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Strategies, Returns, and Skill in Decentralized Finance: Evidence from Automated Market Making

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Evgeny Lyandres and Alexander Zaidelson*

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Abstract

This paper studies liquidity provision in concentrated liquidity pools (Uniswap V3) on the Ethereum blockchain. We show that its core components—non-concentrated liquidity provision and liquidity concentration—generate negative returns on average, but modestly positive returns among frequent liquidity providers (LPs). Performance exhibits persistence and learning and is systematically related to several position and LP characteristics, indicating the presence of skill. Comparing quantitative and discretionary strategies, we find that quantitative LPs significantly underperform discretionary ones. This underperformance is not fully explained by observable strategy differences, and successful quantitative LPs employ strategies similar to those of successful discretionary LPs.

Keywords: Decentralized finance (DeFi), Automated Market Makers (AMM), Concentrated liquidity, Uniswap V3, Quantitative investments

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1. Introduction

In this paper we provide an in-depth empirical analysis of one of the most important strategies in decentralized finance (DeFi)—provision of liquidity into pools on decentralized exchanges (DEXes) that operate via automated market makers (AMMs). Our paper makes four main contributions. First, we compile data on the whole population of close to one million liquidity provisions into thousands of concentrated liquidity pools on the Ethereum blockchain and nearly 50 million trades in these pools. We back out returns of every liquidity position by reverse-engineering the history of all transactions in all liquidity pools.

Concentrated liquidity provision is a combination of several strategies. The core components of liquidity provision are: 1) non-concentrated liquidity provision, which is a combination of a bet on trading volume in the pool and a reverse bet on the volatility of the exchange rate of the pool's assets, and 2) liquidity concentration in a particular range of exchange rates of the pool's assets, which defines the extent to which the position is leveraged. In addition, the performance of a liquidity provision strategy depends on the holding returns of the two pool assets. Finally, provision of liquidity entails transaction (gas) costs.

Conveniently, the profit-and-loss (P&L) of a liquidity position can be expressed as a combination of P&Ls of the aforementioned components. This unique decomposition—that allows an in-depth dive into various components of the liquidity providers' skills—is our paper's second (methodological) contribution.

The third contribution is a detailed analysis of performance of various components of liquidity provision and the relation between the performance of a strategy and each of its components on one hand and several measurable characteristics of the strategy (duration, size, position range), of the liquidity pool (exchange rate volatility), and of the liquidity provider (experience, size, past performance, diversification/specialization), on the other hand. To our knowledge, this is the most detailed, large-scale academic study of the performance of concentrated liquidity provision strategies in DeFi.[1]

Our paper's fourth contribution is to the broader literature examining performance of quantitative investment strategies. Quantitative/systematic/rules-based investment strategies, in contrast with discretionary/fundamental strategies, apply repeatable and data-driven approach to identify investment opportunities across many securities (e.g., AQR (2017)). Quantitative investments appear to constitute an important segment of overall investment landscape: 7% of mutual funds assets under management (AUM) and a quarter of hedge funds' AUM is managed via quantitative strategies (e.g., Abis (2023) and Harvey et al. (2017), respectively). Due to limited reporting requirements, there are two significant problems with examining quantitative strategies in traditional markets. First, quantitative strategies are not easily identifiable.[2] Second, quant strategy performance is difficult to measure. While there are several anecdotal examples of abnormal (positive and negative) performance of quantitative strategies,[3] there is no systematic assessment of the performance of quantitative strategies- either in absolute terms or in relation to discretionary strategies.[4]

In the DeFi market both issues are moot. All strategies by all market participants are observable and decomposable, and the performance of each aspect of a strategy is measurable precisely. An additional advantage of the DeFi setting is that there is significantly less fundamental information in crypto assets than in assets traded in traditional markets, potentially making quantitative strategies especially suitable in the DeFi market. By examining performance of various components

[1]Existing studies of performance of concentrated liquidity provision are Heimbach et al. (2022), Carteo et al. (2023), and Aquilina et al. (2024). The analyses in Carteo et al. (2024) and Carteo et al. (2023) are limited to a single liquidity pool. They find that liquidity providers' returns in this pool are negative on average but stop short of examining profitability of various components of the liquidity provision strategy and their determinants. Heimbach et al. (2022) examine four most active pools and focus on active position management. Aquilina et al. (2024) examine top 250 pools and compare performance of sophisticated versus retail liquidity providers.

[2]Identification of quant strategies is typically based on self-reported investment approach (e.g., Lakonishok and Swaminathan (2010) and McQuiston et al. (2017)) or textual analysis of fund prospectuses (e.g., Abis (2023)) and is quite imprecise. There is little evidence on the types of strategies quantitative investors employ.

[3]A prime example of outstanding performance of quantitative strategies is Jim Simons' Medallion fund that achieved 66% average annual return across several decades.

[4]Lakonishok and Swaminathan (2010), Harvey et al. (2017), McQuiston et al. (2017), and Abis (2023) do not find that quantitative strategies are abnormally profitable. There is some evidence of variation in performance of quantitative strategies across asset classes (see AQR (2017)).

of liquidity provision strategies, this paper sheds light on the types of skill quantitative investors may possess.

Notably, the overall capitalization of the crypto market is around $3 trillion as of December 2025, which is dwarfed by the capitalization of over $125 ($145) trillion of global equity markets (global debt markets). The crypto market's decentralized part (DeFi) is orders of magnitudes smaller yet, with total liquidity of around $120 billion as of December 2025. Yet, for aforementioned reasons, this market presents an excellent laboratory for an in-depth analysis of quantitative strategies' nature and performance.

Our main findings are as follows. First, liquidity provision to concentrated liquidity pools is not a profitable endeavor on average. We estimate that the value-weighted average return to the core components of liquidity provision is -12 basis points per day. The performance of active liquidity providers is better: the combined value-weighted return to the core components of liquidity provision is 2 basis points per day within a subsample of liquidity providers with at least 10 positions.

Second, there is significant persistence in both the overall returns to liquidity provision and its components. One-standard-deviation increase in mean returns to both non-concentrated liquidity provision and liquidity concentration of past positions is associated with 11-15 basis points increases in a position's daily return. In addition, there seems to be learning, as past experience tends to be positively associated with returns to liquidity provision.

Third, turning to the analysis of liquidity providers' strategies, we find that there are several characteristics that distinguish successful liquidity providers from less successful ones. Successful liquidity providers establish positions that are four times smaller on average than those of unsuccessful ones. Successful liquidity providers' positions are also three times shorter and significantly more concentrated. In addition, successful liquidity providers tend to favor higher-volatility pools.

Fourth, and perhaps surprisingly, using a direct method of classification of liquidity providers to quantitative and discretionary that is based on the nature of their interactions with liquidity pools, we find that quant liquidity providers significantly underperform discretionary ones on average. The value-weighted mean return to the core components of liquidity provision is roughly zero for quantitative liquidity providers, whereas it is 25 basic points per day for discretionary ones.

In addition, the fractions of quant liquidity providers belonging to the 1%, 5%, and 10% top performers on the core dimensions of liquidity provision are three to five times lower than the corresponding fractions of discretionary liquidity providers. While part of the quantitative liquidity providers' underperformance can be explained by measurable differences in strategy, liquidity provider, and liquidity pool characteristics, much of the difference in performance persists after controlling for these characteristics.

Fifth, within a subsample of successful liquidity providers, we examine differences between strategies employed by quant and discretionary ones. These differences tend to be insignificant, except for quant liquidity providers being more likely to deploy highly concentrated liquidity to stable coin pools with very low exchange rate volatility.

Both the theoretical and empirical literatures on DeFi and AMM-based DEXes in particular is young but it is expanding rapidly. On the theory side, Aoyagi (2020), Park (2023), Aoyagi and Ito (2025), Lehar and Parlour (2025), and Capponi and Jia (2025) examine the benefits and costs of automatic market making relative to traditional order-book market design. Fabi and Prat (2025) use microeconomic theory to describe the inner workings of AMM-based trading and liquidity provision. Hasbrouck et al. (2022) and Angeris et al. (2020) model optimal fee-setting in an AMM-based liquidity pool. Milionis et al. (2022) and Milionis et al. (2023) focus on losses of liquidity providers to arbitrageurs. Canidio and Fritsch (2023) propose enhancements to AMM-based trading aimed at reducing these losses of liquidity providers. Hasbrouck et al. (2022) develop an options-themed economic model of concentrated liquidity provision. Closest to our setting, Carteo et al. (2024), Carteo et al. (2023), He et al. (2023), and Heimbach et al. (2022) model optimal liquidity provision into concentrated liquidity pools.

On the empirical side, Lehar and Parlour (2025) compare AMM-based trading with centralized limit-order book and show conditions under which the AMM design dominates a limit-order market. Barbon and Ranaldo (2024) and Capponi et al. (2025) examine the relative efficiency of DEX pricing and price discovery. Lehar et al. (2023) and Heimbach et al. (2022) analyze behavior of various types of liquidity providers in AMMs. Zhu et al. (2025) examine factors affecting liquidity in pools, while Caparros et al. (2023) provide empirical evidence of reallocation of liquidity across pools. Adams and Liao (2022) compare returns to passive liquidity provision in concentrated versus non-concentrated liquidity pools. Capponi et al. (2025) and Wan and Adams (2022) examine the phenomenon of "just-in-time (JIT)" liquidity in concentrated pools. Malinova and Park (2024) and Foley et al. (2023) calibrate AMM-based trading technology to traditional (non-crypto) assets and show that AMM-based trading could enhance market depth for small, high-volume, low-volatility assets. Perhaps closest to our study, Heimbach et al. (2022) analyze four liquidity pools and conclude that significant returns to liquidity provision are obtained only via active management of liquidity in volatile pools, and Aquilina et al. (2024) examine performance of sophisticated versus retail liquidity providers in 250 most active concentrated liquidity pools and find that sophistication of liquidity providers is positively related to profits from liquidity provision.

We complement this evidence along several dimensions. First, we decompose the liquidity provision strategy into several skills that liquidity providers may possess, focusing on the core components of liquidity provision: the choice of pools to which to provide liquidity and the choice of the concentration of a liquidity position. We find that liquidity provision is not a profitable endeavor on average. Second, we analyze position-level, pool-level, and liquidity-provider-level determinants of performance of liquidity positions. Third, we compute performance of various components of strategies employed by quantitative and discretionary liquidity providers, where the classification is based on the nature of interactions between liquidity providers and liquidity pools. We find that quantitative liquidity providers significantly underperform discretionary ones, and that this underperformance is largely unrelated to measurable characteristics of liquidity provision strategies and of liquidity providers.

The remainder of the paper proceeds as follows. In Section 2, we describe the setting for our analysis, providing an overview of decentralized exchanges, constant product automated market making, and concentrated liquidity provision. Section 3 discusses our data acquisition strategy, computation of returns to liquidity provision and their decomposition. In Section 3, we also discuss summary statistics at the levels of: a) liquidity pool, b) liquidity position, and c) liquidity provider. Section 4 examines the performance of liquidity provision strategies and their components, and compares the characteristics of strategies of successful and unsuccessful liquidity providers. Section 5 discusses the identification of quantitative liquidity providers, examines their relative and absolute performance, and studies the determinants of this performance. Section 6 concludes.

2. Setting

2.1. Decentralized exchanges: Overview

The setting of our analysis is decentralized exchanges of crypto assets (DEXes). Traditional (centralized) crypto exchanges (CEXes), such as Binance, Coinbase, and Kraken, among over 250 spot crypto exchanges as of November 2025,[5] rely on order book technology, akin to that employed by stock exchanges. DEXes, facilitating trades in crypto assets on public blockchains, largely rely on an entirely different type of trading technology, called "Automated Market Making (AMM)". This alternative trading technology has become possible thanks to two characteristics of public blockchains. The first is the transparency of all transactions on a blockchain. The second is the ability of smart contracts—computer programs that operate on the blockchain—to facilitate transactions that are recorded directly on the blockchain ("on-chain") without requiring custody of user funds at any point by intermediaries, such as CEXes.

AMM-based trading, first introduced to the crypto trading market by Bancor and Uniswap

[5]See leading crypto data providers, such as Coinmarketcap (www.coinmarketcap.com) and Coingecko (www.coingecko.com).

protocols in 2017-2018,[6] gained popularity during the summer of 2020, often referred to as the "decentralized finance (DeFi) Summer". The popularity of AMM-based trading may be attributed to three main elements. The first is the problematic nature of CEXes that involves centralized custody of users' funds in a largely unregulated environment, as was clearly illustrated by the monstrous collapse in November 2022 of FTX—the third largest crypto exchange at the time. Second, unregulated crypto exchanges are plagued by fake trading, hurting individual traders.[7] Third, AMM-based trading reduces the extent of adverse selection that noise traders are exposed to, as a counterparty to any AMM-based trade is a blind pool of liquidity, as opposed to a (potentially better informed) trader.

2.2. Constant product automated market making

Automated market making allows trading (swapping) two assets using a "liquidity pool" containing these assets.[8] (In what follows, we will use the terms "trade" and "swap" interchangeably.) Once liquidity has been deposited into a pool, a trader can withdraw any amount of one of the pool's assets, "asset out" (up to the total amount of that asset in the pool) by depositing a deterministic amount of the other asset ("asset in") into the pool. The "amount out" is a function of just two arguments—the amounts of the two assets in the pool at the time of the trade and the "amount in". In other words, the outcome of the trade is a function of only the trade size and the state of liquidity in the pool at the time of the trade and is never a function of a trader's identity or type.

The economics of liquidity provision to AMM-based DEXes consists of the following elements. Liquidity providers (LPs) to a pool receive fractional trading fees for every swap involving the assets in the pool in either direction. Any time an LP deposits assets into a pool ("establishes a new

[6] See Hertzog et al. (2017) and Adams et al. (2020) for Bancor and Uniswap white papers, respectively.

[7] See Aloosh and Li (2024), Cong et al. (2023), and Amiram et al. (2024) for analyses of fake (wash) trading on CEXes.

[8] Two-asset liquidity pool design is the most popular implementation of the AMM trading technology. However, protocols such as Balancer and Curve have developed AMM-based trading employing liquidity pools consisting of multiple assets. See Martinelli and Mushegian (2019) and Egorov (2019) for Balancer and Curve white papers, respectively.

liquidity position"), she receives newly minted "liquidity pool (LP) tokens", in proportion to the newly established position relative to overall pool size. LP tokens constitute an on-chain, verifiable representation of every liquidity position. A LP to a pool is able to withdraw her liquidity from the pool partially or fully at any time by sending her LP tokens to the smart contract governing the pool, i.e "burning" them.

Liquidity provision is not a risk-free proposition. In addition to the usual risk of holding the two assets deposited into the pool, LPs are subject to the "impermanent loss" risk. Impermanent loss occurs whenever an arbitrageur makes a profitable trade in the pool in response to exogenous changes in the two assets' relative values. In other words, impermanent loss is a loss compared to a situation in which there were no trades in the pool following exogenous changes in prices of the pool's assets. Impermanent loss may be reversed if/when the exchange rate of the two assets returns to the one at which the liquidity was provided. However, impermanent loss becomes permanent if the exchange rate at the time of liquidity withdrawal by an LP differs from the exchange rate at the time of the establishment of her liquidity position. Impermanent loss is a one-sided risk—i.e. expected impermanent loss is always positive and is increasing in the volatility of the exchange rate between the pool's assets.[9]

Trading curves in AMM pools take various configurations. The earliest and still the most common type of AMM is "constant product market making", in which trading in assets X and Y is defined by a constant:[10]

$$X \times Y = K. \tag{1}$$

[9]See Milionis et al. (2022) and Deng et al. (2023) for theoretical analyses of impermanent loss and a related concept of "loss-versus-rebalancing" in liquidity provision. See Fabi and Prat (2025) for a theoretical analysis of automated market making.

[10]The curvature of the trading function involves the following tradeoff. On the one hand, the flatter the trading curve the lower the trading costs due to lower price impact. On the other hand, the flatter the trading curve the larger the impermanent loss to liquidity providers, as a flatter curve leads to larger arbitrage trades and higher arbitrage profits in response to exogenous changes in prices of pool's assets, requiring higher pool fees to compensate LPs for the higher impermanent loss risk. Optimal trading curve balances these two considerations. While constant product curve dominates trading on DEXes, other curves, such as the combination of constant product and constant sum, introduced by Curve protocol, $X \times Y + \xi \times (X + Y) = K$, which is flatter around the spot exchange rate, are also being used. See Capponi and Jia (2025) and Angeris et al. (2020) for models of optimal design of trading curves on an AMM.

Consider an example. Assume that there are two LPs who deposit liquidity into a pool of assets X and Y at 1:2 exchange rate.[11] Assume that the first (second) LP deposits 50 (100) and 100 (200) units of assets X and Y into the pool, respectively, resulting in the following pool composition: $X = 150$ and $Y = 300$. The two LPs' positions and the resulting trading curve in the pool are depicted in Figure 1a.

[Figure 1 here]

Under constant product trading curve, the amount of asset Y, ΔY, that a trader receives from the pool in return to sending (selling) ΔX units of asset X to the pool equals

$$\Delta Y = Y - \frac{X \times Y}{X + \Delta X(1-f)} = \frac{\Delta X(1-f) \times Y}{X + \Delta X(1-f)} \tag{2}$$

where f is the pool's fractional trading fee. Assume that in our example, a trader wishes to sell 15 units of asset X, i.e. $\Delta X = 15$. Assume also that the trading fee in the pool is 0.003, i.e. 0.3% of an asset sent to the pool stays in the pool, whereas the rest is exchanged for the other asset (asset out). The resulting amount of asset out is: $\Delta Y = \frac{15\times0.997\times300}{150+15\times0.997} = 27.198$. This trade is illustrated in Figure 1b, where pool composition moves along the trading curve.

2.3. Concentrated liquidity

A problem with the constant-product-based liquidity provision, sometimes referred to as "Uniswap V2" or simply "V2", as most constant-product pools are governed by either the second version of open-source smart contracts deployed by the Uniswap protocol[12]—an undisputed leader in the DEX market—or their clones ("forks"), is that most of the liquidity provided to pools is idle, resulting in relatively low capital efficiency. Consider the example illustrated in Figure 1. As a rule of thumb,

[11] The first liquidity position in a pool is typically established at the "correct" exchange rate, corresponding to either an exogenously given exchange rate on another DEX or CEX or the exchange rate based on the market's assessment of the two assets' valuations. Providing liquidity at any other rate would lead to an immediate arbitrage opportunity and result in impermanent loss to liquidity providers. Any subsequent deposit/withdrawal of liquidity occurs at the exchange rate in the pool at the time of liquidity provision/withdrawal.

[12] See `https://defillama.com/protocol/uniswap`

the price impact of a trade roughly equals the ratio of trade size to the pool's liquidity. Thus, trades making use of a large fraction of the pool's liquidity rarely occur.

In May 2021, Uniswap deployed revolutionary new smart contracts allowing for "concentrated liquidity provision", usually referred to as "Uniswap V3" or "V3".[13] The idea is that optimal liquidity would not be distributed evenly along the full trading curve, as in Figure 1. Instead, optimal liquidity allocation would be characterized by higher liquidity deployed to the portion of the trading curve in which the majority of trades occur, i.e. around the spot exchange rate.

More formally, when providing concentrated liquidity, an LP sets the lower and upper bounds of the exchange rate between which her liquidity is concentrated. As long as the exchange rate in the pool remains between the two bounds, the LP's effective ("virtual") liquidity is larger than her actual liquidity deployed to the pool. This larger de-facto liquidity results in LP's larger share of the pool and higher fraction of the pool's trading fees. By the time the exchange rate leaves these predetermined bounds, the entire LP's liquidity has been swapped to the one of the two assets (the one that has depreciated relative to the other asset) and becomes idle until the exchange rate returns to the range of the liquidity position or until the liquidity position is withdrawn/rebalanced.

Consider the following modification of the example above. Assume that the second LP continues to provide standard, non-concentrated liquidity of $X = 100$ and $Y = 200$, illustrated by in Figure 2a. A non-concentrated liquidity provision into a concentrated liquidity pool is equivalent to setting the lower and upper exchange rate bounds at 0 and ∞, respectively.

[Figure 2 here]

The first LP decides to concentrate her liquidity in a way that would result in five-fold concentrated liquidity within a certain range and idle liquidity outside that range. The first LP's real liquidity is still $X = 50$, $Y = 100$, resulting in $K = 50 \times 100 = 5,000$. To achieve the desired level of five-fold liquidity concentration, define virtual liquidity, $K^* = K \times 5^2 = 125,000$. Denote by

[13] See Adams et al. (2021) for detailed explanation of Uniswap V3 AMM as well as Barbon and Ranaldo (2024) for a discussion of differences between Uniswap V2 and V3 AMM.

$p_b = \left(\frac{Y}{X}\right)_b > p_a = \left(\frac{Y}{X}\right)_a$ the upper and lower bounds (exchange rates) of virtual liquidity provision. Virtual concentrated liquidity is given by

$$(X + (\frac{K^*}{p_b})^{0.5}) \times (Y + (K^* \times p_a)^{0.5}) = K^*. \quad (3)$$

Assume that the chosen upper bound of the exchange rate is $p_b = 2.5$. Plugging $X = 50$, $Y = 100$, and $K^* = 125,000$ into (3) results in lower bound, p_a, of 1.228, i.e. five-fold concentrated liquidity is possible in the range of exchange rates $(1.228, 2.5)$. The first LP's resulting virtual trading curve is depicted by the upper solid curve in the range $(1.228, 2.5)$, which is the linear transposition of the real (lower solid) trading curve that fits the chosen exchange rate bounds. Note that the pool's resulting trading curve is discontinuous, due to the fact that the first LP's liquidity is active within the exchange rate bounds and is idle outside of the bounds.

Assume now that a trader swaps 15 units of asset X for Y in the concentrated liquidity pool. Assume temporarily that the pool's post-trade exchange rate would still be inside the first LP's concentrated liquidity bounds—a conjecture we will verify. This trade, illustrated by the movement of the pool's liquidity from the green dot to the black one along the green trading curve in Figure 2b, results in the following amount of asset Y received by the trader: $\Delta Y = \frac{15 \times 0.997 \times 700}{350 + 15 \times 0.997} = 28.684$. Note that trading occurs over the virtual trading curve: $(100+50\times5)\times(200+100\times5) = 245,000$ instead of the real trading curve in the non-concentrated liquidity example: $(100+50)\times(200+100) = 45,000$. The resulting price impact of the trade is 4.09%, compared with the price impact of 9.04% in the non-concentrated liquidity pool. The post-trade exchange rate in the pool, $\frac{300-28.684}{150+15} = 1.644$ is within the concentrated liquidity bounds, consistent with the conjecture that the trade is possible along the virtual trading curve.

In reality, the exchange rate plane is divided into "ticks" using a fine grid,[14] and virtual trading curve within each tick is a combination of the virtual liquidity of all non-idle liquidity positions in

[14]There are 1,774,544 ticks. "Tick spacing", i.e. the set of ticks that can serve as lower upper bounds of liquidity ranges, depends on pool fee. In pools with fee equal to 0.01% (0.05%, 0.3%, 1%) tick spacing equals 1 (10, 60, 200) ticks.

that tick. A trade can occur within a tick or across multiple ticks. Within each tick, the proportion of trades served by each of the liquidity positions active in this tick as well as the fees accruing to each liquidity position are proportional to the virtual liquidity positions within the tick.

3. Data

3.1. Data acquisition

3.1.1. Data sources

Our primary data consist of all liquidity provision events, liquidity withdrawals, and trades in all concentrated liquidity ("V3") pools on Uniswap protocol and its clones, which copied ("forked") Uniswap V3 smart contracts on the Ethereum blockchain, which is the first blockchain enabling smart contracts and remains responsible for over half of all DeFi activity.[15] The sample period begins on May 6, 2021—the date of establishment of the first concentrated liquidity pool on Uniswap, and ends on December 31, 2024. These data are vast, encompassing over 22,000 liquidity pools, over two million liquidity provision and withdrawal events, and nearly 50 million trades.

We begin with blockchain data made publicly available by Google's BigQuery Public Datasets on Google Cloud.[16] The data are maintained by the Blockchain ETL project.[17] The data are organized in several tables on Google BigQuery, contain the full history of the Ethereum blockchain, and are being updated in near-real time. In particular, the two main sets of tables that we use are the "event logs table" and the "transactions table".

Ethereum event logs table (`bigquery-public-data.crypto_ethereum.logs`) contains data records generated by smart contracts during transactions. They are emitted by smart contracts and are stored on-chain.[18] The data in event logs are organized by topics—an array of up to four

[15] See `https://defillama.com/chain/ethereum`
[16] See `https://cloud.google.com/bigquery/public-data`
[17] See `https://github.com/blockchain-etl`
[18] The logs table contains over 5 billion rows. The variables are: block in which a transaction occurred and its timestamp, the transaction's position within a block, transaction hash, block hash, the address of the contract that issues the log, the transaction's "topic", and additional multiple 32-bytes non-indexed arguments of the log.

hexadecimal strings used to store event arguments that are marked with an indexed keyword.

The transactions table (`bigquery-public-data.crypto_ethereum.transactions`) contains all transactions (nearly 3 billion), and provides a block identifier used to obtain associated block-specific information associated with each transaction. The transactions table also includes information on gas usage, which the logs table lacks. In addition, the transactions table identifies transactions that failed and did not end up being recorded on the blockchain—which we exclude from eventual dataset.

Finally, we use metadata tables extracted from Etherscan, the most popular Ethereum blockchain explorer:[19] `bigquery-public-data.crypto_ethereum.pools`—a table containing information about liquidity pools, their tokens and fees, and `bigquery-public-data.crypto_ethereum.Contract_info`—a table containing metadata for Ethereum contracts, such as the contract's name, the name of the source file, and contract class.

3.1.2. Identifying relevant transactions

To build a dataset of liquidity provisions, we extract all relevant data pertaining to Uniswap V3 Concentrated Liquidity AMM Pool contract. The relevant events are: Swap (a trade involving two assets), Mint (establishing or extending a liquidity position), and Burn (removing a liquidity position).[20] In addition, we use the following events issued by Uniswap NonfungiblePositionsManager: Transfer (a trade duplicate record) and DecreaseLiquidity (reduction in the size of a liquidity position).[21] These events allow identifying token ID—a non-funglible token (NFT) associated with

[19] See `https://etherescan.io`

[20] For Swap events, the signature is swap(address sender, address recipient, int256 amount0, int256 amount1, uint160 sqrtPriceX96, uint128 liquidity, int24 tick) and the signature hash is: `0xc42079f94a6350d7e6235f29174924f928cc2ac818eb64fed8004e115fbcca67`. For Mint events, the signature is mint(address sender, address owner, int24 tickLower, int24 tickUpper, uint128 amount, uint256 amount0, uint256 amount1) and the signature hash is: `0x7a53080ba414158be7ec69b987b5fb7d07dee101fe85488f0853ae16239d0bde`. For Burn events, the signature is burn(address owner, int24 tickLower, int24 tickUpper, uint128 amount, uint256 amount0, uint256 amount1) and the signature hash is: `0x0c396cd989a39f4459b5fa1aed6a9a8dcdbc45908acfd67e028cd568da98982c`.

[21] For Transfer events, the signature is transfer(address from, address to, uint256 tokenId) and the signature hash is: `0xddf252ad1be2c89b69c2b068fc378daa952ba7f163c4a11628f55a4df523b3ef`. For DecreaseLiquidity events, the signature is DecreaseLiquidity(uint256 indexed tokenId, uint128 liquidity, uint256 amount0, uint256 amount1) and the signature hash is: `0x26f6a048ee9138f2c0ce266f322cb99228e8d619ae2bff30c67f8dcf9d2377b4`.

the liquidity position's establishment and/or (partial) termination. By matching these tables with their respective LP events, we are able to attach token ID to a significant fraction of the events.[22] Overall, combining the data from the five aforementioned events enables us to obtain the full picture of liquidity provisions and withdrawals as well as trades in all pools of Uniswap V3 and its forks on the Ethereum blockchain.

3.2. Computing changes to position composition and accumulated fees

Our goal is to compute returns for every liquidity position. Unlike Uniswap V2, in which fee accrual is passive and automatic—each liquidity position grows by the amount of the proportional share of the fee after each served swap, in Uniswap V3 fees are not added back to the pool reserves. Instead, they accrue separately in the smart contract, tracked for each position, and LPs must actively claim (collect) their fees. Thus, it is impossible to rely on claims of accrued fees when computing returns to a liquidity position, as these claims happen at random times, often before a position is closed, and it is difficult to link a fee claim transaction to a closed liquidity position.

In order to compute returns for every closed position, we reproduce the Uniswap V3 smart contracts and re-run all transactions (liquidity provisions ("mints"), withdrawals ("burns"), and swaps) in every pool since its inception.[23] For every mint and burn transaction, we update the set of liquidity positions active in every tick. For every swap and every tick in which the swap is executed, we compute the proportion of the swap executed using liquidity of each position active in the tick, and the resulting a) changes in each position's virtual and real reserves of the two assets and b) fees accruing to each position. We begin by computing whether the trade can be executed within a current tick (i.e the tick in which the previous swap finished or the tick defined by the first liquidity position in a currently empty pool). If not, we move to the next tick, and repeat until the

[22]The reason that token ID cannot be attached to all events is that token ID values are only logged when the position is opened or closed through Uniswap's Nonfungible Positions Manager, i.e. when LP actions are performed through the Uniswap frontend. LP actions performed by interacting with the pool contract via other, proprietary position managers do not have logged values of token ID.

[23]This exercise is similar to that performed in Aquilina et al. (2024), who re-run transactions in top-250 pools on Uniswap V3.

trade is fully executed. We record the overall fees (in one of the two assets) accruing to each active liquidity position after each swap. We then proceed to the next event and repeat these steps until we reach either the last transaction in the pool or the end of the sample period.

For this process to yield precise calculations of returns to each liquidity position, it is crucial that within our reverse-engineering exercise of the outcome of all transactions in a pool a) no transactions are missed and all transactions are executed in the correct order (across blocks and within each block), and b) the computation of the virtual liquidity of every position in every tick and the resulting changes in each active position in every tick following a trade are identical to the changes that were recorded on the blockchain in reality. The reason why it is crucial to not miss a single transaction is that differences in actual liquidity positions and our estimated ones due to missing/incorrect transactions would propagate to all future transactions in the pool, resulting in incorrect allocation of trades to liquidity positions, which would lead to an incorrect allocation of transaction fees and to incorrect liquidity position return calculations.

While intermediate changes in each liquidity position following a trade are unobservable to us, we verify our calculations in two ways. First, after every swap, we verify that the calculated price at which the swap finished is identical to the one present in the event log. Second, for every burn, and for every mint in which the position range is identical to the range of an existing position set up by the same blockchain address, we compare the ratio of the two assets in the mint or burn to the calculated ratio of the two assets in the existing position and verify that these ratios are identical. These two checks ensure that the calculated shares of each swap served by each position in every tick and the resulting accumulation of fees to each position are identical to the ones that occurred in reality.

Associating each closure of a liquidity position (burn) with its opening (mint) is not always trivial. In most cases, matching can be done via the associated position ID. When position ID is absent, in many cases matching can be done by a combination of the blockchain address of position deployer and the range of the position. However, sometimes the assets in a closed position are withdrawn to an address that is different from the address from which the position was opened. In cases in which there are multiple open positions in the same range, it is impossible to associate such burns with particular mints. In such cases, we assume that all unmatched mints and burns happened from one wallet, and we exclude these transactions from the final analysis (although we include them while reverse-engineering the pool's history).

3.3. Estimating asset prices at initiation and termination of the position

Computing liquidity position returns and their various components requires prices of the two assets in the pool to which liquidity is provided at a time when the position is initiated and when it is terminated. Pools can be split into two types. The first type are pools that include at least one of the four most popular assets, in which trading is very liquid, and whose prices are updated frequently as a result: two major stable coins (`USDC` and `USDT`), Wrapped Ether—the ERC20-compatible version of Ether (`ETH`), the currency that powers the Ethereum blockchain (`WETH`), and Wrapped Bitcoin, the representation on the Ethereum blockchain of Bitcoin, `BTC`, the crypto currency with the largest market cap (`WBTC`).[24,25] The second type of pools includes those in which neither of the two pool's assets belongs to the set of the four aforementioned assets.

To ensure that we use the most up-to-date and unbiased prices in the estimation of liquidity position returns, we focus on the 4,656 pools of the first type. Notably, such pools are responsible for over 85% of all liquidity positions. We estimate asset prices in the following way. We begin by estimating prices of a pool's asset that belongs to the {`USDC`, `USDT`, `WETH`, `WBTC`} set (there can be one or two such assets in the pool). Unlike the most actively used stable coin in DeFi—`USDC`, which had a significant depegging event in March 2023, `USDT` has never had a depegging event (i.e.

[24] Most crypto assets on the Ethereum blockchain are combatible with the ERC20 standard. `ETH` was created before ERC20 was introduced. Thus, to be part of the Ethereum decentralized finance ecosystem, `WETH`, an ERC20-compatible representation of `ETH` was created. `BTC` resides outside of the Ethereum blockchain (on the Bitcoin blockchain); `WBTC` is the "bridged version" of `BTC` on Ethereum.

[25] The addresses on the Ethereum blockchain of `USDC`, `USDT`, `WETH`, and `WBTC` are `0xa0b86991c6218b36c1d19d4a2e9eb0ce3606eb48`, `0xdac17f958d2ee523a2206206994597c13d831ec7`, `0xc02aaa39b223fe8d0a0e5c4f27ead9083c756cc2`, and `0x2260fac5e5542a773aa44fbcfedf7c193bc2c599`, respectively.

its price has never deviated from $US1 in an economically meaningful way) throughout our sample period. Thus, `USDT` acts as a numeraire, and its value is assumed to be $US1 at all points in time.

`USDC` price at any point in time is defined as either a) the `USDC/USDT` exchange rate at the end of the most recent trade in the most active `USDC-USDT` pool,[26] or b) the product of the most recent `WETH/USDT` exchange rate in the `USDT-WETH` pool[27] and the most recent `USDC/WETH` exchange rate in the `USDC-WETH` pool,[28] depending on which of the two prices can be computed most recently.

Similarly, `WETH` price is computed as either the most recent `WETH/USDT` exchange rate in the `USDT-WETH` pool, or as the product of the `WETH-USDC` exchange rate in the `USDC/WETH` pool and the `USDC/USDT` exchange rate in the `USDC-USTD` pool. Finally, `WBTC` price is computed as either a) the most recent `WBTC/WETH` exchange rate in the `WBTC-WETH` pool[29] and the exchange rate in the `USDT-WETH` pool) or b) the product of the most recent `WBTC/WETH` exchange rate and the most recent `WETH/USDC` exchange rate and the most recent `USDC/USDT` exchange rate. In case the second asset in the pool does not belong to the {`USDC`, `USDT`, `WETH`, `WBTC`} set, its price is computed based on the most recent swap in the pool, i.e it is the most recent price of the first asset times the exchange rate at which the most recent swap in the pool finished.

Notably, all the qualitative results reported below are robust to including pools for which we cannot perform the algorithm above to obtain up-to-date prices (i.e. pools that do not feature `USDC`, `USDT`, `WETH` and `WBTC`). For these pools, we obtain daily asset prices from Coingecko,[30] one of the largest crypto data aggregators. However, using daily prices is not optimal for two reasons. First, Coingecko (or any other such aggregator) is not transparent regarding the way it aggregates prices from various centralized and decentralized trading venues. Second, as discussed below, many liquidity provision strategies in our sample have short durations, thus using daily prices may lead

[26] The pool's address is `0x3416cf6c708da44db2624d63ea0aaef7113527c6`; it has the fifth-largest number of swaps—over 1 million throughout our sample period.

[27] The pool's address is `0x11b815efb8f581194ae79006d24e0d814b7697f6`; it is the second-most-active pool with over 4 million swaps.

[28] The pool's address is `0x88e6a0c2ddd26feeb64f039a2c41296fcb3f5640`; it is the most active pool with close to 8 million swaps.

[29] The pool's address is `0x4585fe77225b41b697c938b018e2ac67ac5a20c0`; it is the third-most-active pool with roughly 1.5 million swaps

[30] See `https://coingecko.com`.

to inaccurate strategy return estimations. For these reasons, in the main analysis we focus on the subset of 4,656 pools for which we can compute on-chain Defi pool-based prices.

3.4. Return decomposition

The overall return of a concentrated liquidity position i in pool X, Y, initiated (minted) at time t_0 corresponding to block b_0 and terminated (burned) at time t_1 corresponding to block b_1 is:

$$R^i(t_0, t_1) \equiv R = \frac{(P_1^X x_1 + P_1^Y y_1) + \sum_{b=b_0}^{b_1} f_b - (g_0 + g_1)}{P_0^X x_0 + P_0^Y y_0} - 1, \tag{4}$$

where P_0^X, P_0^Y, P_1^X, and P_1^Y are prices of assets X and Y at the time of initiation (termination) of liquidity position i, $x_0^i \equiv x_0$, $y_0^i \equiv y_0$, ($x_1^i \equiv x_1$, $y_1^i \equiv y_1$) are amounts of assets x and y deposited into (withdrawn from) the pool, f_b is the fee accruing to position i during block b, and $g_0^i \equiv g_0$ and $g_1^i \equiv g_0$ are gas costs paid during position initiation (termination).

Sometimes, the return to liquidity provision includes another component that we cannot track. Specifically, it is common for issuers of low-cap tokens, representing new/upcoming projects, to contract with professional market makers to supply liquidity into newly created pools involving these tokens. As these pools are expected to be characterized by thin trading, at least initially, trading fees are unlikely to compensate liquidity providers for expected impermanent loss. Thus, token issuers tend to reward liquidity providers by allocating them their newly-issued tokens as an extra compensation. Unfortunately, it is nearly impossible to track these allocations and associate them with particular liquidity positions. Thus, the overall returns to liquidity provision reported in our study, and especially those to liquidity positions established by professional market makers, are likely understated. Importantly, however, all the qualitative results are robust to examining only the top 50 pools (by the number of swaps), involving established tokens that are unlikely to involve compensation to professional market makers. These pools represent over 75% of all liquidity positions.

In the following subsections, we describe the decomposition of the return in (4).

3.4.1. *Holding return*

Holding return, or return from investing (holding) x_0 units of asset X and y_0 units of asset Y equals:

$$R^{XY,i}(t_0,t_1) \equiv R^{XY} = \frac{P_1^X x_0 + P_1^Y y_0}{P_0^X x_0 + P_0^Y y_0} - 1. \tag{5}$$

As this return originates from investing in ("picking") the two assets, we sometimes refer to it as the "asset picking" component of liquidity provision.

3.4.2. *Impermanent loss*

Impermanent loss, which is the return due to the change in a position's weights as a result of trading, relative to holding return, equals:

$$IL^{XY,i} \equiv IL^i = \frac{(P_1^X x_1 + P_1^Y y_1) - (P_1^X x_0 + P_1^Y y_0)}{P_0^X x_0 + P_0^Y y_0}. \tag{6}$$

Impermanent loss can be further decomposed into two parts. The first is the impermanent loss of a (hypothetical) non-concentrated liquidity position initiated and terminated at the same times as the actual position. The second part is the impermanent loss due to liquidity concentration.

In a non-concentrated liquidity pool, in equilibrium

$$\frac{x_1}{y_1} = \frac{P_1^Y}{P_1^X} \text{ and } \frac{x_0}{y_0} = \frac{P_0^Y}{P_0^X}. \tag{7}$$

In addition, under the constant product formula, $x_0 y_0 = x_1 y_1 = k$, hence

$$x_1 = x_0 \frac{P_1^Y}{P_0^Y}\frac{P_0^X}{P_1^X} \text{ and } y_1 = y_0 \frac{P_1^X}{P_0^X}\frac{P_0^Y}{P_1^Y}. \tag{8}$$

Plugging (8) into (6) results in

$$NCLIL = \frac{2\sqrt{P_{X0}\, P_{X1}\, P_{Y0}\, P_{Y1}}}{P_{X0}P_{Y1} + P_{X1}P_{Y0}} - 1, \tag{9}$$

The part of the impermanent loss that is due to the concentration of liquidity position is, thus:

$$CLIL = IL - NCLIL. \tag{10}$$

In the absence of limits to arbitrage, the theoretical non-concentrated-liquidity impermanent loss, $NCLIL$ in (9), is always lower in absolute value than the total impermanent loss, IL in (6). However, in reality this inequality does not always hold. In cases in which it does not hold, we make the following two adjustments. First, we assume that $NCLIL = IL$. Second, we subtract $NCLIL - IL$ from the holding return, R^{XY}. In other words, we adjust both the impermanent loss and the holding return in a way that keeps the total return of the liquidity position constant but conforms to the constraint that impermanent loss associated with liquidity concentration is nonnegative.[31]

3.4.3. Fee rate

The fee rate, which is the ratio of trading fees accruing to a liquidity position relative to the value of the position at its initiation, equals:

$$\phi^{XY,i} \equiv \phi^{i} = \frac{\sum_{b=b_0}^{b_1} f_b}{P_0^X x_0 + P_0^Y y_0}. \tag{11}$$

The fee rate can be further decomposed into two parts. The first is the fee rate that would accrue to a (hypothetical) non-concentrated liquidity position. The ratio of this hypothetical non-concentrated fee rate to the actual one equals the ratio of hypothetical non-concentrated impermanent loss to

[31] The inequality $|NCLIL - IL| \leq 0$ is violated in less than 5% of cases. The results are robust to excluding these observations from the analysis.

the realized impermanent loss:

$$NCL\phi^{XY,i} \equiv NCL\phi^{i} = \frac{NCLIL}{IL}\phi^{i}. \tag{12}$$

The second part of the fee rate is due to liquidity concentration:

$$CL\phi = \phi - NCL\phi. \tag{13}$$

3.4.4. Gas cost rate

"Gas" costs are fees required for recording blockchain transactions and constitute transaction costs in the context of DeFi. Records of transactions and their outcomes on a public decentralized blockchain, such as Ethereum, are maintained and updated by a set of decentralized blockchain validators, while ensuring consensus of records across validators. Gas fees compensate the validators for these services.

The total gas cost for a transaction is the product of two components. The first is the amount of gas used, which reflects the computational work required for executing a transaction (and is constant for all transactions of a given type using a given smart contract). The second component is the gas price, which is the price of one unit of gas. The gas price is market-driven and fluctuates with the demand for executing and recording transactions on the blockchain—rising during network congestion and falling when activity is low. Gas cost rate is the ratio of the combined transaction costs paid during the initiation and termination of a position to the position's initiation value:

$$G^{i} \equiv G = -\frac{g_0 + g_1}{P_0^X x_0 + P_0^Y y_0}. \tag{14}$$

Some liquidity positions involve extensions of existing positions, whereas some others involve partial liquidity withdrawals. In such cases, we assume that a liquidity position is closed and a new one (a larger one in the case of extensions and a smaller one in the case of partial withdrawals) is established. In both cases, the relevant gas costs are allocated equally to the old and the newly recorded position.

3.5. Liquidity providers' skill components

For the purpose of analyzing components of liquidity providers' skill, the return decomposition above can be reorganized as follows:

1. Pool choice, $NCL\phi + NCLIL$';
2. Liquidity concentration, $CL\phi + CLIL$;
3. Asset choice, R^{XY};
4. Transaction costs: G.

In the empirical analysis, we will focus on examining these skill components and their determinants, while focusing on the first two components, which are at the core of liquidity provision into concentrated liquidity pools.

3.6. Summary statistics

3.6.1. Pool-level summary statistics

Our sample, of all liquidity pools governed by Uniswap V3 smart contracts, which have a least one liquidity provision event and one swap, and features at least one of the assets in the set (`USTD`, `USTC`, `WETH`, and `WBTC`) comprises 4,656 pools. The summary statistics at the level of the liquidity pool are presented in Table 1.

Table 1 here

The proportional swap fee that traders are charged for swaps ranges from 1 to 100 basis points.[32] Pools in which exchange rate volatility is high tend to charge higher fees to compensate for a larger

[32]In Uniswap V3, possible fee tiers include 1, 5, 30, and 100 basis points. The results tend to be robust to subsamples of various fee tiers.

expected impermanent loss. Most pools feature quite volatile exchange rates, leading to the mean (median) fee rate of 70 (100) basis points.

Pool duration is defined as the time between the first liquidity provision into the pool and the last pool event (either last swap or last liquidity provision/withdrawal or the end of the sample period). The mean (median) pool duration is around one year (8 months), and the longest pool encompasses our whole sample period. The volatility of the exchange rate of a pool's assets exhibits a wide variation—from 0% for pools of two stable coins without a depegging event to a mind-blowing 730% daily standard deviation for a short-lived pool of very volatile assets with low market capitalization.

19% (13%) of all pools feature `USDC` (`USDT`)—two major stable coins—as one of the two pool's assets. The majority of pools (66%) feature `WETH`, whereas `WBTC` appears in just 2.3% of pools. Pools vary widely in the amount of liquidity provision activity in them—the number of liquidity positions ranges between 1 to over 52,000, with the mean (median) of 80 (6) throughout a pool's life. The mean number of positions that are active contemporaneously ranges from 0 (for a pool in which only short-lived liquidity positions existed throughout its life) to 1,820 with the mean (median) of 3.4 (1.1). The distribution of the size of the liquidity positions is quite skewed, as evident from the Herfindahl index (HHI) of contemporaneous LP positions, with both mean and median HHI exceeding 0.65.

The mean (median) of the total value of the pool's liquidity positions (TVL—"total value locked") throughout the pool's life is around $800 thousand ($26 thousand). The mean (median) pool serves over 10,000 (nearly 600) trades, with the largest pool in the sample serving nearly 8 million swaps. On average 46 trades occur in a pool on a daily basis. The mean (median) total trading volume in a pool is $5 million ($135 thousand), whereas over $41 billion worth of swaps happened in the most active pool. Mean (median) daily trading volume in a pool is $46,000 ($1,300). The overall pool fees collected by liquidity providers in a pool range between zero to over $82 million, with the mean (median) of $16,000 ($800). Relative to the value of a pool's liquidity, daily fees range between zero to 75%, with the mean (median) of 0.4% (0%).

3.6.2. Liquidity-position-level summary statistics

Our initial sample contains over 950,000 liquidity positions valued at $100 or more, across 4,656 pools. There are two types of liquidity positions that we remove from the sample. The first is positions defined by "out-of-range" liquidity provision. In Uniswap V3, most positions involve supplying liquidity that consists of both assets of the pool. Two-asset liquidity positions are active in facilitating trades and accumulate trading fees from their establishment. It is also possible, however, to supply "single-asset" liquidity, by defining a position range outside of the current exchange rate of the pool's two assets. Such positions are inactive until the exchange rate moves inside the position's range, at which point the asset supplied by the liquidity provider is exchanged for the other pool's asset, and the position is active so long as the exchange rate is in-range. Out-of-range, single-asset liquidity provisions typically involve narrow position ranges and they are more akin to a (collection of) limit orders than to liquidity provision aimed at generating trading fees. Nearly 17% of liquidity positions in our sample are out-of-range, and we discard them from the sample used in the final analysis.

The second type of peculiar liquidity positions that we do not include in the sample are "just-in-time" (JIT) liquidity positions. These are positions with zero duration. Transactions sent to the blockchain appear in the "memory pool" from which they are picked up by "block builders" to be included in the next block. Self-interested block builders have full discretion as to which transactions to include in a block and in which order. Large swaps, generating substantial trading fees, which appear in the memory pool, tend to attract immediate liquidity (supplied/recorded in the same block as the proposed swap and placed before it in the block, and withdrawn in the same block and placed after the swap). JIT transactions are akin to active market making, in which instantaneous liquidity providers trade off the trading fees that they obtain at the expense of non-zero-duration liquidity positions, while also exposing themselves to adverse price movements as a result of the trade. While an important part of the liquidity provision landscape, JIT liquidity provision is not the focus of our analysis. In addition, given that JIT liquidity transactions have zero duration, it is impossible to compute their returns per-unit-of-time (e.g., daily returns), which is the focus of our analysis. Nearly quarter of all liquidity provision in our sample are of the JIT kind, and are discarded from the final sample.

In addition to the aforementioned exclusions, nearly 7% of all positions are either still open by December 31, 2024 or are untraceable to a particular liquidity provider, as explained above, and these are also excluded from the final sample. After removing out-of-range liquidity positions, JIT liquidity provisions, and open/untraceable positions, we are left with the final sample of 503,273 liquidity positions for which we can compute returns and all their components. Table 2 depicts the main characteristics of liquidity positions in our sample.

Table 2 here

The mean (median) size of a liquidity position is nearly $150 thousand ($10 thousand), with the largest position exceeding $180 million. These positions range from very narrow ones (encompassing one tick) to the widest (non-concentrated positions) spanning all 1,774,544 ticks. The second row of the table reports the ratio of the range of the position relative to full range ("normalized tick range"). The mean (median) position is quite concentrated, spanning just 5.4% (0.3%) of the full range.

The Duration of liquidity positions exhibits large variation. After having removed zero-duration (JIT) positions from the sample, the median liquidity position is active for 1.55 days, whereas the mean position duration is slightly over one month. The longest liquidity position has been active throughout our sample period. One third of liquidity positions originate as an extension of an existing position, while 28% of positions involve partial withdrawals.[33] The mean (median) liquidity position is involved in settling swaps totaling over $300 thousand ($15 thousand), while

[33]The qualitative results below are robust to examining positions that were never extended and/or partially closed.

one position was involved in swaps amounting to over 2.5 billion dollars. The mean (median) ratio of swaps that are partially served by a liquidity position to position size is 6.5 (1.8).

Daily return volatility refers to a somewhat different construct from that in Table 1, in which it measured the daily exchange rate volatility throughout a pool's life. Here, we measure daily exchange rate volatility for a period of 30 days prior to the establishment of a particular liquidity position (thus, different liquidity positions in the same pool have different volatilities). This measure is more useful for analyzing the characteristics of a particular liquidity position. The mean (median) daily exchange rate volatility prior to a liquidity position's establishment is 9.6% (3.9%).

Not only `WETH` is the predominant asset in liquidity pools, `WETH`-based pools tend to be more active, resulting in an even larger dominance of `WETH`, which is one of the two assets in 84% of liquidity positions. `USDC` (`USDT`, `WBTC`) feature in 13% (3.1%, 3.3%) of pools. There is a gradual increase in the liquidity providers' activity as evident from the yearly indicators, with a dip in activity during the "DeFi winter" of 2022.

3.6.3. Blockchain-address-level summary statistics

One of the paper's objectives is to examine the performance and characteristics of LPs, i.e. strategy deployers. For the purposes of this study, a strategy deployer is a blockchain address that performs liquidity deposits and withdrawals, thus the analysis is at the level of a blockchain address.[34] In what follows, we refer to "(blockchain) address" and "(blockchain) address owner" and "LP" interchangeably. Summary statistics at the address-level are presented in Table 3.

Table 3 here

Many blockchain address owners (over 40%) experiment with liquidity provision only once, and

[34]It is possible (and even highly likely) that some LPs deploy liquidity from multiple blockchain addresses. Without a detailed analysis of connection among addresses (a focus of specialized blockchain analytics firms, such as Chainalysis, Elliptic, and TRM Labs among others), it is difficult to identify LPs at a level other than a blockchain address.

the median address does it only twice. The mean number of liquidity positions by an address is 6.2, while one LP established over 6,700 liquidity positions. The mean cumulative value of all positions by an LP is over $800,000, whereas the median is around $8,300. At a given point in time, the mean (median) total value of all positions in which an address is active is $66,000 ($3,900).[35]

The distribution of mean tick ranges at the address-level is similar to that at the position-level in Table 2. For addresses with at least two liquidity positions, we also compute the standard deviation of an address' position tick ranges to measure the degree of specialization in liquidity concentration. Some addresses' liquidity provision concentration strategy is highly specialized (standard deviation of zero), while others establish both more and less concentrated liquidity positions. The same is true for the standard deviation of position durations and exchange rate volatilities—some addresses specialize in short or long positions, or in low-volatility or high-volatility pools, while others are more opportunistic. More than half of LPs provide liquidity to a single pool, as is evident from the HHI of liquidity positions at the address-level (with the median of one). However, some addresses provide liquidity to many pools, as follows from the lowest HHI that equals 0.015.

9.4% of addresses that provide liquidity to pools do so via a proprietary position manager. As discussed in detail below, interaction with a proprietary position manager is used as a basis for identification of quantitative LPs.

[35]The median position size and median position value at the address-level are lower than the respective medians at the position-level, as more frequent strategy deployers tend to have larger positions, tilting the distribution at the position-level upwards.

4. Performance of liquidity provision strategies

4.1. Returns and their components

Panel A of Table 4 presents summary statistics of the daily return to liquidity provision and each of its components.[36]

Table 4 here

Pool choice refers to the difference between the return on a hypothetical non-concentrated (full-range) liquidity position in a pool involving two assets and the return on holding the same initial portfolio of these two assets outside of the pool. A positive return due to pool choice occurs when trading fees accruing to a hypothetical non-concentrated liquidity position outweigh the impermanent loss to the same hypothetical position. While the equally-weighted mean daily return over and above passive holding of a pool's assets is an impressive 0.18%, high returns are more common among relatively small positions, as indicated by the value-weighted mean and median returns (-0.01% and 0%, respectively). This suggests that liquidity providers do not succeed on average in beating a buy-and-hold strategy involving the pool's two assets.

Liquidity concentration measures the return on "doubling down" on the tradeoff between trading fees and impermanent loss, as concentrating liquidity leads to a higher share of a pool's fees accruing to the position, while exposing the position owner to levered impermanent loss. The equally-weighted mean (value-weighted mean, median) daily return to liquidity concentration is -0.04% (-0.11%, 0%), implying that a typical liquidity provider's skills in liquidity concentration is limited.

Equally-weighted and value-weighted holding returns are significantly positive and very high—a testament to the overall increase in crypto valuations during our sample period.[37] Equally-weighted gas cost as a fraction of position size exceeds 1%, driven mostly by small positions, whereas the

[36] To avoid outliers, in calculation of daily returns and their components, when the duration of a position is shorter than one day, we assume that it equals one day. All the results are robust to the subsample of positions with durations exceeding one day.

[37] For example, BTC price on May 6, 2021, the beginning of our sample was around $46,000, whereas it was over $93,000 on December 31, the end of our sample period.

value-weighted average gas cost is merely 3 basis points. Driven by high equally-weighted mean gas cost, overall equally-weighted mean return as well as median return are negative. Due to high holding returns during our sample period, coupled with low value-weighted average gas cost, value-weighted overall return to liquidity provision is positive. Note however, that since the direct exposure to the two assets of the pool is easily hedgeable, for example, using perpetual future contracts,[38] it is not clear what fraction of the holding return and, as a result, the overall return was realized within each liquidity position.

The main takeaway from Panel A of Table 4 is that the negative value-weighted mean returns to the two core components of liquidity provision—pool choice and liquidity concentration—suggest limited ability of liquidity providers to capitalize on the tradeoff between the trading volume in a pool and impermanent loss in it.

As evident from Table 3, the majority of LPs have provided liquidity to concentrated pools only once or twice. In Panel B of Table 4, we exclude such "accidental" liquidity providers and report the summary statistics for the various components of returns to liquidity provision, while limiting the sample of strategies to those deployed by addresses that have established (and terminated) at least 10 liquidity positions.

Within a subsample of relatively frequent strategy deployers, the returns to various components of liquidity provision tend to be higher. The value-weighted mean daily return to pool choice is 4 basis points, whereas for liquidity concentration it is 2 basis points, compared to -1 and -11 basis points respectively in the full sample. The combination of returns to the two quantitative components of liquidity provision strategy is (4-2)=2 basis points per day or about 7% per year. While not overly impressive, it may justify continued provision of liquidity to pools. Other components of returns (holding returns, gas cost rate), and overall return as a result are higher for frequent liquidity providers, with even the equally-weighted mean of 14 basis points being statistically significant.

[38] Hedging exposure to crypto assets using perpetual futures involves taking offsetting positions in future on an underlying cryptocurrency without an expiry date. These instruments are widely traded on centralized exchanges such as Binance Futures (`https://www.binance.com/en/futures/home`) as well as on decentralized derivatives protocols such as dYdX (`https://www.dydx.xyz/`).

Table 5 presents the Spearman rank correlations between the components of the daily returns to liquidity provision.

Table 5 here

All return components contribute to the overall return to liquidity provision, as evident from positive correlations between each return component and overall return. The rest of the correlations between various return components tend to be negligible, with one exception: There is a strong correlation (71%) between the two core components of the liquidity provision strategy: pool choice and liquidity concentration. Choosing a pool in which trading fees outweigh impermanent loss, and concentrating liquidity in the relevant region in such pool are likely to both lead to positive returns, and the opposite is true for a pool in which trading volume is insufficiently high to compensate for the impermanent loss.

4.2. Determinants of returns to liquidity provision

In Table 6 we examine how characteristics of a) position, b) pool, and c) blockchain address that deploys the position are related to the performance of the position and its components. Each column reports the results of position-level OLS regressions, where in the first three columns the dependent variable is the pool choice, liquidity concentration, and holding components of daily return to liquidity provision, respectively, and in column 4 the dependent variable is the overall daily return to a liquidity position. The numbers in parentheses indicate a measure of economic significance—how a one-standard-deviation increase in an independent variable impacts the overall daily return and its components.

Table 6 here

Larger positions have a significantly negative association with the pool choice component of the strategy and a significantly positive association with liquidity concentration. However its economic significance is quite small: a one-standard-deviation increase in log (position size) is associated with a combined (-3+4)=1 basis point increase in the combined daily return to the core components of liquidity provision. Wider positions are significantly negatively associated with pool choice component of return, and the combined economic significance of the relation between log (tick range) and returns to the pool choice and liquidity concentration combined is quite sizable: A one-standard-deviation increase in liquidity concentration is associated with -(-7+2)=5 basis point increase in the combined return to pool choice and liquidity concentration. Longer positions are associated with substantially higher daily returns to liquidity concentration; the economic significance is large: 12 basis points for a one-standard-deviation increase in position duration. Positions in pools that have larger exchange rate volatility are more profitable: increasing the return volatility by one standard deviation is associated with 13 basis points increase in the return to pool choice and with 4 basis points increase in the return to liquidity provision. Overall, positions that have the largest opportunity to benefit from quantitative analysis because more concentrated, longer positions in more volatile pools indeed tend to generate higher returns to the core components of liquidity provision.

Relative position size is positively associated with the return to liquidity concentration, while the number of contemporaneous positions is negatively associated with both the return to pool choice and the return to liquidity concentration. One interpretation is that liquidity providers put more effort into optimizing "important" positions, that is larger ones relative to a given liquidity provider's typical position size and positions that represent an important part of a liquidity provider's contemporaneous portfolio of liquidity positions.

The time that a strategy deployer has been active (i.e. the time from the first position until the current one) is mildly negatively associated with the combined return to the core components of liquidity provision—the economic significance is (-4+2)=-2 basis points. The number of past positions has a somewhat positive association with the combined return to pool choice and liquidity concentration—the economic significance is (-1+5)=4 basis points. Similar result is true for the combined size of past positions—the economic significance is (5+0)=5 basis points. Overall, these results suggest that there is some learning, manifesting itself in higher returns to pool choice and liquidity concentration for positions deployed following several past liquidity provision attempts and those deployed after significant capital has been put at risk by an LP in the past.

Finally, past performance is significantly associated with returns to both pool choice and liquidity concentration. A one-standard-deviation increase in mean past daily return to pool choice (liquidity concentration) is associated with an 11 (15) basis points higher return to the pool choice (liquidity concentration) component of return to the current strategy. This suggests strong persistence of returns to the core components of liquidity provision.

The associations of various position and pool characteristics on one hand and holding component of return and overall return to liquidity provision on the other hand are partially consistent with the associations with returns to pool choice and liquidity concentration discussed above: the holding return and overall return are higher for more concentrated positions and for positions in pools with higher exchange rate volatility. The results for associations of holding and overall returns with the learning variables are inconclusive, as some coefficients are significantly negative, while others are significantly positive. Finally, similar to the core components of return to liquidity provision, holding return and overall return also exhibit persistence.

4.3. Position characteristics of successful and unsuccessful liquidity providers

We proceed to aggregate the data at the level of a blockchain address and examine differences between the mean strategy characteristics of successful LPs and the position characteristics of less successful ones. Defining success is quite arbitrary. In what follows, we define an address with mean overall return to its liquidity positions and mean returns to each of the liquidity positions' return components belonging to top 10% of their respective in-sample distributions as "successful strategy deployers".[39] In Table 7, we examine the mean characteristics of successful and unsuccessful LPs as defined as above. This comparison is restricted to the subsample of wallets with at least 10

[39] All the results below are robust to other success cutoffs, such as 25%, 5% or 1%.

liquidity positions.[40]

Table 7 here

Panel A compares average position characteristics between the subset of addresses that are in the top-10% and those that are in the bottom 90% of returns to the pool choice component of liquidity provision. LPs that are successful in pool choice tend to establish smaller positions—$42 thousand on average compared to $172 thousand in the subset of bottom-90% performers. LPs successful in pool choice tend to withdraw liquidity sooner—after 9 days, compared to 26 days for less successful LPs. These two findings are consistent with successful LPs identifying small, short-lived opportunities and capitalizing on them. Successful LPs tend to establish narrower-range positions, suggesting that there is complementarity in both the pool choice skill and the skill associated with liquidity concentration, examined below. Successful LPs establish more narrow positions despite the higher exchange rate volatility in the pools that they provide liquidity too. Successful LPs are also more opportunistic in their pool choice strategy, as suggested by the a significantly lower pool-level Herfindahl index.

Interestingly, successful LPs' mean gas cost rate is significantly higher (in absolute terms) than that of unsuccessful ones. The reason is twofold. First, the positions of successful LPs are four times smaller on average than those of less successful ones. Second, successful LPs' positions are three times shorter. Given that gas costs are independent of position size and duration, the mean dollar gas cost paid by LPs successful in pool choice is actually lower than that of unsuccessful LPs, suggesting that successful LPs engage in gas cost optimization. Finally, there are no significant differences in the degree of specialization in providing liquidity with a particular duration, width, and pool exchange rate volatility between LPs successful in their pool choice and unsuccessful ones.

We next compare the position characteristics of LPs successful in liquidity concentration and unsuccessful ones. The results, reported in Panel B, reveal similar patterns, which tend to be even

[40] Alternative cutoffs, such as 50 or 100 positions, lead to qualitatively similar results although significantly smaller sample sizes.

more pronounced than those for the pool choice component of liquidity provision. LPs successful in liquidity concentration tend to establish positions that are over 6 times smaller, twice as short, half as wide, and having almost twice the exchange rate volatility compared with the bottom 90% of LPs. Differently from LPs successful in pool choice, LPs successful in liquidity concentration tend to be more opportunistic than their unsuccessful counterparts not only in providing liquidity to a wider range of pools but also in the choice of position characteristics, as evidenced by higher coefficients of variation in position duration, position width, and pool exchange rate volatility.

The results are somewhat different in Panel C, which compares characteristics of positions of LPs with higher mean holding returns with those of LPs with lower mean holding returns. Successful LPs' positions are smaller and shorter, however the differences are not as pronounced as those for the core components of liquidity provision, discussed above. Similar to the results in Panels A and B, successful LPs provide liquidity to more volatile asset pairs. However, different from the results for pool choice and liquidity concentration, LPs successful in asset picking establish wider positions than unsuccessful ones, suggesting that they focus more on holding returns and less on returns from the core components of liquidity provision. LPs successful in asset holding tend to focus more on particular pools, as evident from the significantly higher pool-level Herfindahl index. Given the dominant effect of holding returns to overall returns, the results on overall returns, reported in Panel D, are generally in line with those for holding returns in Panel C.

5. Quant and non-quant liquidity provision strategies

5.1. Identification of quantitative liquidity providers

As discussed in the Introduction, identifying quantitative investors and their strategies, as well as estimating the returns of the latter has proven to be an elusive task in traditional markets. While the DeFi setting allows us to identify investment strategies and compute their overall returns as well as the returns of the strategies' various components, we need a way of identifying quant LPs and separating them from discretionary ones to compare performance of the two groups.

There are two potential ways to classify LPs into quantitative and discretionary ones. The first way is indirect, such as the one employed in (Aquilina et al. (2024)). It relies on proxies for an LP's experience, e.g., the total number of positions deployed by a blockchain address, the cumulative dollar value of positions established by an address, or the length of time an address is active in liquidity provision.

While sensible, such measures are likely to be more direct proxies for LP sophistication—as noted by Aquilina et al. (2024)—as opposed to the quantitative/discretionary nature of LP strategies. Thus, we opt instead for a direct measure of quant LPs, which is based on an analysis of interactions between the address from which the liquidity is provided and liquidity pools. Blockchain addresses are of two types. The first is smart contracts, which are computer programs deployed on the blockchain that are deployed on demand and executed in a decentralized fashion. The second is "externally owned accounts (EOAs)", which contain balances of various crypto assets and can interact with smart contracts.

EOAs cannot interact directly (i.e. provide and withdraw liquidity) with pools governed by Uniswap V3 smart contracts. Instead, EOAs need to interact with a type of smart contract referred to as "position manager" that deploys and terminates liquidity positions. Most such interactions (including but not limited to those triggered by transactions submitted on the Uniswap user interface) involve native Uniswap V3 position manager smart contract. However, some interactions are done via proprietary position managers. The reason to employ such proprietary smart contracts is that they involve additional functionality absent from the native Uniswap V3 position manager. An example is the accounting of fees in the case a blockchain address initiating a transaction is a "vault" that consists of contributions by multiple investors that delegate their liquidity provision to such vault, which allocates liquidity to pools according to some strategy. Such strategies are typically run "off-chain" (but using on-chain data) and trigger on-chain actions (liquidity provisions/withdrawals). Thus, while the actions are fully observable, strategies triggering them are not.

To identify quant LPs, we first identify all addresses that interact with liquidity pools via proprietary position manager smart contracts. We then check the code of 50 such contracts most active in liquidity provision using ChatGPT and Deep Seek and verify that all these smart contracts are indeed used for position management of Uniswap V3 pools and have a vault functionality. As a result, we designate all addresses that interact with pools via any smart contract other than the native Uniswap V3 position manager as "quant liquidity providers" and addresses that interact with pools using the native position manager as "discretionary liquidity providers". To corroborate this classification, we also observe, using contract name tags obtained from Ethereum contract metadata, that many of these smart contracts are associated with known liquidity management services and protocols, such as AlphaVault (`https://alpha.charm.fi/ethereum/vaults`) and Gelato Network (`https://www.gelato.cloud/blog`) among many others. About 9% of all addresses with at least 10 liquidity positions are classified as quant liquidity providers.

5.2. Quantitative strategies' performance

In Table 8 we split the sample of LPs (addresses) to 26 thousand addresses classified as quant LPs and 260 thousand addresses classified as discretionary ones and report equally-weighted and value-weighted mean returns and their components for the two subsamples.

Table 8 here

The equally-weighted mean return to the pool choice component of liquidity provision is significantly higher for discretionary LPs than for the quant ones—23 basis points versus 8 basis points per day. The same qualitative results hold in the case of value-weighted returns to pool choice: 4 basis points for discretionary LPs versus 1 basis point for quant ones. The returns to the liquidity concentration component are similar: the value-weighted mean return in the discretionary (quant) subsample is

3 (-8) basis points per day, and the equally-weighted means are -1 (-3) basis points, respectively.

Overall, the value-weighted evidence points to two somewhat unexpected results. First, consistent with the evidence in Table 4, LPs on average do not obtain superior returns. In particular, value-weighted returns to liquidity concentration are negative in both the quant and discretionary subsamples. Second, and perhaps surprisingly, quant LPs significantly underperform discretionary LPs across all measures of returns of the core components of liquidity provision: The combined mean value-weighted return to pool choice and liquidity concentration is 5 basis points per day (or 18% per year) lower for quant LPs than for discretionary ones.

Quant LPs also underperform discretionary ones in terms of holding returns and, as a consequence, in terms of overall returns. Quant LPs tend to pay lower proportional gas fees, at least on an equally-weighted basis. The reason is that their positions tend to be larger than those of discretionary LPs. Overall, Table 8 paints a consistent picture that suggests underperformance of quant LPs across virtually all dimensions of the liquidity provision strategy.

In Table 9 we examine whether there are systematic explanations for the underperformance of positions deployed by quant LPs. To that end, we estimate regressions in which the dependent variable is a position's return or one of its components, and the independent variables include an indicator for a quant LP, position characteristics and/or characteristics of a blockchain address, as in Table 6. If systematic differences in strategy characteristics deployed by quant and discretionary LPs are related to the quant LPs' underperformance then including these characteristics would reduce the coefficient on the quant indicator, which measures quant LPs' underperformance, ceteris paribus. If, on the other hand, there would not be sizable changes in the coefficient on the quant indicator, this would suggest that quant LPs underperform for reasons that cannot be captured by measurable position and LP characteristics.

Table 9 here

Panel A focuses on the determinants of quant LPs' underperformance in the pool choice component of liquidity provision. The incorporation of log (position size), log (tick range) and log (position duration) one at a time does not have a material impact on the coefficient on the quant indicator. Incorporating the exchange rate volatility reduces the coefficient from 16 basis points to 13 basis points, however incorporating all position characteristics does not impact the coefficient on the quant indicator materially. Further augmenting the regression by characteristics of the account deploying liquidity leads to a reduction in the quant indicator coefficient to 12 basis points. Overall, measurable position and LP characteristics explain roughly a quarter of the underperformance of quant LPs; the rest of the underperformance remains unexplained.

In Panel B we perform the same analysis for the liquidity concentration component of the strategy. The results are similar to those in Panel A: Incorporating all position and account characteristics reduces the underperformance of the liquidity concentration component of strategies deployed by quant LPs' from 13 basis points to 8 basis points. This implies that roughly 40% of this component of underperformance is due to observable differences between their strategies and those of discretionary LPs, however the majority of underperformance remains unexplained.

This is not the case for the holding return component. Position characteristics, especially the volatility of the exchange rate of the pool's assets, explain all of the inferior holding returns of quant LPs, as evident in Panel C. Overall though, measurable position and account characteristics explain roughly one third of the underperformance of quant LPs' positions, as follows from the coefficients on the quant LP indicator in Panel D.

While Tables 8 and 9 demonstrate that quant LPs underperform on average across virtually all dimensions of liquidity provision, it is possible that the distribution of quant LPs' returns is wider than that of discretionary LPs' returns, and we cannot yet rule out superior performance of top quant LPs. To address this possibility, in Table 10 we examine the propensity of quant LPs to be top-performers across various components of liquidity provision.

Table 10 here

Panel A examines the propensity of quant (and discretionary) LPs to belong to a subset of LPs with the best average performance along the pool choice dimension of liquidity provision. The findings indicate that not only quant LPs underperform on average—consistent with the position-level results in Table 8, the pool choice component of quant LPs' performance is significantly worse than that of discretionary LPs (5 basis points versus 23 basis points per day, respectively)—quant LPs are significantly less likely than discretionary LPs to be top performers. Only 0.38% (1.14%, 2.66%) of quant LPs belong to the top 1% (5%, 10%) of top LPs that are successful in pool choice. In other words, quant LPs are roughly 4 times less likely than discretionary LPs to enter the ranks of top 5% or top 10% LPs overall on the pool choice dimension.

Panel B focuses on the liquidity concentration component of liquidity provision. The results are quite similar to those in Panel A. Not only quant LPs significantly underperform discretionary ones on average, the former are 3-6 times less likely to belong to the subset of top 5% or 10% of LPs most successful in liquidity concentration and none of the quant LPs are in the top 1%.

Quant LPs' performance along the holding/asset picking dimension is better, as shown in Panel C. First, the mean value-weighted return of quant LPs is indistinguishable from that of discretionary LPs. Second, quant LPs are disproportionately likely to belong to the top 1% of asset pickers (2.28%), albeit the likelihood of belonging to the top 5% and 10% of asset picking performance is less impressive (3.42% and 7.98%, respectively, both significantly lower than the respective likelihoods of discretionary LPs).

The overall performance of quant LPs relative to discretionary ones, reported in Panel D, is subpar, not only on average but also in terms of belonging to the top 5% and 10% of overall performers, although the underperformance is less sizable than that for the pool choice and liquidity concentration components of liquidity provision. To summarize, not only the LP-level evidence of quant LPs' underperformance is broadly consistent with the position-level evidence, this underperformance manifests itself not only on average but as an overall downward shift of return distribution leading to low propensity of quant LPs to belong to the set of LPs most successful in the core components of liquidity provision—pool choice and liquidity concentration.

5.3. Strategies of successful quant and discretionary LPs

Next, we examine whether there are systematic differences between the liquidity provision strategies of successful LPs that are classified as quants versus those that are classified as discretionary.

Table 11 here

In Panel A we explore the differences in the pool choice component of LP strategies between quant LPs that belong to top 10% of all LPs across this dimension of performance and discretionary LPs that belong to top 10%, that is"successful quant" and "successful discretionary" LPs henceforth.[41] Within the subsample of LPs successful in pool choice, the characteristics of strategies deployed by quants and discretionary LPs are quite similar on average. In particular, while quant LPs' positions tend to be smaller and longer, the differences are not statistically significant. In addition, the degree of specialization of successful quant LPs and successful discretionary ones along the position duration, position length, and exchange rate volatility dimensions is not statistically different either. The differences between strategies of quant and discretionary LPs manifest themselves in quant LPs focusing on very narrow positions in lower-volatility pools on average—both findings are due to their higher propensity to provide liquidity to stable-coin pools with near-zero exchange rate volatility and naturally very high liquidity concentration. Another difference is that quant LPs tend to be more opportunistic in choosing pools to which they provide liquidity—the difference in the pool-level Herfindahl index between the two types of LPs is large,

[41] The results are qualitatively similar for other success cutoffs, such as 5% and 25%.

albeit not statistically significant.

Panel B focuses on the differences between quant and discretionary LPs successful on the liquidity concentration dimension. Similar to pool choice, the differences in strategies manifest themselves in quant LPs focusing on higher-concentration positions in lower-volatility pools. In addition, successful quant LPs tend to pay lower gas costs, suggesting that gas optimization is a more important component of their strategy.

Turning to the differences between the strategies of quant and discretionary LPs successful in the holding/asset picking component and in the overall performance (Panels C and D, respectively), we find that quant LPs tend to establish larger, shorter, and wider positions, and concentrate these positions in a more limited set of pools. These results, which are very different from those in Panels A and B, highlight the large differences between the core components of liquidity provision—pool choice and liquidity concentration—and holding return, which is largely a by-product of the liquidity provision strategy.

6. Conclusions

In this paper we analyze liquidity provision into concentrated liquidity (Uniswap V3) pools on the Ethereum blockchain. After reconstructing each pool's history, we measure every liquidity position's return, as well as those of its components—the return to non-concentrated liquidity provision, return to pool concentration, holding/asset picking return, and transaction (gas) costs.

Liquidity provision into concentrated liquidity pools—at least its core, non-hedgeable components—is not profitable on average. However, more experienced liquidity providers tend to do better than accidental ones. There are several additional pieces of evidence suggesting that some liquidity providers possess skill. First, there is significant persistence in liquidity providers' performance. Second, there is some evidence of learning, i.e. improvement of performance of a given LP over time. Third, some position characteristics and LP characteristics are strongly associated with the performance of liquidity provision strategies.

Quant LPs—defined as those that operate "liquidity vaults" and whose strategies are automated by off-chain optimization—perform significantly worse than discretionary LPs across every component of liquidity provision. This is true both for average returns at the position-level and LP-level and for the propensity of quant LPs to be among the top performers along the core components of liquidity provision—pool choice and liquidity concentration. Within a sample of LPs successful in the core components of liquidity provision, the strategies of quant LPs tend to be quite similar to those of discretionary ones.

Our paper contributes to the emerging empirical DeFi literature by providing an in-depth analysis of one of the most important investment strategies in DeFi, while focusing on differences between quant and discretionary liquidity providers. The latter analysis in a setting in which quant investors are identifiable, their strategies are observable, and their returns are measurable precisely contributes to the wider literature on quantitative investments.

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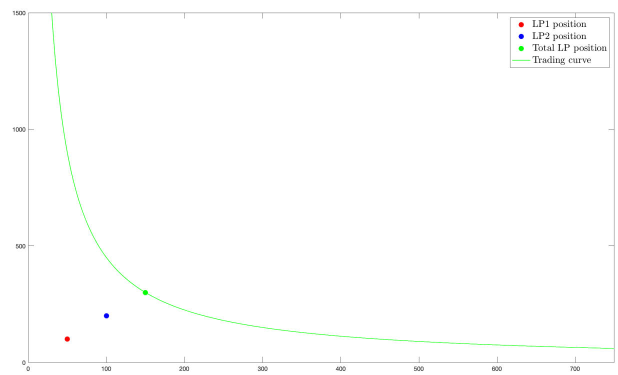
Figure 1: Liquidity provision in constant product pools

Figure 1a presents an example of liquidity provision into a non-concentrated liquidity pool. Red and blue dots represent liquidity positions of two liquidity providers. Green dot is the combined liquidity in the pool. Green curve is the constant product trading curve around the pool's liquidity.
Figure 1b presents an example of trading in the pool. Green dot represents the post-trade liquidity in the pool. Black dot adjacent to is is the pre-trade liquidity in the pool. Red and blue dots represent the two liquidity providers' post-trade positions, whereas black dots adjacent to them represent their pre-trade positions.

(a) Liquidity provision and trading curve



(b) Trading in the pool

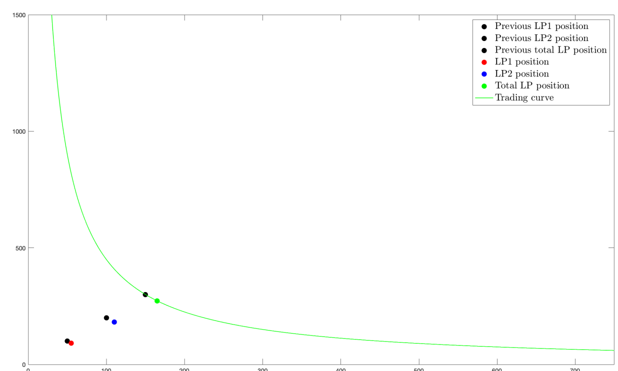
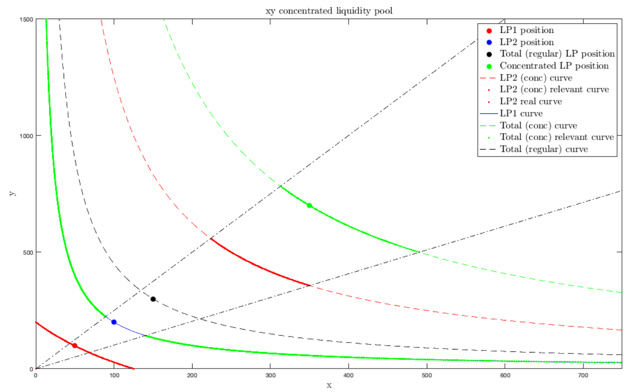


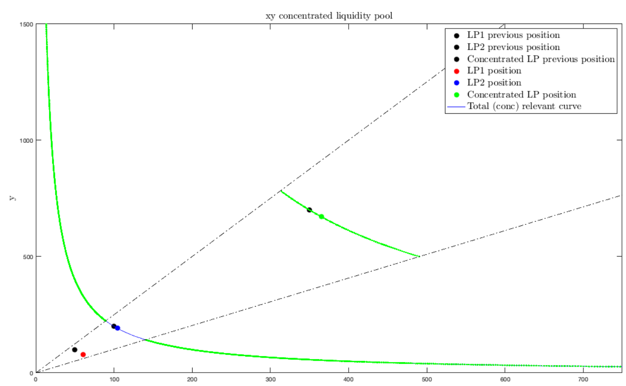
Figure 2: Liquidity provision in concentrated liquidity pools

Figure 2a presents an example of liquidity provision into a concentrated liquidity pool. Red dot represents the first liquidity provider's concentrated liquidity position. The upper red curve represents trading curve resulting from the first LP's position, and the rays coming from the lower left corner represent the concentrated liquidity bounds. Blue dot represents the non-concentrated position of the second liquidity provider. Black dot represents the combined real liquidity in the pool. Green dot represents the combined virtual liquidity in the pool. Green curve represents the trading curve in the pool.
Figures 2b and 2c present examples of trading in the pool. Green dot represents the post-trade liquidity in the pool. Black dot adjacent to is is the pre-trade liquidity in the pool. Red and blue dots represent the two liquidity provider's post-trade positions, whereas black dots adjacent to them represent their pre-trade positions. (In Figure 2c blue dot coincides with green dot and red dot coincides with black dot.)

(a) Concentrated liquidity provision and trading curve



(b) Trading in the concentrated liquidity pool



(c) Inefficient concentrated liquidity

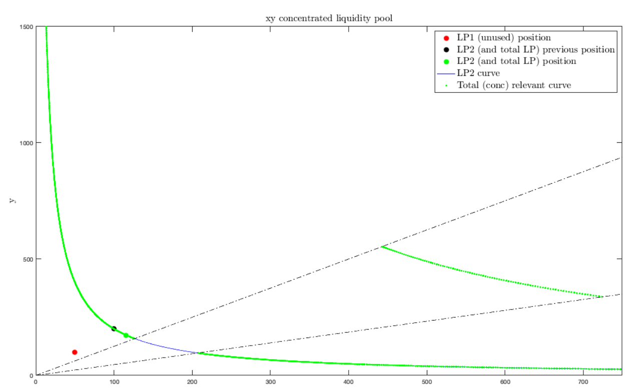


Table 1: Liquidity-pool-level summary statistics

This table reports summary statistics of characteristics of liquidity pools governed by the Uniswap V3 smart contracts on Ethereum. The sample includes all liquidity pools that contain assets whose prices could be estimated as described in Section 3.3. The sample period is May 6, 2021 to December 31, 2024. Pool (proportional) fee is the fee paid by traders in the pool as a fraction of swap size. Pool duration is the difference (in days) between the first liquidity provision into the pool ("pool initiation") and either the last event in the pool (trade or liquidity provision/withdrawal) or the end of the sample period. Daily return st. dev. is the standard deviation of daily changes in the two assets log exchange rates. USDC-x pool (USDT-x pool, WETH-x pool, WBTC-x pool) is an indicator equaling one for pools whose assets include USDC (USDT, WETH, WBTC). Total positions is the number of liquidity positions in the pool that were closed, i.e. whose returns can be computed. Mean contemporaneous positions is the daily average of the number of open liquidity positions in a pool. Mean HHI of LP positions is the daily average of the Herfindahl index of the values of open liquidity positions. The value of each position is computed at its initiation and equals the sum of the products of each of the two assets' prices at position initiation and the number of units of the two assets at initiation. Mean pool TVL (USD) is the daily average of the sum of values of all open positions. Total trades is the total number of swaps that occurred in the pool. Mean daily trades is the ratio of total trades and pool duration. Total trading volume (USD) is the total dollar value of swaps that occurred in the pool. Each swap's dollar value is computed as the number of units of the asset entering the pool times the asset's most recent price, estimated as in Section 3.3. Mean daily trading volume (USD) is the ratio of total trading volume and pool duration. Total pool fees (USD) is the product of total trading volume and pool proportional fee. Mean daily pool fees (USD) is the ratio of total pool fees and pool duration. Mean daily fees/TVL is the daily average of the ratio of daily pool fees and the overall value of all positions that are open in the beginning of the day.

	Min	P25	Median	P75	Max	Mean	Std. Dev.	Num Obs.
Pool (proportional) fee	0.01%	0.30%	1.00%	1.00%	1.00%	0.70%	0.40%	4,656
Pool duration (in days)	0	27.32	234.42	606.55	1,459.69	380.86	413.02	4,656
Daily return st. dev.	0	5.07%	11.31%	23.26%	730.73%	21.51%	41.24%	3,449
USDC-x pool	0	0	0	0	1	0.190	0.392	4,656
USDT-x pool	0	0	0	0	1	0.128	0.334	4,656
WETH-x pool	0	0	1	1	1	0.661	0.473	4,656
WBTC-x pool	0	0	0	0	1	0.023	0.150	4,656
Total positions	1	2	6	25	52,550	80.00	394.94	4,656
Mean contemporaneous positions	0.00	1.00	1.09	2.08	1,819.97	3.41	15.66	4,656
Mean HHI of LP positions	0.001	0.349	0.744	1.000	1.000	0.658	0.348	4,656
Mean pool TVL (USD)	1	5,039	26,520	142,360	764,760K	802,620	6,324,905	4,656
Total trades	2	92	587	3,509	7,733,094	10,413.35	20,924.83	4,656
Mean daily trades	0.001	1.162	5.321	25.043	7101.823	46.212	199.057	4,656
Total trading volume (USD)	0	14,422	135,227	1,043,387	41,030,207K	4,976,207	28,397,657	4,656
Mean daily trading volume (USD)	0	171	1,335	7,453	28,108,927	46,488	216,703	4,656
Total pool fees (USD)	0	72	798	5,997	82,459,637	16,413	81,761	4,656
Mean daily pool fees (USD)	0	1	8	44	43,292	130	651	4,656
Mean daily fees/TVL	0	0	0	0.001	0.749	0.004	0.023	4,656

Table 2: Liquidity-position-level summary statistics

This table reports summary statistics of liquidity positions in pools governed by the Uniswap V3 smart contracts on Ethereum. The sample includes liquidity positions that were a) closed before December 31, 2024, b) are not "out-of-range", and c) have non-zero duration, in pools in Table 1. Position size (USD) is the sum of the products of each of the two assets' prices at position initiation and the number of units of the two assets at initiation. Tick range (normalized) is the ratio of the difference between the upper and lower bounds of the position and 1,774,544. Position duration (days) is the difference in days between the time of position termination and position initiation. Position initiation occurs when either a) the position is established or b) liquidity is partially withdrawn from predecessor position or c) predecessor position is extended. Position termination occurs when either a) liquidity is fully or partially removed from the position or b) position is extended. Position extension is an indicator equaling one if previous position is considered terminated due to its extension. Position partial withdrawal is an indicator equaling one if previous position is considered terminated due to partial (as opposed to full) withdrawal of liquidity. Trades served (USD) is the dollar value of all swaps in the pool for which fees accrued to a position. Each swap's dollar value is computed as the number of units of the asset entering the pool times the asset's most recent price, estimated as in Section 3.3. Trades/position size is the ratio of trades served and position size. Daily exchange rate st. dev. is the standard deviation of daily changes in the two assets log exchange rates estimated for the period of 30 days preceding the day of position initiation. USDC-x pool (USDT-x pool, WETH-x pool, WBTC-x pool) is an indicator equaling one for positions in pools whose assets include USDC (USDT, WETH, WBTC). Year 2021 (Year 2022, Year 2023, Year 2024) is an indicator equaling one if position was initiated in 2021 (2022, 2023,2024).

	Min	P25	Median	P75	Max	Mean	Std. Dev.	Num Obs.
Position size (USD)	100	2,282	9,753	42,166	186,218,622	144,954	1,158,153	503,273
Tick range (normalized)	0	0.001	0.003	0.008	1	0.054	0.206	503,273
Position duration (days)	0	0.21	1.55	8.48	1,459.69	32.28	117.43	503,273
Position extension	0	0	0	1	1	0.342	0.474	503,273
Position partial withdrawal	0	0	0	1	1	0.282	0.450	503,273
Trades served (USD)	0	1,641	15,077	88,587	2,588,556K	307,904	3,601,911	503,273
Trades/position size	0.000	0.265	1.774	6.487	1698.418	6.488	16.577	503,273
Proportional fee	0.01%	0.30%	1.00%	1.00%	1.00%	0.76%	0.35%	503,273
Daily return st. dev.	0.00%	1.48%	3.89%	10.19%	1765.82%	9.61%	22.61%	489,970
USDC-x position	0	0	0	0	1	0.126	0.331	503,273
USDT-x position	0	0	0	0	1	0.031	0.174	503,273
WETH-x position	0	1	1	1	1	0.840	0.366	503,273
WBTC-x position	0	0	0	0	1	0.033	0.179	503,273
Year 2021	0	0	0	0	1	0.231	0.421	503,273
Year 2022	0	0	0	0	1	0.201	0.4	503,273
Year 2023	0	0	0	1	1	0.273	0.445	503,273
Year 2024	0	0	0	1	1	0.296	0.456	503,273

Table 3: Blockchain-address-level summary statistics

This table reports summary statistics of characteristics of blockchain addresses that established at least one liquidity position in liquidity pools governed by Uniswap V3 smart contracts on Ethereum, which satisfy the criteria described in Table 2. Total number of positions is the number of positions, closed before December 31, 2024, which were established by a given blockchain address. Total value of positions (USD) is the cumulative dollar value of these positions, where each position's value is estimated at initiation, as described in Table 2. Mean TVL deployed is the daily average of the value of open positions during the period the address is active (see below). Mean position value (USD) is the mean dollar value of all positions established and closed by the address. Address active (days) is the difference between the latest of a) full withdrawal of liquidity from the last liquidity position by the address or b) December 31, 2024, on one hand, and the initiation of the first liquidity position by the address on the other hand. Mean tick range (normalized) is the average tick range (normalized), computed as described in Table 2 across all positions by the address that were closed before the end of the sample period. St. dev. of tick range (normalized) is the standard deviation of tick range (normalized) across all positions by a given address, as described above. Mean position duration (days) is the average position duration across all positions by a given address, as described above. Position duration is computed as in Table 2. St. dev. position duration is the standard deviation of position durations across all positions established by a given address. Mean daily return st. dev. is the average of the standard deviations of exchange rates computed prior to position establishment, as in Table 2 across all positions established by a given address. St. dev. of daily return st. dev. is the standard deviation of daily exchange rate volatility across all positions established by a given address. Mean HHI of positions across pools is the Herfindahl index of values of cumulative liquidity provision by the address to liquidity pools. Proprietary position manager is an indicator equaling one if the address interacts with pools via a proprietary position manager (as opposed to the default, which is Uniswap V3 position manager).

	Min	P25	Median	P75	Max	Mean	Std. Dev.	Num. Obs.
Total number of positions	1	1	2	4	6,763	6.22	34.40	66,011
Total value of positions (USD)	100	1,646	8,317	54,690	3,471,902K	818,861	20,763,885	66,011
Mean TVL deployed	100	851	3,306	15,079	100,035,806	71,802	811,073	66,011
Mean position value (USD)	100	1,033	3,911	16,809	100,035,806	65,871	692,433	66,011
Address active (in days)	0.00	3.00	25.75	181.20	1,459.69	153.13	257.06	66,011
Mean tick range (normalized)	0.000	0.002	0.005	0.008	1.000	0.070	0.222	66,011
St. dev. of tick range (normalized)	0.000	0.000	0.001	0.003	0.707	0.035	0.122	36,312
Mean position duration (days)	0.00	1.13	6.98	42.63	1,459.69	71.29	174.02	66,011
St. dev. of position duration (days)	0.00	1.22	6.53	45.39	1,031.58	53.73	108.31	36,312
Mean daily return st. dev.	0.00%	1.45%	4.36%	11.68%	1207.62%	10.35%	22.78%	63,818
St. dev. of daily return st. dev.	0.00%	0.10%	1.14%	4.91%	789.41%	4.84%	14.38%	35,099
Mean HHI of positions across pools	0.015	0.680	1.000	1.000	1.000	0.853	0.252	66,011
Proprietary position manager	0	0	0	0	1	0.094	0.275	66,011

Table 4: Returns to liquidity positions and their components

This table reports summary statistics of returns to liquidity positions in pools governed by Uniswap V3 smart contracts on Ethereum, and components of position returns. The sample includes liquidity positions in pools in Table 1 that a) were closed before December 31, 2024, b) are not "out-of-range", and c) have non-zero duration. Panel A presents results for the full sample, whereas Panel B presents results for positions deployed by addresses with at least 10 closed positions ("Positions by active addresses"). Daily return—pool choice is the combination of (9) and (12). Daily return—concentration is the combination of (10) and (13). Daily return—holding is computed as in (5). Daily gas cost rate is computed as in (14). Daily return—overall is computed as in (4). If position duration is lower than one day, it is assumed that the duration is one day. The weighting in value-weighed returns is by position value at its establishment, as described in Table 2. *** (**, *) denotes statistical significance of the mean at 1% (5%, 10%) level.

Panel A: All positions

	Min	P25	Median	P75	Max	Mean (EW)	Mean (VW)	Num obs.
Daily return—pool choice	-99.87%	-0.01%	0.00%	0.09%	418.97%	0.18%***	-0.01%**	503,273
Daily return—concentration	-100.00%	-0.01%	0.00%	0.14%	112.92%	-0.04%***	-0.11%***	503,273
Daily return—holding	-72.86%	-1.24%	0.00%	1.19%	14139.99%	0.82%***	0.60%***	503,273
Daily gas cost rate	-99.54%	-0.58%	-0.11%	-0.02%	0.00%	-1.09%***	-0.03%***	503,273
Daily return—overall	-100.00%	-2.05%	-0.09%	1.33%	14550.41%	-0.28%***	0.44%***	503,273

Panel B: Positions by active addresses

	Min	P25	Median	P75	Max	Mean (EW)	Mean (VW)	Num obs.
Daily return— pool choice	-99.74%	0.00%	0.00%	0.10%	150.73%	0.22%***	0.04%***	286,455
Daily return—concentration	-100.00%	-0.01%	0.00%	0.20%	112.92%	0.02%***	-0.02%***	286,455
Daily return—holding	-59.78%	-1.41%	0.00%	1.45%	1230.09%	0.67%***	0.74%***	286,455
Daily gas cost rate	-99.54%	-0.43%	-0.10%	-0.02%	0.00%	-0.73%***	-0.02%***	286,455
Daily return—overall	-100.00%	-1.84%	-0.03%	1.76%	1301.27%	0.14%***	0.74%***	286,455

Table 5: Correlations among components of returns to liquidity positions

This table reports Spearman rank correlation coefficients among the components of daily returns to liquidity provision and overall daily return to luquidity provision. All return components are computed as in Table 4.

	Daily return—pool choice	Daily return—concentration	Daily return—holding	Daily return—overall
Daily return—pool choice	1	0.713	0.075	0.236
Daily return—concentration		1	-0.014	0.175
Daily return—holding			1	0.840
Daily return—overall				1

Table 6: Determinants of liquidity position returns

This table reports coefficients of OLS regressions in which the dependent variable is Daily return—pool choice, Daily return—concentration, Daily return—holding, and Daily return—overall (in columns 1-4, respectively). All return components are computed as in Table 4. The sample contains all liquidity positions that are not the first (chronologically) for a given address. The calculation of liquidity position return and its components is described in Table 4. log refers to natural logarithm. Position size (USD), Tick range, Position duration (days), Daily return st. dev. are defined in Table 2. Relative position size is the ratio of position size to cumulative size of all positions by the same address that are open at the time of position initiation. Num. contemporaneous positions is the number of all positions by the same address that are open at the time of position initiation. Time address active is the difference (in days) between the time position is initiated and the first position initiation by the address. Num. past positions is the number of positions by the same address that were closed before current position initiation. TVL past positions (USD) is the cumulative value of all positions by the same address that were closed before current position initiation. Average past daily (corresponding) return—is the average daily return (pool choice, concentration, holding, and overall in columns 1-4, respectively) across all positions by the same address that were closed before current position initiation. The numbers in parentheses indicate a measure of economic significance—how a one standard deviation increase in an independent variable impacts daily overall return and its components. *** (**, *) denotes statistical significance of coefficients at 1% (5%, 10%) level.

	Daily return—pool choice	Daily return—concentration	Daily return—holding	Daily return—overall
Intercept	0.0088***	-0.0023***	0.0338***	-0.0355***
Position characteristics				
log (Position size) (USD)	-0.0001***	0.0002***	-0.0010***	0.0055***
	(-0.03%)	(0.04%)	(-0.21%)	(1.17%)
log (Tick range)	-0.0003***	0.0001***	-0.0004*	-0.0007**
	(-0.07%)	(0.02%)	(-0.09%)	(-0.14%)
log (Position duration (days))	0.0000	0.0004***	-0.0012***	0.0009***
	(0.00%)	(0.12%)	(-0.35%)	(0.27%)
log (daily return st. dev.)	0.0008***	0.0003***	0.0034***	0.0041***
	(0.13%)	(0.04%)	(0.52%)	(0.62%)
Position importance				
Relative position size	0.0000	0.0007***	-0.0037**	0.0027*
	(0.00%)	(0.03%)	(-0.15%)	(0.11%)
log (Num. contemporaneous positions)	-0.0003***	-0.0007***	0.0023**	-0.0012
	(-0.02%)	(-0.05%)	(0.17%)	(-0.09%)
Experience/learning				
log (Time address active (days)	-0.0002***	0.0001**	0.0000	0.0006*
	(-0.04%)	(0.02%)	(-0.01%)	(0.14%)
log (Num. past positions)	0.0000	0.0002***	-0.0015***	-0.0007
	(-0.01%)	(0.05%)	(-0.31%)	(-0.14%)
log (TVL) past positions (USD)	0.0001***	0.0000	0.0001	0.0001
	(0.05%)	(0.00%)	(0.06%)	(0.08%)
Past performance				
Average past daily (corresponding) return	0.0861***	0.0754***	0.0031*	0.0048***
	(0.11%)	(0.15%)	(0.08%)	(0.12%)
Num. Obs.	480,719	480,719	480,719	480,719
R squared	0.68%	0.37%	0.08%	0.20%

Table 7: Characteristics of liquidity positions by "successful" and "unsuccessful" deployers

This table reports equally-weighted mean characteristics of liquidity positions established by "successful" and "unsuccessful" strategy deployers (in columns 1 and 2, respectively). The sample includes positions established by addresses with at least 10 closed positions. Successful deployers are those that belong to the top 10% of mean Daily return—pool choice (in Panel A), top 10% of mean Daily return—concentration (in Panel B), top 10% of mean Daily return—holding (in Panel C), and top 10% of mean Daily return—overall (in Panel D). Unsuccessful deployers are all other addresses in the sample. All return components are computed as in Table 4. Position size (USD), Tick range, Position duration (days), Daily return st. dev. are defined in Table 2. Coeff. Var. refers to coefficient of variation and is computed as the ratio of mean and st. dev. of the corresponding variable. HHI pools is the Herfindahl index of total position sizes deployed to various liquidity pools. Daily gas cost rate is the ratio of gas cost to position size raised to the power of the minimum of one over position duration (in days) and one. Diff. column reports the difference between characteristics of successful and unsuccessful subsamples. *** (**, *) denotes statistical significance of coefficients at 1% (5%, 10%) level.

Panel A: Daily return—pool choice

	Successful	Unsuccessful	Diff.
Mean position size	42,061	172,281	-130,220***
Mean position duration	8.64	25.87	-17.23***
Mean normalized tick range	0.0373	0.0531	-0.0158***
Mean daily return volatility	14.50%	8.70%	5.80%***
Coeff. Var. position duration	0.671	0.669	0.001
Coeff. Var. normalized tick range	1.938	1.943	-0.004
Coeff. Var. daily return volatility	2.038	1.914	0.124*
HHI pools	0.501	0.546	-0.045***
Mean daily gas cost rate	-1.98%	-1.38%	-0.61%***

Panel B: Daily return—liquidity concentration

	Successful	Unsuccessful	Diff.
Mean position size	28,236	173,816	-145,580***
Mean position duration	12.61	25.43	-12.83***
Mean normalized tick range	0.0254	0.0544	-0.0290***
Mean daily return volatility	14.76%	8.67%	6.09%***
Coeff. Var. position duration	0.701	0.666	0.034**
Coeff. Var. normalized tick range	2.076	1.927	0.149**
Coeff. Var. daily return volatility	2.079	1.909	0.170***
HHI pools	0.506	0.545	-0.039***
Mean daily gas cost rate	-1.87%	-1.39%	-0.48%***

Table 7: Characteristics of liquidity positions by "successful" and "unsuccessful" deployers—Continued

Panel C: Daily return—holding

	Successful	Unsuccessful	Diff.
Mean position size	92,155	166,718	-74,563***
Mean position duration	15.54	25.11	-9.57***
Mean normalized tick range	0.1148	0.0445	0.0703***
Mean daily return volatility	16.78%	8.45%	8.34%***
Coeff. Var. position duration	0.677	0.669	0.008
Coeff. Var. normalized tick range	2.006	1.936	0.070
Coeff. Var. daily return volatility	2.106	1.907	0.199***
HHI pools	0.584	0.536	0.048***
Mean daily gas cost rate	-1.90%	-1.39%	-0.51%***

Panel D: Daily return—overall

	Successful	Unsuccessful	Diff.
Mean position size	90,635	166,887	-76,252***
Mean position duration	13.62	25.32	-11.70***
Mean normalized tick range	0.1017	0.0459	0.0557***
Mean daily return volatility	15.75%	8.56%	7.19%***
Coeff. Var. position duration	0.690	0.667	0.023*
Coeff. Var. normalized tick range	2.192	1.916	0.276***
Coeff. Var. daily return volatility	2.091	1.909	0.182**
HHI pools	0.576	0.537	0.039***
Mean daily gas cost rate	-1.38%	-1.44%	0.06%

Table 8: QUANT AND DISCRETIONARY POSITION MEAN RETURNS

This table reports equally-weighted (in the to 5 rows) and value-weighted (in the bottom 5 rows) returns to various components of liquidity provision. The sample includes positions established by addresses with at least 10 closed positions. The calculation of liquidity position return and its components is described in Table 4. The weighting in value-weighed returns is by position value at its establishment, as described in Table 2. Mean return components of positions established via interaction with a proprietary position manager ("Quant") are reported in the first column. Mean return components of positions established via interaction with Uniswap V3 position manager ("Discretionary") are reported in the second column. Diff. column reports the difference between the means of Quant and Discretionary position returns. *** (**, *) denotes statistical significance of the mean at 1% (5%, 10%) level.

	Mean quant	Mean discretionary	Diff.
Daily return—pool choice (EW)	0.08%***	0.23%***	-0.15%***
Daily return—concentration (EW)	-0.08%***	0.03%***	-0.11%***
Daily return—holding (EW)	0.53%***	0.69%***	-0.16%***
Daily gas cost rate (EW)	-0.97%***	-0.71%***	-0.26%***
Daily return—overall (EW)	-0.46%***	0.20%***	-0.66%***
Daily return—pool choice (VW)	0.01%***	0.04%***	-0.03%***
Daily return—concentration (VW)	-0.03%***	-0.01%***	-0.02%**
Daily return—holding (VW)	-0.10%***	0.93%***	-1.03%***
Daily gas cost rate (VW)	-0.02%***	-0.02%***	0.00%
Daily return—overall (VW)	-0.13%***	0.94%***	-1.07%***
Num. Obs.	26,069	260,386	

Table 9: Daily returns and quant indicator

This table reports coefficients of OLS regressions in which the dependent variable is Daily return—pool choice (in Panel A), Daily return—concentration (in Panel B), Daily return—holding (in Panel C), and Daily return—overall (in Panel D). The sample contains all liquidity positions established by addresses with at least 10 positions. All return components are computed as in Table 4. log refers to natural logarithm. The main independent variable is Quant—an indicator equaling one for positions established via interaction with pools via a proprietary position manager. Position size (USD), Tick range, Position duration (days), Daily return st. dev. are defined in Table 2. Account characteristics in column 7 include: Relative position size; Num. contemporaneous positions; Time wallet active; Num. past positions; TVL past positions (USD); Average past daily (corresponding) return—all defined in Table 6. *** (**, *) denotes statistical significance of coefficients at 1% (5%, 10%) level.

Panel A: Daily return—pool choice

Intercept	0.0025***	0.0055***	0.0031***	0.0025***	0.0047***	0.0103***	0.0111***
Quant	-0.0016***	-0.0015***	-0.0017***	-0.0016***	-0.0013***	-0.0015***	-0.0012***
log (Position size) (USD)		-0.0003***				-0.0002***	-0.0003***
log (Tick range)			-0.0001***			-0.0004***	-0.0004***
log (Position duration (days))				0.0000		0.0001***	0.0001***
log (daily return st. dev.)					0.0007***	0.0008***	0.0008***
Account characteristics	No	No	No	No	No	No	Yes
Num. Obs.	279,900	279,900	279,900	279,900	279,900	279,900	279,900
R squared	0.07%	0.18%	0.07%	0.07%	0.33%	0.50%	0.77%

Panel B: Daily return—liquidity concentration

Intercept	0.0005***	-0.0003	-0.0006**	0.0006***	0.0011***	0.0002	0.0004
Quant	-0.0013***	-0.0013***	-0.0011***	-0.0011***	-0.0012***	-0.0009***	-0.0008***
log (Position size) (USD)		0.0001***				0.0002***	0.0002***
log (Tick range)			0.0001***			0.0000	0.0000
log (Position duration (days))				0.0004***		0.0005***	0.0005***
log (daily return st. dev.)					0.0002***	0.0004***	0.0003***
Account characteristics	No	No	No	No	No	No	Yes
Num. Obs.	279,900	279,900	279,900	279,900	279,900	279,900	279,900
R squared	0.04%	0.11%	0.05%	0.04%	0.18%	0.27%	0.41%

Table 9: Quant and discretionary position mean returns—continued

Panel C: Daily return—holding

Intercept	0.0065***	0.0187***	0.0009	0.0063***	0.0153***	0.0224***	0.0260***
Quant	-0.0013*	-0.0010	-0.0006	-0.0017**	0.0000	-0.0003	0.0009
log (Position size) (USD)		-0.0013***				-0.0009***	-0.0012***
log (Tick range)			0.0007***			0.0000	-0.0002
log (Position duration (days))				-0.0008***		-0.0007***	-0.0009***
log (daily return st. dev.)					0.0027***	0.0022***	0.0022***
Account characteristics	No	No	No	No	No	No	Yes
Num. Obs.	279,900	279,900	279,900	279,900	279,900	279,900	279,900
R squared	0.00%	0.07%	0.02%	0.06%	0.16%	0.22%	0.30%

Panel D: Daily return—overall

Intercept	0.0025***	0.0287***	0.0042***	0.0027***	0.0063***	-0.0171***	-0.0124***
Quant	-0.0069***	-0.0079***	-0.0071***	-0.0066***	-0.0063***	-0.0067***	-0.0048***
log (Position size) (USD)		0.0032***				0.0038***	0.0036***
log (Tick range)			-0.0002**			-0.0007***	-0.0008***
log (Position duration (days))				0.0006***		0.0010***	0.0008***
log (daily return st. dev.)					0.0012***	0.0034***	0.0031***
Account characteristics	No	No	No	No	No	No	Yes
Num. Obs.	279,900	279,900	279,900	279,900	279,900	279,900	279,900
R squared	0.04%	0.42%	0.04%	0.06%	0.06%	0.61%	1.12%

Table 10: Quant and discretionary deployer returns

This table reports statistics for return component distributions of addresses deploying quant and discretionary strategies. The sample includes all addresses with at least 10 closed strategies. Quant (discretionary) deployers are addresses interacting with pools via a proprietary position manager (Uniswap V3 position manager)—in column 1 (2). Panel A (B, C, D) reports statistics for Daily return—pool choice (Daily return—concentration, Daily return—holding, Daily return—overall). All return components are computed as in Table 4. The statistics for each return component are: equally-weighted mean return and proportions of deployers with equally-weighted mean returns belonging to top 1%, 5%, and 10% of the distribution of respective mean deployer-level return component. Diff. column reports the difference between the means of returns of addresses deploying Quant and Discretionary strategies. *** (**, *) denotes statistical significance of the mean at 1% (5%, 10%) level.

Panel A: Daily return—pool choice

	Quant	Discretionary	Diff.
Mean daily return—pool choice	0.05%	0.23%	-0.18%***
Prop. top 1%—pool choice	0.38%	1.02%	-0.64%***
Prop. top 5%—pool choice	1.14%	5.14%	-4.00%***
Prop. top 10%—pool choice	2.66%	10.28%	-7.62%***

Panel B: Daily return—liquidity concentration

	Quant	Discretionary	Diff.
Mean daily return—concentration	-0.05%	0.02%	-0.08%**
Prop. top 1%—concentration	0.00%	1.04%	-1.04%***
Prop. top 5%—concentration	0.76%	5.15%	-4.39%***
Prop. top 10%—concentration	3.04%	10.27%	-7.22%***

Panel C: Daily return—holding

	Quant	Discretionary	Diff.
Mean daily return—holding	0.82%	0.76%	0.06%
Prop. top 1%—holding	2.28%	0.95%	1.33%***
Prop. top 5%—holding	3.42%	5.05%	-1.63%***
Prop. top 10%—holding	7.98%	10.07%	-2.09%***

Panel D: Daily return—overall

	Quant	Discretionary	Diff.
Mean daily return—overall	-0.21%	0.14%	-0.35%
Prop. top 1%—overall	2.28%	0.95%	1.33%***
Prop. top 5%—overall	3.42%	5.05%	-1.63%***
Prop. top 10%—overall	6.84%	10.12%	-3.27%***
Num. obs.	263	6,751	

Table 11: Characteristics of liquidity positions by successful quant and successful discretionary deployers

This table reports equally-weighted mean characteristics of liquidity positions established by "successful quant" and "successful discretionary" strategy deployers (in columns 1 and 2, respectively). The sample includes positions established by addresses with at least 10 closed positions that belong to the top 10% of of mean Daily return—pool choice (in Panel A), top 10% of mean Daily return—concentration (in Panel B), top 10% of mean Daily return—holding (in Panel C), and top 10% of mean Daily return—overall (in Panel D). All return components are computed as in Table 4. Position size (USD), Tick range, Position duration (days), Daily return st. dev. are defined in Table 2. Coeff. Var. refers to coefficient of variation and is computed as the ratio of mean and st. dev. of the corresponding variable. HHI pools is the Herfindahl index of total position sizes deployed to various liquidity pools. Daily gas cost rate is the ratio of gas cost to position size raised to the power of the minimum of one over position duration (in days) and one. All mean characteristics are address-level means of position characteristics described in Table 7. Diff. column reports the difference between characteristics of successful and unsuccessful subsamples. *** (**, *) denotes statistical significance of coefficients at 1% (5%, 10%) level.

Panel A: Daily return—pool choice

	Successful	Unsuccessful	Diff.
Mean position size	25,079	42,232	-17,153
Mean position duration	11.55	8.61	2.94
Mean normalized tick range	0.0015	0.0377	-0.0362***
Mean daily return volatility	6.87%	14.58%	-7.71%***
Coeff. Var. position duration	0.648	0.671	-0.023
Coeff. Var. normalized tick range	2.378	1.934	0.444
Coeff. Var. daily return volatility	3.452	2.022	1.430
HHI pools	0.364	0.502	-0.138
Mean daily gas cost rate	-1.96%	-1.98%	0.02%

Panel B: Daily return—liquidity concentration

	Successful	Unsuccessful	Diff.
Mean position size	29,149	28,226	923
Mean position duration	10.44	12.63	-2.20
Mean normalized tick range	0.0027	0.0256	-0.0229***
Mean daily return volatility	6.51%	14.85%	-8.34%***
Coeff. Var. position duration	0.629	0.701	-0.072
Coeff. Var. normalized tick range	1.695	2.080	-0.385
Coeff. Var. daily return volatility	1.503	2.085	-0.581**
HHI pools	0.609	0.505	0.104
Mean daily gas cost rate	-1.06%	-1.88%	0.82%**

Table 11: Characteristics of liquidity positions by "successful" and "unsuccessful" deployers—Continued

Panel C: Daily return—holding

	Successful	Unsuccessful	Diff.
Mean position size	153,617	90,257	63,360
Mean position duration	10.95	15.68	-4.73
Mean normalized tick range	0.2112	0.1118	0.0994
Mean daily return volatility	12.71%	16.90%	-4.19%
Coeff. Var. position duration	0.613	0.679	-0.066
Coeff. Var. normalized tick ra	1.975	2.006	-0.031
Coeff. Var. daily return volat	2.208	2.104	0.104
HHI pools	0.812	0.577	0.234***
Mean daily gas cost rate	-2.25%	-1.89%	-0.37%

Panel D: Daily return—overall

	Successful	Unsuccessful	Diff.
Mean position size	137,252	89,406	47,846
Mean position duration	11.15	13.69	-2.54
Mean normalized tick range	0.2007	0.0990	0.1017
Mean daily return volatility	9.88%	15.89%	-6.02%**
Coeff. Var. position duration	0.614	0.692	-0.078
Coeff. Var. normalized tick ra	2.386	2.189	0.197
Coeff. Var. daily return volat	2.400	2.087	0.313
HHI pools	0.742	0.572	0.170**
Mean daily gas cost rate	-1.13%	-1.39%	0.26%