified as high-frequency ($hfr$). All other wallets are classified as low-frequency ($lfr$). The variable vector is defined in Equation (32).The benchmark return is computed from Binance mid-prices of ETH-USDC. Appendix A provides detailed definitions of all variables used in the analysis. The sample period runs from 06/05/2021 to 12/07/2022. All data are in block frequency. * denotes significance at the 10 per cent level, ** at the 5 per cent level, and *** at the 1 per cent level.

| DEX(5) | | | | DEX(30) | | | |
|---|---|---|---|---|---|---|---|
| *Panel A: Mixed order types vs pure liquidity provision* | | | | | | | |
| $swap^{mix}_{(5)}$ | 0.075*** | $swap^{pure}_{(5)}$ | 0.073*** | $swap^{mix}_{(30)}$ | 0.094*** | $swap^{pure}_{(30)}$ | 0.075*** |
| $mint^{b,mix}_{(5)}$ | −0.014*** | $mint^{b,pure}_{(5)}$ | −0.016 | $mint^{b,mix}_{(30)}$ | −0.005 | $mint^{b,pure}_{(30)}$ | −0.004 |
| $mint^{a,mix}_{(5)}$ | −0.001 | $mint^{a,pure}_{(5)}$ | −0.004 | $mint^{a,mix}_{(30)}$ | −0.001 | $mint^{a,pure}_{(30)}$ | −0.018** |
| $burn^{b,mix}_{(5)}$ | 0.013*** | $burn^{b,pure}_{(5)}$ | 0.051*** | $burn^{b,mix}_{(30)}$ | 0.004 | $burn^{b,pure}_{(30)}$ | −0.071** |
| $burn^{a,mix}_{(5)}$ | −0.001 | $burn^{a,pure}_{(5)}$ | −0.007 | $burn^{a,mix}_{(30)}$ | 0.001 | $burn^{a,pure}_{(30)}$ | 0.000 |
| *Panel B: Liquidity repositioning* | | | | | | | |
| $swap_{(5)}$ | 0.073*** | | | $swap_{(30)}$ | 0.082*** | | |
| $mint^{b,repo}_{(5)}$ | −0.012*** | $mint^{b,other}_{(5)}$ | −0.039** | $mint^{b,repo}_{(30)}$ | −0.008 | $mint^{b,other}_{(30)}$ | 0.009 |
| $mint^{a,repo}_{(5)}$ | −0.006 | $mint^{a,other}_{(5)}$ | 0.000 | $mint^{a,repo}_{(30)}$ | −0.006* | $mint^{a,other}_{(30)}$ | −0.006 |
| $burn^{b,repo}_{(5)}$ | 0.011*** | $burn^{b,other}_{(5)}$ | 0.038** | $burn^{b,repo}_{(30)}$ | 0.008 | $burn^{b,other}_{(30)}$ | −0.021** |
| $burn^{a,repo}_{(5)}$ | 0.003 | $burn^{a,other}_{(5)}$ | −0.002 | $burn^{a,repo}_{(30)}$ | −0.004 | $burn^{a,other}_{(30)}$ | 0.012 |
| *Panel C: Frequency of liquidity orders* | | | | | | | |
| $swap_{(5)}$ | 0.073*** | | | $swap_{(30)}$ | 0.082*** | | |
| $mint^{b,hfr}_{(5)}$ | −0.012*** | $mint^{b,lfr}_{(5)}$ | −0.043* | $mint^{b,hfr}_{(30)}$ | −0.004 | $mint^{b,lfr}_{(30)}$ | 0.010 |
| $mint^{a,hfr}_{(5)}$ | −0.001 | $mint^{a,lfr}_{(5)}$ | 0.007 | $mint^{a,hfr}_{(30)}$ | −0.006* | $mint^{a,lfr}_{(30)}$ | −0.002 |
| $burn^{b,hfr}_{(5)}$ | 0.011*** | $burn^{b,lfr}_{(5)}$ | 0.042* | $burn^{b,hfr}_{(30)}$ | 0.003 | $burn^{b,lfr}_{(30)}$ | −0.019 |
| $burn^{a,hfr}_{(5)}$ | −0.001 | $burn^{a,lfr}_{(5)}$ | −0.005 | $burn^{a,hfr}_{(30)}$ | −0.004 | $burn^{a,lfr}_{(30)}$ | 0.323** |

## Table B4: Arbitrage deviations and CIRF of DEX orders

This table reports the cumulative impulse response function (CIRF) of ETH-USDC returns to order flow shocks on DEX at a 60-block horizon. We estimate the VAR model following the methodology of Hasbrouck (1991a). The CIRF estimates the effect of a 1 million USDC net order flow shock of a given type on the ETH-USDC return. Panel A reports summary statistics of the percentage price difference between DEX and CEX markets, defined as $ppd = 100 \times (prc^{DEX} - prc^{CEX})/prc^{CEX}$, where $prc^{DEX}$ is the observed DEX pool price. Panel B reports the distribution of the absolute percentage price difference $|ppd|$. Panel C presents CIRF estimates conditional on the magnitude of arbitrage opportunities between DEX and CEX markets. Order flow observations are split by $|ppd|$: orders that are submitted when $|ppd|$ is greater than or equal to 36 basis points are classified as *highpd*, corresponding to deviations large enough to exceed median DEX transaction costs (gas, pool fees, and slippage). Orders below this threshold are classified as *lowpd*. Appendix A provides detailed definitions of all variables used in the analysis. The sample period spans from 06/05/2021 to 12/07/2022. All data are sampled at the block level. * denotes significance at the 10 per cent level, ** at the 5 per cent level, and *** at the 1 per cent level.

*Panel A: Distribution of ppd*

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| DEX(5) | 2,753,596 | 0.0042 | 0.4250 | -30.82 | -0.0554 | -0.0023 | 0.0515 | 27.06 |
| DEX(30) | 2,753,596 | 0.0028 | 0.4128 | -31.82 | -0.1681 | -0.0096 | 0.1521 | 12.62 |

*Panel B: Distribution of |ppd|*

| | count | mean | std | 50% | 75% | 95% | 99% | max |
|---|---|---|---|---|---|---|---|---|
| DEX(5) | 2,753,596 | 0.1058 | 0.4117 | 0.0535 | 0.0897 | 0.2858 | 0.9759 | 30.82 |
| DEX(30) | 2,753,596 | 0.1874 | 0.3678 | 0.1604 | 0.2513 | 0.3622 | 0.5386 | 31.82 |

*Panel C: CIRF of DEX orders conditional on arbitrage*

| DEX(5) | | DEX(30) | |
|---|---|---|---|
| $swap^{hpd}_{(5)}$ | 0.088*** | $swap^{hpd}_{(30)}$ | 0.048*** |
| $swap^{lpd}_{(5)}$ | 0.073*** | $swap^{lpd}_{(30)}$ | 0.098*** |
| $mint^{b,hpd}_{(5)}$ | −0.171** | $mint^{b,hpd}_{(30)}$ | 0.024* |
| $mint^{b,lpd}_{(5)}$ | −0.012*** | $mint^{b,lpd}_{(30)}$ | −0.010* |
| $mint^{a,hpd}_{(5)}$ | −0.289** | $mint^{a,hpd}_{(30)}$ | −0.007 |
| $mint^{a,lpd}_{(5)}$ | −0.001 | $mint^{a,lpd}_{(30)}$ | −0.006* |
| $burn^{b,hpd}_{(5)}$ | 0.187** | $burn^{b,hpd}_{(30)}$ | −0.011 |
| $burn^{b,lpd}_{(5)}$ | 0.012*** | $burn^{b,lpd}_{(30)}$ | 0.010* |
| $burn^{a,hpd}_{(5)}$ | 0.015 | $burn^{a,hpd}_{(30)}$ | 0.031 |
| $burn^{a,lpd}_{(5)}$ | −0.001 | $burn^{a,lpd}_{(30)}$ | −0.003 |

# C Alternative VAR Orderings

To assess the robustness of our identification strategy, we explore three alternative recursive orderings of the VAR system, summarized in Table C1. These specifications vary the contemporaneous relationships between DEX and CEX order flow, as well as between market and limit orders on CEX. All models include the same set of endogenous variables defined in equation (26), but differ in the structure imposed on the contemporaneous impact matrix $A$ in equation (25).

- In the first variant ("Ordering 1"), DEX orders are allowed to contemporaneously affect CEX order flow, and CEX market orders can contemporaneously affect limit orders.
- The second ("Ordering 2") removes this link and instead allows CEX limit orders to affect market orders contemporaneously.
- The third ("Ordering 3") combines both, allowing DEX orders to affect CEX orders and limit orders to affect market orders.

Across all three specifications, we maintain the assumption that CEX order flow (market and limit) can contemporaneously affect returns, but not vice versa. In contrast, DEX activity affects returns only with a lag, consistent with the absence of a mechanical pricing link between DEX trades and Binance mid-prices.

## Table C1: CIRF of net orders on returns: Alternative Ordering

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 60 blocks. The methodology is based on Hasbrouck (1991a) with vector of endogenous variables consisting of DEX net swap flows and DEX net liquidity provision (mints and burns), CEX market and limit order flows, and the ETH-USDC return on CEX. The estimates are the effect of a 1 standard deviation shock to a net order flow on the ETH-USDC return. *market* is the market order flow in the CEX market, *swap* is the swap order flow from the corresponding DEX pool, and *limit* is the limit order flow in the CEX market. $mint^b$ ($mint^a$) is the flow of minted liquidity in the corresponding DEX pool within (away from) 5 tick ranges of the current price, and $burn^b$ ($burn^a$) is the flow of burned liquidity within (away from) 5 tick ranges. The benchmark return is based on bid-ask prices of Binance ETH-USDC. The models differ in the structure imposed on the contemporaneous impact matrix $A$ in equation (25). The orderings are as follows. "Ordering 1" – DEX orders are allowed to contemporaneously affect CEX order flow, and CEX market orders can contemporaneously affect limit orders; "Ordering 2" – DEX orders do not affect CEX order flows contemporaneously and CEX limit orders are allowed to affect market orders contemporaneously; "Ordering 3" – DEX orders are allowed to contemporaneously affect CEX order flow and CEX limit orders are allowed to affect market orders contemporaneously. Across all three specifications, we maintain the assumption that CEX order flow (market and limit) can contemporaneously affect returns, but not vice versa. In contrast, DEX activity affects returns only with a lag. The sample period ranges from 06/05/2021 to 12/07/2022. All data are in block 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.

| | Ordering 1 | Ordering 2 | Ordering 3 |
|---|---|---|---|
| *Panel A:* DEX(5) | | | |
| $swap_{(5)}$ | 0.024*** | 0.024*** | 0.024*** |
| $mint^b_{(5)}$ | −0.100*** | −0.096*** | −0.103*** |
| $mint^a_{(5)}$ | −0.001 | −0.001 | −0.001 |
| $burn^b_{(5)}$ | 0.129*** | 0.129*** | 0.129*** |
| $burn^a_{(5)}$ | −0.003 | −0.003 | −0.003 |
| *Panel B:* DEX(30) | | | |
| $swap_{(30)}$ | 0.038*** | 0.038*** | 0.038*** |
| $mint^b_{(30)}$ | −0.011 | −0.011 | −0.011 |
| $mint^a_{(30)}$ | −0.005** | −0.005** | −0.005** |
| $burn^b_{(30)}$ | 0.012 | 0.012 | 0.016 |
| $burn^a_{(30)}$ | 0.000 | 0.000 | 0.000 |
| *Panel C:* CEX | | | |
| *market* | 0.011*** | 0.008*** | 0.008*** |
| *limit* | 0.011*** | 0.012*** | 0.012*** |