Active vs Passive: Passive liquidity and AMM contribution to price discovery*

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Abstract

Automated market makers (AMMs) are flawed. They quote stale prices. We examine the contribution of AMMs to price discovery in cryptocurrency markets. We analyze 73 trading pairs listed on both Binance and Uniswap and find that large AMM pools lead contribute to price discovery 24.7% of the time. Informed traders trade in AMMs when they are cheaper and more profitable. Regardless, AMMs are slow to impound information into prices. Our findings show AMMs are an important informational market and they can contribute to price discovery.

`Keywords:` Decentralized exchange, automated market maker, price discovery, cryptocurrency
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1 Introduction

Automated market makers (AMMs) are flawed, they offer stale prices. AMMs can only update prices through trades. To facilitate trades in an AMM, liquidity providers (LPs) add funds to a liquidity pool and let a mathematical function define prices. Trades occur against the liquidity pool and LPs earn a fee in return for facilitating trades. This fee becomes a source of passive income as the LP does not have to update their position. Passive liquidity provision is possible if LPs accept the risk of offering stale prices by letting traders dictate prices. However, having traders update prices could have detrimental effects on price discovery.

Market making is a game for active players. The concept of passive liquidity provision contradicts the core principles of market making. Market makers in traditional limit order book (LOB) markets want to avoid offering stale prices. They update their quotes based on all available information. As a result, quotes lead price discovery because they are constantly updating to new information entering the market (Brogaard, Hendershott, and Riordan, 2019).

The reality of passive investing is that is not very passive. Easley et al. (2021) show that ETFs, a passive investment vehicle, are actually growing in activeness. The active ETFs are gaining market share from less active ETFs. In an AMM, passive LPs are the market makers. Is the passive liquidity provision in AMMs active enough to facilitate price discovery?

In this paper, we explore how AMMs contribution to price discovery with their passive liquidity provision. Our research centers on two primary questions. First, do AMMs contribute to price discovery? Second, under what conditions do AMM contribute to price discovery?

Price discovery is a key function of financial markets. It is the process of information entering prices. Understanding price discovery in AMMs is crucial, as they may revolutionize financial markets. Foley, O'Neill, and Putniņš (2023) suggests AMMs are a more efficient market design for trading high volume, low volatility assets. Moreover, liquidity in AMMs is more stable (Adams et al., 2023). Malinova and Park (2023) argue that using AMMs could save billions of dollars in transaction costs and improve capital allocation.

We estimate the price discovery shares between Uniswap and Binance. Uniswap is the largest decentralized exchange and AMM. Uniswap offers over 180k unique asset pairs and 150k unique assets for trading. We compare Uniswap's contribution to price discovery with Binance. Binance is the largest centralized cryptocurrency exchange which trades using a

LOB. CCData reports that Binance's average daily volume is approximately $8 billion.

Our focus is on the trading pairs that are listed on both Uniswap and Binance. Uniswap has a long tail of small assets that can only be traded in an AMM. In these markets, price discovery can only occur in the AMM. We want to understand how AMMs contribute to price discovery when another LOB market exists.

We use the information leadership share to measure each market's contribution to price discovery following Putniņš (2013) and Yan and Zivot (2010). Other common measures of price discovery such as the Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) component share (CS) both measure a mix of information leadership and an avoidance of noise (Yan and Zivot, 2010). Measuring the price discovery shares through the CS or IS will lead to results that bias the market with less noise, in this case the limit order book.

The AMMs share of price discovery is on average 16.3% in our sample period from June 2020 to March 2023. AMM liquidity pool size matters. Large liquidity pools with over $50 million in total value locked (TVL) on average have a 24.7% share of price discovery. This result suggests that AMMs are an informationally informative market.

To understand the conditions where AMMs lead price discovery, we focus on where informed traders would trade. We hypothesize informed traders will trade in AMM when they can profit more from their information. Collin-Dufresne and Fos (2015) shows informed traders are conscious of the liquidity in the market when timing their trades. When selecting a venue to trade, the informed trader will trade in the more liquid market as it allows them to profit more on their information. Informed traders can maximize their profit by trading in high liquidity low fee AMM pools.

The AMMs' share of price discovery is positively related with liquidity and negatively correlated with spread (swap fees), supporting this hypothesis. However, price discovery in the AMM is at the cost of the liquidity provider. For the AMM to be more profitable to trade, the market makers in the LOB must not accept the risk posed by informed traders. If the market makers are not willing to accept the risk, then LPs must be worse off for facilitating the trade.

Regardless of their contribution to price discovery, AMMs are a slow market. We calculate the cross correlation of returns and find that the AMM lags the LOB. We also estimate the generalized impulse response function and find that the AMM is slow to respond to shocks in the LOB price. The risks associated with trading on the blockchain limit the speed of the AMM.

Our findings have implications for the design of AMMs. For an AMM to contribute to price discovery, it can be designed to increase trading activity and liquidity. However, there needs to be a balance between LP incentives and promoting trading activity/liquidity. Activity can be promoted by decreasing fees, explicit (gas) and implicit (swap fee). Liquidity can be increased by changing the pricing function to suit the needs of the market.

There is a rich literature that focuses on the contribution of price discovery between different markets. Cabrera, Wang, and Yang (2009) explore the role of the futures market in price discovery. Several studies explore the price discovery dynamics between stock and options markets (Muravyev, Pearson, and Paul Broussard, 2013; Patel et al., 2020; Hsieh, Lee, and Yuan, 2008; Chakravarty, Gulen, and Mayhew, 2004). Ates and Wang (2005) examine the contribution of price discovery between open outcry and electronic markets. Similarly, Booth et al. (2002) study the information content of trades between upstairs and downstairs markets.

Many studies also examine the role of price discovery across geographical regions (Chen and Choi, 2012; Fricke and Menkhoff, 2011; Eun and Sabherwal, 2003). Alexander, Heck, and Kaeck (2022) and Conlon et al. (2022) measure the price discovery in cryptocurrency markets. We add to this literature by highlighting the contribution of AMMs to price discovery in cryptocurrency markets.

Our paper relates to studies on AMMs and decentralized exchanges. Aoyagi and Ito (2021) present a theoretical framework for the interaction of AMMs and LOB markets. Similarly, Barbon and Ranaldo (2022) quantify the costs of trading on DEXs. Lehar and Parlour (2021) show that AMMs and DEXs can function as stable markets. Heimbach, Schertenleib, and Wattenhofer (2022) provide an analysis on the profitability of liquidity provision. Moreover, Milionis et al. (2022) and Milionis, Moallemi, and Roughgarden (2023) quantify the un-diversifiable risk of providing liquidity in AMMs. Xu et al. (2022) provide an in-depth overview of the different AMM designs. We contribute to this growing area of literature by examining the role that AMMs play in price discovery.

Existing papers explore the contribution of price discovery between AMMs and centralized exchanges. Capponi, Jia, and Yu (2023) show that informed traders bid higher gas fees to reduce execution risk and compete in decentralized exchanges. Alexander et al. (2023) examine the ETH USDC trading pair and the contribution to price discovery across Uniswap, Coinbase and Bitstamp. They find the AMMs share of price discovery increases with the liquidity improvements gained from the concentrated liquidity market design. The study investigates Uniswap's price discovery shares, but the differences in noise could lead to an underestimation.

2 Background

AMMs algorithmically provide liquidity in markets. They are market design that allows for passive provision of liquidity. AMMs are not new to DeFI, they have history being used in prediction markets (Hanson, 2003). The lack of liquidity sensitivity in AMM designs limits their use case beyond prediction markets. Othman and Sandholm (2011) and Othman et al. (2013) provide new invariants to deal with the challenge of liquidity sensitivity in AMMs.

AMMs have been popularized in decentralized finance. AMMs make trading on chain possible by reducing the cost of on chain data storage needed to operate a market. The cost of running a LOB on a blockchain is extremely expensive. By using AMMs, traders do not have to trust a centralized exchange, providing security benefits to users.

In decentralized finance, AMMs can facilitate trades because LPs add assets to a liquidity pool. Any user can trade against this liquidity pool on the blockchain. When a trader arrives at the AMM intending to trade, a mathematical function known as the pricing function determines the price. As trades occur in the liquidity pool, prices move with the demand of each asset. In return for facilitating trading, LPs expect to earn a share of the trade volume as a fee. The fee acts as an incentive for LPs to provide liquidity.

There are many AMM designs. We specifically focus on Uniswap. Uniswap is the first and largest AMM, it has 3 versions with slightly different pricing functions for the AMM. Uniswap v1 and v2 employ a simple pricing function known as the constant product market maker (CPMM). This pricing function takes the form of

$$xy = k$$

where x and y are the reserves of the two assets in the pool and k is a constant equal to their product. When swapping against the CPMM, k is held constant with by the change in reserves

$$(x + \Delta x)(y + \Delta y) = xy = k$$

By holding the invariant k constant prices follow the demand for each asset. To add and remove liquidity in the CPMM, LPs must add both assets proportional to their current weighting in the pool. Adding and removing liquidity does not change the price of the pool. For more detail on the CPMM of Uniswap, we refer to the Zhang, Chen, and Park (2018).

Uniswap v3 introduces concentrated liquidity on top of the CPMM. In a concentrated liquidity market, liquidity is added to the pool between two prices. In the CPMM, liquidity can be thought of as being distributed from $(0, \infty)$. Concentrated liquidity is instead bounded between two prices (p_a, p_b) where the amount of liquidity added follows the pricing function

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

Bounding prices gives LPs the ability to leverage their reserves. Prices p are bounded to discrete price ticks to maintain simple data storage costs. The concentrated liquidity market is like the LOB because liquidity is provided across discrete price ticks and the CPMM because $\sqrt{k} = L$. Different LPs can provide liquidity across different price ranges. The liquidity L can be added up for each position within one discrete tick interval. Users trade against L in the current tick as they would in the CPMM market with k. As trades move across the discrete price ticks, the reserves of one token are depleted. Different price has different levels of liquidity L which impact the sensitivity of prices. All else equal a larger L results in less price impact for a trade. Adams et al. (2021) provide a detailed explanation of the Uniswap v3 pricing function.

In AMMs, the fees are often taken as a haircut of the assets entering the pool. This artificially creates a spread for these markets. Both buying or selling incur a percentage cost on the trade size. The fee in Uniswap v2 is 0.3% while the fees in Uniswap v3 vary but are static for each pool. The Uniswap v3 pools can be set with a 1%, 0.3%, 0.05% or 0.01% fee. Each pool is unique and the same trading pair may different fee pools with their own liquidity.

Between AMMs and centralized cryptocurrency exchanges, there are significant frictions to arbitrage. These frictions are driven by the uncertainty of operating on a blockchain. Transactions on a blockchain have uncertainty on whether they will get included in the next block. Transactions need to be propagated to the network to reach a builder. For arbitrage to occur between a CEX and a DEX, the arbitrageur will risk the market moving while waiting for the trades to be confirmed. The arbitrage opportunity may disappear during this time, creating a level of execution risk.

Capponi, Jia, and Yu (2023) explore how the execution risk impacts price discovery on DEXs. They find informed traders are willing to compete and bid higher to be included in the next block, reducing the execution risk. However, this also introduces the chance to be frontrun by other parties.

Frontrunning on blockchains is commonly known as a miner extractable value (MEV). MEV is created when the proposer of a block has an incentive to include or reorder the transactions in the block for monetary gain. The proposer can earn extra from a block if they frontrun other transactions. This malicious trading is outlined in Daian et al. (2019).

3 Hypothesis generation

To understand the role of AMMs in price discovery, we first pose the question of which venue would an informed trader trade, the AMM, or the LOB? There are a variety of factors that influence this question, but it ultimately comes down to the informed trader being a profit maximizing agent. To maximize their profit, they will enter the most liquid market. However, the informed trader also needs to consider whether trading in each market will reveal any information to other agents.

A more liquid market allows informed traders to profit more from their information. Collin-Dufresne and Fos (2015) find that informed traders are selective of liquidity when timing trades. Aoyagi and Ito (2021) suggests that the number of informed traders will increase with the liquidity in the AMM.

Informed traders seek liquidity for higher profits, while market makers aim to reduce losses from informed traders. In illiquid pairs, market makers adjust for adverse selection by increasing spreads (Easley et al., 1996). Additionally, Koski and Michaely (2000) found that spreads are larger, depth is lower, and there is greater price impact during information events. In an AMM, liquidity providers cannot directly adjust their spread (fee), however thy can choose to remove their liquidity from the pool. By removing liquidity from the pool they would also disincentivize informed traders, reducing the adverse selection cost.

Informed traders also need to consider the information leakage from their trades. To effectively profit on information in a LOB, they must split their order. When informed traders split their order, they risk market makers learning from their order flow (Chae, 2005). Market makers can then update their order to minimize the adverse selection cost and reduce the profit of an informed trader. In an AMM, order splitting does not have the same benefit as in a LOB. If there are no other trades, the AMM price will be the same for a parent order, as it is when the parent order is split, removing much of the benefit from splitting orders.

Informed traders must decide if splitting their order through the LOB is more profitable than trading directly in the AMM. The benefit of trading on the AMM is that there is less chance that market makers learn from the order flow. However, on the LOB, strategic market makers can not only learn from the order flow, but can exploit the informed trader through "back running" (Yang and Zhu, 2020). Regardless, if it is still more profitable to trade on the LOB, because the cost of trading on the AMM is too high, the informed trader will trade on the LOB.

To maximize their profit, the informed trader also need to consider the trading costs. Trading costs on an AMM are better for large orders but worse for small orders (Barbon and Ranaldo, 2022). Barclay, Hendershott, and Mccormick (2003) provides evidence to suggest that informed trading makes trading costs higher. This is because market makers can choose to internalize the trades. In an AMM, all trades are internalized by the liquidity providers. These findings suggest informed traders prefer the AMM for larger trades.

The mechanism to increase trading costs in response to informed traders is different between the LOB and AMM. In a LOB, market makers can increase their spread and reduce the depth of the market by updating their orders. However, in an AMM, liquidity providers can only remove liquidity from the pool. If the liquidity provider believes the adverse selection cost is too high, they can earn more trading fees by providing liquidity to a higher fee pool. This would be like a market maker widening their spread.

All traders are affected by the changes in trading cost, although at different rates (Dávila and Parlatore, 2021). In an AMM, the depth (liquidity) in the pool can be increased directly by changing the swap fee. A 1% decrease in the fee will lead to a 1% increase in depth, all else equal. The swap fee acts like a haircut, reducing the size of the order before applying the pricing function. For an informed trader, a reduction in fees or an increase in liquidity would allow them to receive greater profit from their information.

We hypothesize AMMs will lead price discovery when informed traders can profit more from their information. This profit would come from deep, low fee AMM pools. Deeper pools let informed trades trade more to move the market to a certain price. Similarly, reducing the fee creates more depth around the current mid-quote price, creating more opportunity for informed traders to profit on smaller price innovations.

4 Data and Sample

We focus our analysis on a sample period from June 2020 to March 2023. Uniswap v2 was deployed in May 2020 and acts as a pivotal point in the adoption of AMMs. From an Ethereum node, we gather data on both Uniswap v2 and Uniswap v3 pools. We collect historic Binance trade and quote data from Tardis.Dev.

Uniswap and Binance both trade a variety of unique assets. As of April 2023 date, Uniswap has roughly 170 thousand different asset pairs covering 157 thousand unique tokens.

Uniswap is a permissionless exchange where any user can deploy their own token to be traded. In contrast, Binance only has roughly 1200 asset pairs, including over 350 unique assets and fiat currency.

There are 279 asset pairs listed on both Uniswap and Binance. Although a market exists for these pairs, many on Uniswap are inactive and/or illiquid. We focus our study on pairs with over 500 trades within a month and over $500k TVL in the Uniswap pools. Stablecoin to stablecoin pairs are excluded to prevent conflicting price discovery results because of their connection to the USD. Where possible, we consider the wrapped version of tokens which give them the ERC-20 standard and allow them to be traded on Uniswap[1]. Our sample comprises 73 asset pairs[2].

Uniswap can have several liquidity pools for the same asset pair. We aggregate the prices in different pools into a single price series. This is consistent with Uniswaps order routing, which provides users with the best trade price across all Uniswap pools. When only one pool has traded within a block, we take the mid-quote price from that pool. If there are two or more pools that trade within a block, we take the median mid-quote price between the pools. We calculate the mid-quote for Uniswap v2 pools as the ratio between the two reserves in the pool ($\frac{reserves1}{reserves0}$). In Uniswap v3 pools, we calculate the mid-quote as the $\sqrt{P}^2$. $\sqrt{P}$ is a tracked variable within the smart contract of the Uniswap v3 pools.

Table 1 presents the summary statistics on Uniswap and Binance from pair month observations. We find that the Uniswap Average and Median trade size are much larger than Binance across the whole percentile range. Similarly, the effective spread is much larger for Uniswap compared to Binance. Although the effective spread is 4 times larger in Uniswap than Binance, the average and median trade size is 30-40 times larger. Notably, there is high turnover in Uniswap liquidity positions based on the value of the Mints and Burns. Binance is less volatile than Uniswap. However, this is consistent with the larger average trade size.

[Insert Table 1 Here]

We consider how the difference in pool size can contribute to a difference in summary statistics. Table 2 presents a difference in means for comparable summary statistics based on Uniswap liquidity pool size. We define large pools as those with over $50 million in

[1] i.e. Ethereum (ETH) pairs are compared to Wrapped Ethereum (WETH) pairs

[2] We also remove assets that no longer represent the same value, such as those from token contract migrations.

TVL. Medium pools have between $10 and $50 million in TVL. Small pools have less than $10 million in TVL. We find that the difference in means is consistent across the various pool sizes. Larger pools on Uniswap have more trade volume and activity, and they are also cheaper to trade in. There is a noticeable difference in trade volume between Binance's medium pool size and the small pools. Showing that there might be a preference to trade some assets on Uniswap over Binance. Binance trading cost, volatility, and trade size are lower when Uniswap pool size is larger, suggesting similar risk characteristics across markets.

[Insert Table 2 Here]

5 Method

We measure the price discovery shares of Uniswap and Binance through the information leadership shares (ILS), following Putniņš (2013). We use mid-quote returns from Binance and Uniswap based on the Ethereum block time. The target time for a block in Ethereum is 12 seconds. We employ a vector error correction model (VECM) with 300 lags, which equates to roughly 1 hour based on a 12 second block time (Estimation details can be found in Appendix A).[3]

Other common empirical measures of price discovery are the Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) component share (CS). Both measures break down price changes into permanent and temporary components. The IS measures if the market incorporates new information and/or impounds fewer liquidity shocks (less noise). The CS measures the sensitivity of each market relative to each other markets lagged transitory shocks. Both measures of price discovery measure a relative avoidance of noise. There is a significant difference in the level of noise between the Uniswap and Binance, as noted in Table 2. We use the ILS of Putniņš (2013) to measure information incorporation in prices, regardless of noise.

[3]When Ethereum was proof of work the timestamps would vary based on the probability of completing a block. With Ethereum's transition to Proof of Stake, blocks are now closer to 12 seconds, only changing when a slot is missed.

6 AMM Price Discovery

6.1 Price Discovery Shares

The average ILS for Uniswap is 16.3%. This is lower than Uniswap's average volume contribution of 47.3%. For the amount of volume, the ILS is significantly lower than the amount of volume. However, if we compare the contribution of price updates in each markets Uniswap's share of price updates is 0.8%. Price updates are trades for the AMM and top of book quotes for LOB. When comparing the share of trades in each market, the AMM share is 8.4%. The AMMs contribution to volume is much higher than the contribution to price discovery, however, there are fewer price updates in the AMM.

The amount of liquidity in the Uniswap pools is related to their price discovery shares. Figure 1 presents the average ILS for different AMM pool sizes from June 2020 to March 2023. We define large pools as those with over $50 million in TVL. Medium pools have between $10 and $50 million in TVL. Small pools have less than $10 million in TVL. On average, the large pools have an average ILS of 24.7%, however, there is a clear trend starting at the start of 2022 where the ILS is increasing to over 50%. There is a similar trend for the medium pools with the average ILS at 17.0%. The small pools appear to have no trend overtime with an average ILS of 14.1%.

Figure 1 suggests that pool size (liquidity) is positively related to the ILS. This supports our hypothesis that price discovery would occur in more liquid pools. Large Uniswap pools play a major role in price discovery, highlighting the informational significance of AMMs as a market design.

[Insert Figure 1 Here]

Analyzing return correlation between markets helps us understand their lead-lag relationship. Figure 2 presents the mean cross correlation of returns between Uniswap and Binance measured at a block time frequency. The lagged values from -100 to -1 on the left show when Uniswap is leading Binance, similarly when the lagged values are on the right 1 to 100, this show that Binance is leading Uniswap. The highest correlation is at lag -1, which would be consistent with Uniswap leading Binance. However, from lags 1-30, there is a clear positive correlation across the full range, which is consistent with the findings of the ILS.

Figure 2 highlights the difference in speed between the two markets. Binance is quick to respond to changes in the Uniswap price. However, Uniswap is slow to respond, with returns being correlated up to 30 lags (6 minutes) ahead.

[Insert Figure 2 Here]

We can measure the speed of the response between Uniswap and Binance through the impulse response function. We follow Pesaran and Shin (1998) to calculate the generalized impulse response function (GIRF) from the moving average representation of the VECMs estimated to calculate the price discovery shares.

Figure 3 presents the cumulative GIRF for a one standard deviation shock between Uniswap and Binance. Noting how large pools have higher ILS, we also split the GIRF by the different pool sizes. The first column represents the response of Uniswap to a one standard deviation shock in Binance. The second column represents the response of Binance to a one standard deviation shock in Uniswap. Each row represents the different pool sizes. The first row is for large Uniswap pools, the second row is for medium Uniswap pools, and the third row is for small Uniswap pools. The shaded area represents the 5% and 95% confidence intervals.

Consistent with the findings in the cross correlation, Binance is quick to respond to a shock in the Uniswap price. Similarly, Uniswap is slower to react to a shock in the Binance price. The speed of response does not change drastically with the different pool sizes, although there is a slight increase in the speed for larger pools.

[Insert Figure 3 Here]

The frictions to arbitrage between these markets explains why Uniswap is much slower than Binance in responding to a shock. On Binance, quotes can be updated to respond to the shock without trading or needing arbitrage to move the price. For the AMM, trades are required to update the price, leaving arbitragers open to several risks associated with blockchains. To trade on the AMM, the transaction needs to be propagated to the network and then included into the next block. This takes time, in which the LOB market may move to close the arbitrage without trading as in Brogaard, Hendershott, and Riordan (2019). Propagation through the network also introduces the risk that another trader may front run the arbitrage. There are methods that an arbitrageur can use to mitigate the risk of being front run. However, these often increase the time taken to be included in to block. These methods are like those used by users trying to mitigate maximal extractable value (MEV) (Daian et al., 2019).

6.2 Determinants Price Discovery

We hypothesize informed traders seek to maximize profit by trading on the more liquid market. To test this hypothesis, we regress measures of liquidity and trading cost on the ILS. We estimate the following regression:

$$ILS_{i,t} = \alpha_{i,t} + Spread_{i,t} + Liquidity_{i,t} + Determinants_{i,t} + controls_{i,t} + \epsilon_{i,t} \tag{1}$$

where spread is the Uniswap fee, liquidity is a measure of the liquidity in the Uniswap pools, either total value locked or the dollar value of the invariant. Determinants include the trade volume, number of trades, volatility, and trade cost. We control for the cost of gas to transact on the blockchain and if the trading pair contains a stablecoin. We also control for fixed effects in these regressions.

We consider two regression frameworks, the first with the metics in absolute terms and the second in relative terms. The absolute measures are the natural log, while the relative measures are the natural log of the ratio between the Uniswap and Binance.

Table 3 reports coefficient estimates from beta regressions following Equation 1 using absolute measures. In all regressions, the spread in the AMM shows a negative relationship with the ILS. In contrast, the ILS shows a negative relationship with the spread of the AMM in all regressions. The effective spread is also insignificant, which would suggest that any reduction in fee is an increase in profit for an informed trader. This finding supports our hypothesis that informed traders prefer to trade in AMMs which are liquid and have low fees to maximize their profits.

Volatility is positively related to the ILS. This is consistent with Aoyagi and Ito (2021) where more informed trading on the AMM leads to greater volatility. Volume and the number of trades also have the large positive coefficients, highlighting the need for activity to update prices.

We find that gas fees are insignificant in these regressions. Informed traders will reveal information in the mempool when bidding for priority inclusion in the block (Capponi, Jia, and Yu, 2023). This would support our findings that informed traders are not concerned with the underlying explicit cost of trading.

[Insert Table 3 Here]

Table 4 reports coefficient estimates from beta regressions following Equation 1 using relative measures. The ratio of spread is negatively related to ILS in Regression 3 when we include pair and month fixed effects, further supporting our hypothesis that informed traders select their market maximize profit.

We find that more trading activity leads to an increase in price discovery. The ratio or trades show a positive correlation with the examined metric when we include pair and month fixed effects. While volume is significant in Regressions 1 and 2, its significance diminishes in regression 3 when we include pair and month fixed effects. Effective Spread is significant in Regressions 1 and 2, yet it is insignificance in Regression 3. Consistent with Aoyagi and Ito (2021), both volatility and the volatility ratio exhibit an increasing trend with the ILS.

Moreover, we find that L and TVL are positively related to the ILS. However, L is more significant. L is the dollar value of accessible reserves and reflects how sensitive prices are to order flow. All else equal, a smaller L means prices move more from a trade. L is highly correlated with the depth in the market. With concentrated liquidity, liquidity providers leverage their real reserves into virtual reserves. Prices are determined on the amount of virtual reserves in the current tick. L in concentrated liquidity pools is based on the virtual reserves. Very concentrated liquidity will have larger L and be deeper than the equivalent Uniswap v2 pool.

[Insert Table 4 Here]

Informed traders aim to maximize profits. We find price discovery shares are larger when trading costs on AMMs are lower. The insignificant coefficients for the effective spread suggest that informed traders can trade larger volumes for the same underlying information. Additionally, we find price discovery shares are positively related to more liquidity within the AMM pools. This supports out hypothesis that informed traders strategically select venues for profit maximization.

LPs in the AMM bear the cost of facilitating price discovery. For informed traders to be able to profit more on the AMM it would mean that market makers in the LOB are not willing to accept the risk of trading against the informed trader. If the market maker in the LOB is not willing to trade at that price, then the LP in the AMM is worse off for facilitating that trade.

AMMs rely on activity to drive price discovery. Without trades, the price can not be updated to reflect new information. Lowering both implicit and explicit fees (Swap fee, Gas) can encourage greater activity, as it reduces arbitrage bounds. Increasing liquidity would allow for cheaper trading. We can improve liquidity by changing the pricing function of the market, like adding concentrated liquidity in Uniswap v3. However, reducing fees and increasing liquidity reduce the profitability of liquidity providers. Achieving the right balance between activity and incentives is vital for sustainable AMM design.

7 Conclusion

AMMs and LOB markets are very different market designs. Despite having passive liquidity provision, AMMs are an informationally important market for cryptocurrencies. We find that, on average, AMMs contribute 16.3% to price discovery, and this share increases to 24.7% in larger liquidity pools.

The AMM price discovery share increases when it is cheap and more liquid to trade in the AMM. Informed traders strategically maximize profits by trading in AMMs when they are cheaper and more liquid. These findings suggest that price discovery in AMMs comes at a cost to LPs. Informed traders benefit from the liquidity and potentially lower fees in AMMs, LPs bear the cost of facilitating price discovery.

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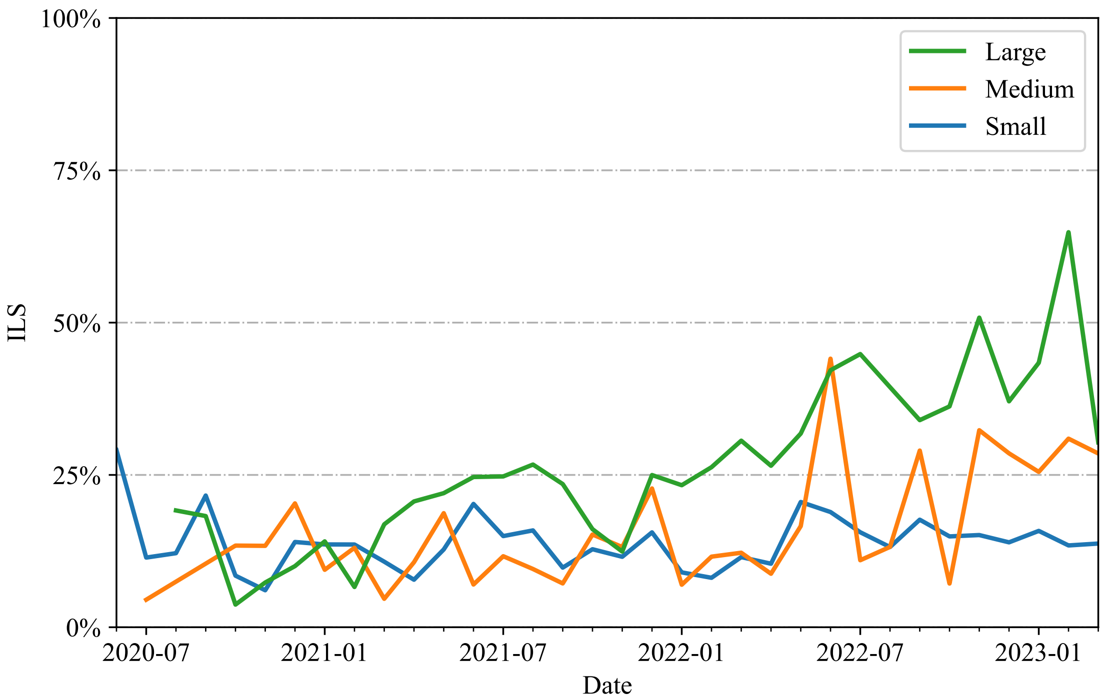

Figure 1. Price discovery shares.
This figure plots the Yan-Zivot-Putnins information leadership share (ILS) from 73 trading pairs during the period June 2020 to March 2023. The plotted ILS is the mean price discovery share for Uniswap in the month based on pool size. Large is the average ILS for pairs with over $50m in total value locked. Medium is the average ILS for pairs with a total value locked between $10m and $50m. Small is the average ILS for pairs with less then $10m in total value locked.

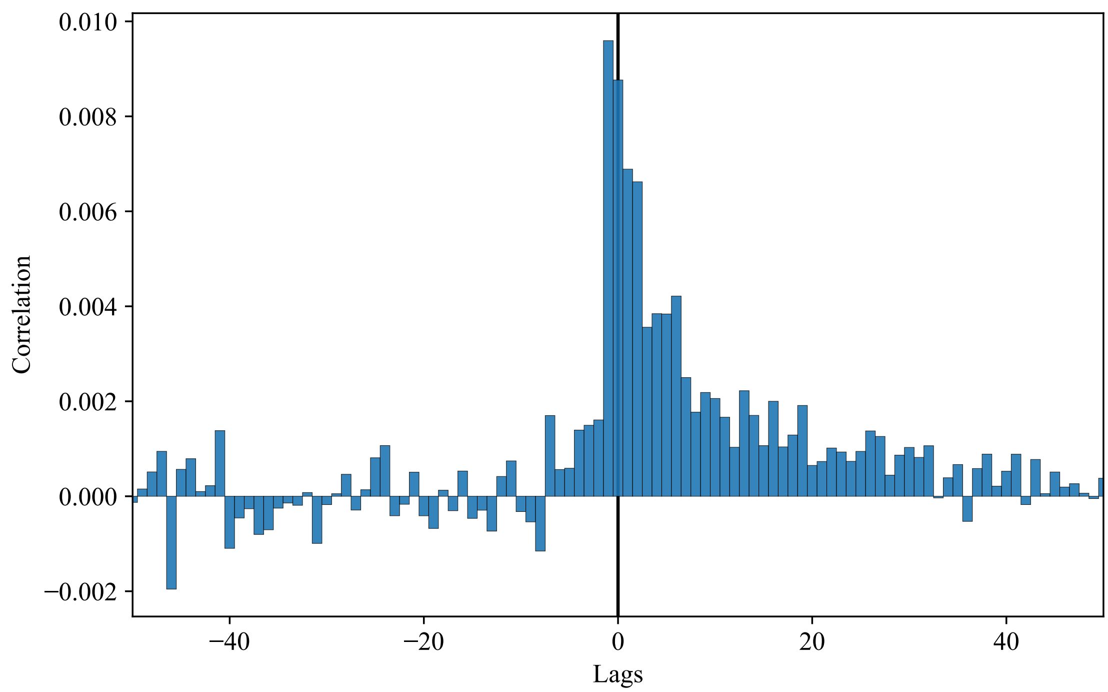

Figure 2. Cross-correlation of Uniswap and Binance returns.
This figure shows the mean cross-correlations of Uniswap and Binance midquote returns by pair month observations. The cross-correlations are computed as the correlation of midquote returns from Uniswap to Binance measured at a blocktime frequency for each lag -50 to 50. The negative lagged values indicate that Uniswap leads Binance, and the positive lagged values indicate that Binance leads Uniswap.

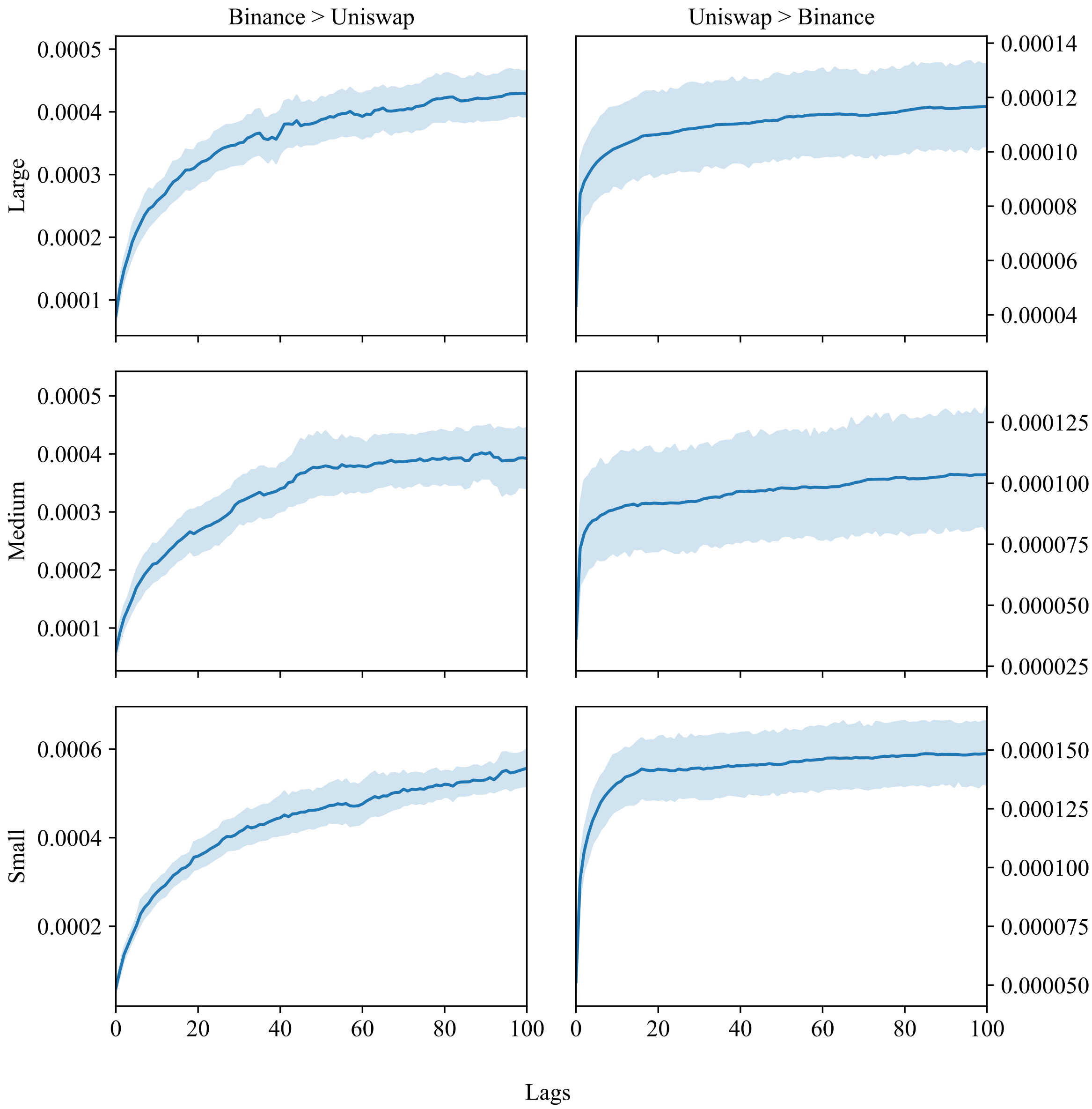

Figure 3. Cumulative generalized impulse response functions
This figure presents the mean cumulative generalized impulse response functions (GIRF) based on pool size. The GIRF is calculated from the moving average representation of the VECM estimated for the price discovery shares on pair month observations. The shaded region represents the 5-95% confidence intervals. The first column represents the response of Uniswap to a one standard deviation shock in Binance. The second column represents the response of Binance to a one standard deviation shock in Uniswap. The first row represents the large Uniswap pools with over $50 million in total value locked. The second row represents the medium Uniswap pools with under $50 million and over $10 million in total value locked. The third row represents the small Uniswap pools with under $10 million in total value locked. The x-axis represent the lags from the shock at time 0.

Table 1. Summary statistics for Uniswap and Binance

This table presents the summary statistics for Uniswap (Panel A) and Binance (Panel B) based on pair month observations. There are 965 observations from 73 pairs between June 2020 to March 2023. Trades is the number of thousands of trades for the month. Quotes is the number of thousands of top of book quotes on Binance for the month. Volume is the value of trade volume in millions of dollars. Average trade size is the average trade size in dollars for the pair in the month. Median trade size is the median trade size in dollars for the pair in the month. Volatility is the standard deviation of one-minute mid quote returns. Spread for Uniswap is the volume weighted swap fee for the pair month. Spread for Binance is the quote weighted spread for the pair month. Effective Spread is the volume weighted effective spread. The Uniswap effective spread is winsorized at 1% and 99% to control for large outliers. TVL is the end of month dollar value of reserves in the Uniswap pools. Mints and burns is the number of mints and burns in the Uniswap pools for the month. Similarly, Mint value and burn value is the dollar value in millions of dollars of the mints and burns in the Uniswap pool.

Panel A. Uniswap Summary Statistics

	Mean	Std Dev	p1	p25	p50	p75	p99
Trades	24.36	64.14	0.54	1.53	3.13	10.98	342.39
Volume ($M)	822.45	3,211.52	0.63	5.21	16.36	133.46	20,657.50
Average Trade Size ($)	15,040.03	26,784.34	768.61	2,818.57	6,056.11	13,249.52	146,265.10
Median Trade Size ($)	5,856.42	11,209.81	181.31	1,309.83	2,881.56	5,607.07	65,298.94
Volatility (%)	100.34	206.52	10.96	36.94	57.98	93.29	908.76
Spread (%)	0.32	0.17	0.01	0.30	0.30	0.30	0.97
Effective spread (%)	1.11	0.89	0.14	0.50	0.90	1.48	4.16
TVL ($M)	56.67	134.36	0.52	1.22	3.09	17.56	621.24
Mints	485.52	1,558.10	0.00	4.00	32.00	253.00	8,832.00
Mint value ($M)	490.13	3,146.99	0.00	0.05	1.35	90.26	9,503.60
Burns	473.72	1,287.15	0.00	7.00	42.00	304.00	6,573.04
Burn value ($M)	483.15	3,119.90	0.00	0.07	1.38	97.98	9,496.50

Panel B. Binance Summary Statistics

	Mean	Std Dev	p1	p25	p50	p75	p99
Trades	4,069.11	19,508.70	6.76	33.96	83.27	379.21	81,555.90
Quotes	3,729.49	5,051.20	212.78	664.44	1,613.98	4,313.14	22,424.31
Volume ($M)	4,749.57	20,836.80	0.91	6.19	23.15	176.83	112,039.00
Average Trade Size ($)	471.08	477.49	47.42	177.74	290.39	512.61	2,081.32
Median Trade Size ($)	143.70	158.42	9.33	47.27	89.73	165.01	742.30
Volatility (%)	32.11	18.03	8.11	19.66	27.80	39.16	92.67
Spread (%)	0.33	0.28	0.00	0.10	0.28	0.51	1.06
Effective spread (%)	0.26	0.32	0.01	0.08	0.19	0.33	1.28

Table 2. Difference in means based on pool size

This table presents the difference in means for descriptive variables in Uniswap and Binance markets split based on pool size. Panel A presents the difference in means for large pools in uniswap with over $50 million USD in TVL. Panel B presents the difference in means for medium sized pools in uniswap with a TVL between $10 million and $50 million USD. Panel C presents the difference in means for small pools in uniswap with under $10 million USD in TVL. There are 171 pair month observations for large pools, 108 pair month observations for medium sized pools and 686 pair month observations for small pools. Trades is the number of thousands of trades for the month. Volume is the value of trade volume in millions of dollars Average trade size is the average trade size in dollars for the pair in the month Median trade size is the median trade size in dollars for the pair in the month Volatility is the standard deviation of one-minute midquote returns. Spread for Uniswap is the volume weighted swap fee for the pair month. Spread for Binance is the quote weighted spread for the pair month. Effective Spread is the ratio of the volume weighted effective spread on Uniswap to Binance. The Uniswap effective spread is winsorized at 1% and 99% to control for large outliers. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Difference in means for large Uniswap pools

	Uniswap Mean	Binance Mean	Δ	t-statistic
Trades	11.36	723.56	−712.20	−7.39***
Volume	4,408.35	10,270.01	−5,861.66	−3.64***
Mean trade	51,366.09	1,080.29	50,285.80	14.08***
Median trade	15,343.68	324.90	15,018.78	8.62***
Volatility (%)	89.44	21.59	67.85	5.71***
Spread (%)	0.20	0.08	0.13	12.60***
Effective spread (%)	0.34	0.07	0.27	21.72***

Panel B. Difference in means for medium Uniswap pools

	Uniswap Mean	Binance Mean	Δ	t-statistic
Trades	1.50	224.45	−222.95	−2.76***
Volume	238.88	3,606.06	−3,367.18	−2.41**
Mean trade	18,413.92	544.09	17,869.83	16.37***
Median trade	7,652.08	173.74	7,478.34	10.81***
Volatility (%)	178.57	24.13	154.44	3.80***
Spread (%)	0.32	0.17	0.15	7.43***
Effective spread (%)	0.67	0.15	0.51	13.05***

Panel C. Difference in means for small Uniswap pools

	Uniswap Mean	Binance Mean	Δ	t-statistic
Trades	0.36	356.71	−356.35	−4.25***
Volume	20.46	3,553.51	−3,533.06	−4.27***
Mean trade	5,453.82	307.72	5,146.09	26.87***
Median rade	3,208.82	93.80	3,115.02	25.95***
Volatility (%)	90.75	35.98	54.76	8.97***
Spread (%)	0.35	0.42	−0.08	−6.21***
Effective spread (%)	1.38	0.32	1.05	28.13***

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3. Absolute determinants of price discovery in AMMs.

This table reports coefficient estimates from beta regressions using pair-month observations. ILS is the Yan-Zivot-Putnins information leadership share. $Spread_{uniswap}$ is the volume weighted swap fee across the uniswap pools for a trade pair. $TVL_{uniswap}$ is the end of month dollar value of reserves in the Uniswap pools. $L_{uniswap}$ is the monthly average dollar value of the invariant from the constant product equation $\sqrt{xy} = L$ converted to a dollar amount based on the reserves of y. $Volume_{uniswap}$ is the Uniswap dollar trade volume. $Trades_{uniswap}$ is the number of Uniswap trades. $Volatility_{uniswap}$ is the standard deviation of one-minute midquote returns from Uniswap. $EffectiveSpread_{uniswap}$ is the volume weighted effective spread on Uniswap winsorized at 1% and 99% to control for large outliers. $MintBurn_{uniswap}$ is the ratio between the dollar value of mints and burns in the Uniswap pools. Gas is the dollar value of Ethereum used to pay gas to transact on Uniswap. $Stable$ is a dummy variable equal to 1 if the asset pair is traded against a stablecoin. All explanatory variables are in natural log form (except for the Dummy variables). The sample comprises 965 observations from 73 trading pairs during the period June 2020 to March 2023. t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	ILS	ILS	ILS	ILS	ILS	ILS	ILS	ILS
$Spread_{uniswap}$	−0.389***	−0.415***	−0.432***	−0.454***	−0.375***	−0.389***	−0.303***	−0.291***
	(−5.99)	(−6.35)	(−6.90)	(−7.23)	(−3.35)	(−3.45)	(−2.73)	(−2.61)
$TVL_{uniswap}$	0.061**				0.110*			
	(2.47)				(1.85)			
$L_{uniswap}$		0.020***				0.025		
		(3.28)				(1.59)		
$Volume_{uniswap}$			0.107***				0.183***	
			(5.33)				(4.08)	
$Trades_{uniswap}$				0.188***				0.361***
				(6.48)				(5.23)
$Volatility_{uniswap}$	0.305***	0.301***	0.240***	0.219***	0.252***	0.252***	0.187***	0.181***
	(7.53)	(7.51)	(5.56)	(5.03)	(5.28)	(5.28)	(3.63)	(3.60)
$EffectiveSpread_{uniswap}$	−0.147*	−0.194***	0.008	0.023	−0.147	−0.198*	−0.021	−0.030
	(−1.71)	(−2.96)	(0.10)	(0.31)	(−1.32)	(−1.93)	(−0.19)	(−0.28)
$MintBurn_{uniswap}$	0.008	0.009	0.007	0.006	0.008	0.011	0.008	0.006
	(0.67)	(0.74)	(0.61)	(0.48)	(0.59)	(0.84)	(0.64)	(0.47)
Gas	−0.089*	−0.086	−0.128**	0.007				
	(−1.65)	(−1.62)	(−2.42)	(0.14)				
$Stable$	−0.185**	−0.513***	−0.233***	−0.268***				
	(−2.45)	(−3.95)	(−3.07)	(−3.46)				
$Intercept$	−4.563***	−4.201***	−4.708***	−5.542***	−4.484***	−4.074***	−4.638***	−4.493***
	(−9.06)	(−8.61)	(−9.65)	(−10.63)	(−5.05)	(−5.18)	(−6.17)	(−6.2)
$Precision$	1.507***	1.515***	1.533***	1.549***	1.799***	1.798***	1.813***	1.826***
	(32.98)	(33.07)	(33.49)	(33.79)	(38.69)	(38.68)	(38.99)	(39.22)
Month FE	N	N	N	N	Y	Y	Y	Y
Pair FE	N	N	N	N	Y	Y	Y	Y
Pseudo R^2 (%)	15.0	15.4	17.0	18.1	34.3	34.2	35.1	35.8

Table 4. Relative determinants of price discovery in AMMs.

This table reports coefficient estimates from beta regressions using pair-month observations. ILS is the Yan-Zivot-Putnins information leadership share. $Spread$ is the ratio of the Uniswap volume weighted fee and the Binance quote weighted spread. $TVL_{uniswap}$ is the end of month dollar value of reserves in the Uniswap pools. $L_{uniswap}$ is the monthly average dollar value of the invariant from the constant product equation $\sqrt{xy} = L$ converted to a dollar amount based on the reserves of y. $Volume$ is the ratio of Uniswap dollar volume to Binance dollar volume. $Trades$ is the ratio of the number of Uniswap trades to the number of Binance trades. $Volatility$ is the ratio of the standard deviation of one-minute midquote returns of Uniswap to the standard deviation of one-minute midquote returns of Binance. $EffectiveSpread$ is the ratio of the volume weighted effective spread on Uniswap to Binance. The Uniswap effective spread is winsorized at 1% and 99% to control for large outliers. $Volatility_{binance}$ is the standard deviation of one-minute midquote returns from Binance. Gas is the dollar value of Ethereum used to pay gas to transact on Uniswap. $Stable$ is a dummy variable equal to 1 if the asset pair is traded against a stablecoin. All explanatory variables are in natural log form (except for the Dummy variables). The sample comprises 965 observations from 73 trading pairs during the period June 2020 to March 2023. t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
Dependent variable:	ILS	ILS	ILS
$Spread$	−0.033	−0.037	−0.137*
	(−0.85)	(−0.93)	(−1.85)
$TVL_{uniswap}$	0.035	0.037	0.100
	(1.21)	(1.27)	(1.59)
$L_{uniswap}$	0.024***	0.021***	0.034**
	(4.74)	(2.81)	(1.99)
$Volume$	0.111**	0.136***	0.018
	(2.56)	(2.78)	(0.27)
$Trades$	−0.047	−0.078	0.202**
	(−1.11)	(−1.58)	(2.45)
$Volatility$	0.243***	0.251***	0.283***
	(5.78)	(5.9)	(5.94)
$EffectiveSpread$	−0.194***	−0.182***	−0.062
	(−3.98)	(−3.64)	(−0.86)
$Volatility_{binance}$	0.146*	0.157**	0.323**
	(1.89)	(1.96)	(2.41)
Gas		−0.071	
		(−1.18)	
$Stable$		0.049	
		(0.33)	
$Intercept$	−2.100***	−1.682***	−1.090
	(−4.79)	(−2.98)	(−0.95)
$Precision$	1.513***	1.515***	1.816***
	(32.98)	(33.02)	(38.94)
Month FE	N	N	Y
Pair FE	N	N	Y
Pseudo R^2 (%)	15.2	15.3	35.0

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

A Estimation of price discovery shares

We estimate the following VECM model to calculate the price discovery shares:

$$\begin{aligned}
\Delta p_{1,t} &= \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{300} \psi_i \Delta p_{1,t-i} + \sum_{j=1}^{300} \delta_j \Delta p_{2,t-j} + \epsilon_{1,t}, \\
\Delta p_{2,t} &= \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{300} \phi_k \Delta p_{1,t-k} + \sum_{m=1}^{300} \varphi_m \Delta p_{2,t-m} + \epsilon_{1,t},
\end{aligned} \tag{2}$$

To calculate the ILS of Putniņš (2013), we first calculate the IS and CS from the error correction parameters and variance–covariance of the error terms, following Baillie et al. (2002). The component shares are obtained from the normalized orthogonal to the vector of error correction coefficients, $\alpha_\perp = (\gamma_1, \gamma_2)'$, and the component shares as

$$CS_1 = \gamma_1 = \frac{a_2}{a_2 - a_1}, \quad CS_2 = \gamma_2 = \frac{a_1}{a_1 - a_2} \tag{3}$$

Given the covariance matrix of the reduced form VECM error terms

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{4}$$

and its Cholesky factorisation, $\Omega = MM'$, where

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2\sqrt{1-\rho^2} \end{pmatrix} \tag{5}$$

The IS are calculated through

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \quad IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{6}$$

With the IS and CS the ILS calculations follow

$$ILS_1 = \frac{|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}|}{|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}| + |\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}|}, \quad ILS_2 = \frac{|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}|}{|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}| + |\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}|} \tag{7}$$