The Value of Uninformed Orderflow on the Uniswap Protocol

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Abstract

We analyze how *uninformed orderflow* – orders that are not predictive of future price movements – affect the revenue earned by liquidity providers on the Uniswap Protocol. We also present an opinionated framework for how much the protocol should value liquidity. We conclude by providing a recommended upper bound on how much the protocol should pay for uninformed orderflow.

1 Introduction

The Uniswap protocol. The Uniswap protocol is a collection of smart contracts that enable liquidity providers (LPs) to passively make a market on pairs of fungible tokens. LPs deposit tokens into a pool, and traders can place orders against the liquidity in the pool. The price that traders receive is computed in smart contracts based on the state of the pool; importantly, LPs are not required to change their liquidity positions to facilitate trades on the pool. Instead of earning revenue by charging a bid-ask spread, Uniswap's LPs earn a fee on each order that is proportional to the order's volume.

Since the tokens traded on Uniswap have time-dependent demand, and the price quoted by an Uniswap pool does not utilize a time term, the prices quoted by the pool do not always align with those of external trading venues. In the case of Uniswap V2, the only way of changing the price quoted by a pool is to place an order on the pool [AZR20]. Although this is technically not the case in Uniswap V3, since LPs can set their liquidity positions with different price bounds, the cost of blockspace makes it impractical for LPs to affect price discovery by updating and cancelling liquidity positions [Ada+21]. This is in contrast to the prevailing orderbook-based centralized exchanges, where liquidity providers can remove limit orders to adjust the price, all without incurring cost when cancelling orders. In both Uniswap V2 and V3, price discovery is primarily driven by arbitrageurs.

Under most conditions, taking the other side of an arbitrageur's trade is a very bad deal for LPs. The more general phenomenon of trading between parties with asymmetric information is known in game theory as *adverse selection*. Perhaps obviously, agents with more information about the "true" value of a financial product than their counterparty can use this information to place better trades. And since bilateral exchange of common-value assets is a zero-sum game, it follows that the agent who gets the better deal – typically the agent with better information – profits at the expense of their counterparty. This is relevant in the case of Uniswap, where LPs' trading strategy is fixed by the automated market maker, and arbitrageurs make money at the expense of LPs.

Intuitively, LPs should earn more when they face non-arbitrage volume. To study this, we introduce the notion of orderflow information.

Orderflow information. We can formally define uninformed flow using price expectations. Let t_0 be the current time, let $h > 0$ be a fixed time interval that we choose, let P_t be the instantaneous pool price of token0 relative to token1 at a time t, let O be a random variable representing the next order in the pool,

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and let $x(O)$ be the number of token0 purchased in order O ($x(O)$ is negative if token0 is sold). We say that an order o is *informed* if the expected value of the change in pool price is in the same direction as the order:

$$\operatorname{sign}\left(\mathbb{E}[P_{t_0+h} - P_{t_0} \mid O = o]\right) = \operatorname{sign}\left(x\right). \tag{1}$$

In contrast, we say that an order o is *uninformed* if statement 1 is false.

Notice that this is a permissive characterization of orderflow information. For instance, if order o is executed at time t_0, and the next order is executed at time $t_1 > t_0 + h$, then order o will necessarily be characterized as informed, since o pushes the pool price in the direction of x. This can be resolved by selecting a sufficiently large h parameter, for which we provide a methodology in Section 2.

Furthermore, this characterization considers orders informed even when $\operatorname{sign}\left(\mathbb{E}[P_{t_0+h} - P_{t_0}]\right) = \operatorname{sign}(x)$. That is, if the pool price is expected to move in the same direction as order o, even if o did not exist, we would still characterize o as informed. Put another way, an order o can be informed, even if it does not bring new information about price changes. Since an informed order *can* bring new information about price changes, we define uninformed orders with conditional expectation.

Related work. The profitability of Uniswap LPs is not a new topic of research. Angeris et al. provided analytic formulas for the profitability of Uniswap LPs between discrete points in time [Ang+19]. White demonstrated that Uniswap LPs with nearly-zero fees outperform those with higher fees under specific volatility and drift conditions. A number of reports have shed light on the historical profitability of Uniswap V3.

This paper. The aim of this paper is to find the value that uninformed orderflow creates for the protocol. To achieve this, we begin in section 2 by finding the marginal revenue that uninformed orderflow creates for liquidity providers, and along with the marginal increase in liquidity that we would expect to come from an increase in revenue. In section 3 we provide an opinionated framework for how much the protocol should value an increase in liquidity. We provide protocol recommendations and directions for future research in section 4, and we conclude this research in section 5.

2 Value of Uninformed Orderflow for LPs

We proceed with the following methodology to determine the revenue that uninformed orderflow creates for LPs in an Uniswap V3 pool. First, we use historical order data to filter orders into informed vs uninformed orders, and we estimate the distribution of sizes of uninformed orders. Next, we run a number of simulations in which we sample from this estimated distribution of uninformed order sizes and compute the amount of revenue generated to LPs from that uninformed order; this revenue quantity includes the revenue that would be generated by sandwiching the uninformed order. This allows us to both determine the value created by uninformed orders of various sizes and determine the mean value per dollar of uninformed orderflow. We then use these values to estimate the influx of LP positions that we would expect to see as a result of an increase in LP revenue. To do this, we use historical pool data to filter positions into *active* and *passive*, based on how long they have been open, and we assume that the active positions will behave more rationally with respect to increases in LP revenues, whereas we assume that passive positions will be less responsive. By doing this, we can place a conservative estimate on the influx of new LP positions that would result from an increase in LP revenues.

2.1 The distribution of uninformed order sizes.

We estimate the distribution of uninformed order sizes by filtering historical orders into informed and uninformed orders, then approximating the distribution of historical trade sizes. To perform this filtering, we

2.2 Simulating uninformed orderflow's impact on LP revenue.

2.3 Relating LP revenue to LP positions.

3 Value of LPs for the Protocol

4 Discussion

5 Conclusion

References

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