Can Automated Market Makers provide price discovery?*

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Draft November 11, 2024

Abstract

We investigate whether Automated Market Makers (AMMs) can facilitate price discovery, given that prices are determined by a mathematical function rather than by liquidity providers (LPs). Through a variance decomposition, we test if AMMs can provide price discovery when they are the only market to trade an asset. We find AMMs can provide price discovery and that LPs are sensitive to adverse selection from private information sources. We test if AMMs can lead price discovery and find that on average they lag the LOB. AMM price leadership is influenced by trading costs (spreads) in both AMM and LOB markets. Our findings suggest AMMs are a viable market structure for low-cost trading.

`Keywords:` Decentralized exchange, automated market maker, price discovery, cryptocurrency
`JEL classification: G14, D47`

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How well do Automated Market Makers provide price discovery?

Abstract

We investigate whether Automated Market Makers (AMMs) can facilitate price discovery, given that prices are determined by a mathematical function rather than by liquidity providers (LPs). Through a variance decomposition, we test if AMMs can provide price discovery when they are the only market to trade an asset. We find AMMs can provide price discovery and that LPs are sensitive to adverse selection from private information sources. We test if AMMs can lead price discovery and find that on average they lag the LOB. AMM price leadership is influenced by trading costs (spreads) in both AMM and LOB markets. Our findings suggest AMMs are a viable market structure for low-cost trading.

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1 Introduction

For a market to succeed, it must provide two core functions: liquidity and price discovery. Automated Market Makers (AMMs) challenge the common understanding of how these functions operate in a successful market. Unlike traditional market structures, where liquidity providers (LPs) actively manage and adjust prices based on real-time information, AMMs rely on passive liquidity provision. Prices are determined based on a mathematical function known by all market participants. Prices are updated by traders arriving at the market looking to trade. This passive approach to liquidity provision introduces a fundamental challenge—AMM LPs face greater exposure to adverse selection, a key driver of illiquidity in markets (Kyle, 1985; Glosten and Milgrom, 1985).

In traditional limit order book (LOB) markets, LPs manage adverse selection risks by adjusting quotes based on all available information. In an AMMs, LPs cannot update their quotes, instead they can step away from the market. By stepping away, the LP is no longer vulnerable to traders with superior information. However, the market is more illiquid, which would suggest that price efficiency and discovery should be worse. This raises questions about the efficiency of these markets and whether AMMs can truly facilitate price discovery while avoiding the pitfalls of inefficiency and illiquidity.

This paper explores the role of AMMs in the price discovery process, addressing two key research questions. First, it examines if AMMs can provide price discovery when they are the only market to trade an asset. Second, the paper investigates whether AMMs can lead the price discovery process and what factors determine price leadership.

AMMs have the potential to change the future of financial markets, particularly in the trading of tokenized assets. AMMs offer a cost-effective solution to facilitate trading of tokenized assets, not only allowing more assets to become tradable but also improving gains from trade in existing tradable assets. Foley, O'Neill, and Putniņš (2023) suggests AMMs are a more efficient market design for trading high volume, low volatility assets. Similarly, liquidity in AMMs does not suffer from intraday illiquidity (Adams et al., 2023). Malinova and Park (2023) argue that using AMMs could save billions of dollars in transaction costs and improve capital allocation. Foreign exchange markets are often discussed as a market which would benefit from trading through an AMM. Led by the Bank of International Settlements Project Mariana shows the cost-saving potential of AMM-based trading systems while also highlighting the drawback of these markets though pre-funding of trades (Bank for International Settlements, 2023).

In this paper, we compare two market structures: Binance, LOB market, and Uniswap, an AMM. First, through a variance decomposition based on the framework of Brogaard et al. (2022), we measure the informational content in an assets price that trade only on AMMs versus those traded on both AMMs and LOBs, assessing whether AMMs can independently facilitate price discovery. Second, we then evaluate AMMs' ability to lead price discovery compared to LOBs, using the price discovery shares method from Putniņš (2013).

Our main finding is that AMMs can provide price discovery even when they are the only market to trade an asset. There is no significant difference in the share of noise-the innovations is price, which cannot be explained by market-wide, private, or public information-between assets only traded on AMMs and a matched sample of assets that also trade on LOBs.

We find that LPs in AMMs react strategically to adverse selection risk by withdrawing liquidity when there is a high share of private information in prices. This behavior suggests that LPs in AMMs are more active and adaptive in their market-making strategies than previously assumed.

In examining AMM price discovery shares, we observe AMMs follow LOB prices due to arbitrage. However, low-fee AMM pools show a stronger contribution to price discovery compared with their high-fee counterparts. Specifically, Uniswap v3 pools with 0.05% and 0.01% fees achieve average information leadership shares (ILS) of 24.1% and 61.1%, respectively, significantly greater than the sample average of 8.7%. Higher trading costs on LOBs, such as wider spreads, correspond with increased AMM price leadership, highlighting the importance of trading costs in shaping market dynamics.

Our findings align with studies by Barbon and Ranaldo (2022) who highlight that explicit costs, such as gas fees, are critical to determining market quality and Capponi, Jia, and Yu (2023) who show that informed traders will pay for priority inclusion on-chain to guarantee order execution. Consistently, we find that AMM information leadership is inversely related to gas fees on Ethereum.

Overall, our research shows that AMMs can provide a fundamental market function—price discovery. By offering a cost-effective trading solution for tokenized assets, AMMs enable a broader range of assets to become tradable and enhance the gains from trade for existing assets, realizing the full potential of tokenized asset markets.

Existing research explores the contribution of price discovery between AMMs and centralized exchanges. Capponi, Jia, and Yu (2023) show that informed traders pay higher gas fees to reduce execution risk and compete in decentralized exchanges. Similarly, Klein et al.

(2023) analyze how different order types and liquidity provision in AMMs contribute to price discovery. 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.

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 how well AMMs provide price discovery.

Our paper also contributes to the literature on informational efficiency. Nguyen et al. (2024) measures the amount of noise in cryptocurrency markets. Foley and Putniņš (2016) and Comerton-Forde and Putniņš (2015) study the impact dark pools have on informational efficiency. Rösch, Subrahmanyam, and Dijk (2017) and Chordia, Roll, and Subrahmanyam (2008) also use high frequency measures of informational efficiency. Boulatov and George (2013) show how hidden liquidity and its impact on informational efficiency. Informative prices are crucial because reduced profitability from acquiring information leads to less information production overall, resulting in less informative prices (Kyle, 1989; Admati and Pfleiderer, 1988).

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. Numerous 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.

2 Institutional Background

Decentralized markets may seem paradoxical, as marketplaces traditionally serve as central locations where participants gather to trade. However, blockchain technology and AMMs enable decentralized trading infrastructure. This type of infrastructure offers several advantages, including censorship resistance, the elimination of trust-dependent intermediaries, and enhanced security. In traditional markets, trust in the marketplace creates a single point of failure, with market outages leading to broader negative impacts on market quality. A decentralized market eliminates this vulnerability, as the failure of a single node in the network does not disrupt overall operations, allowing trading to continue uninterrupted (Eaton et al., 2022).

AMMs have gained popularity as a method for trading cryptocurrencies in DeFi. While there have been attempts to implement on-chain LOB markets, these efforts have largely been unsuccessful because of the high transaction costs on blockchains like Ethereum.[1] AMMs minimize the data storage costs required to operate a market on-chain. For users, trading on-chain offers the additional benefits of security and pseudonymity, as they keep custody of their funds (Aspris et al., 2021).

AMMs are not new to decentralized finance and historically they have been used in prediction markets (Hanson, 2003). Most AMM designs have not been liquidity sensitive, which has limited their use beyond prediction markets. Othman and Sandholm (2011) and Othman et al. (2013) outline invariants to deal with the challenge of liquidity sensitivity in AMMs.

In decentralized finance, AMMs 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 (or invariant) determines the price for the trade. As trades occur in the liquidity pool, prices move with the demand of each asset. LPs earn a share of the trade volume as a fee to incentivize liquidity provision.

There are many AMM designs in decentralized finance. In this paper, we focus on the

[1] Etherdelta was the first notable decentralized exchange on Ethereum to use a LOB design. On Solana, where transactions are cheaper, on-chain LOB are more feasible, with notable examples such as Phoenix and the historically significant Serum.

largest AMM, Uniswap. Uniswap is the 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

$$\sqrt{xy} = L \tag{1}$$

where x and y are the reserves of the two assets in the pool and L is a constant equal to their geometric mean[2]. When swapping against the CPMM, L is held constant by the change in reserves.

$$\sqrt{(x + \Delta x)(y + \Delta y)} = \sqrt{xy} = L \tag{2}$$

By holding the invariant L constant prices follow the demand for each asset. The quote price of asset x in the liquidity pool is simply the ratio of the reserves $\frac{y}{x}$. To add and remove liquidity in the CPMM, LPs must hold the price constant by adding both assets proportional to their current weighting or ratio of assets in the pool. This ensures that any changes in liquidity do not impact the price in the pool. For more detail on the CPMM of Uniswap, we refer to Zhang, Chen, and Park (2018).

Uniswap v3 introduces the idea of ”concentrated liquidity” within the CPMM. Concentrated liquidity more closely resembles traditional LOB markets with a liquidity surface that can vary with price. In the CPMM, liquidity can be thought of as being distributed equally between all prices $(0, \infty)$. In a concentrated liquidity market, liquidity is added to the pool between two prices (p_a, p_b) where the amount of liquidity added follows the pricing function

$$(x + \frac{L}{\sqrt{p_b}})(y + L\sqrt{p_a}) = L^2 \tag{3}$$

In practice, prices p are bounded to discrete price ticks to maintain data storage costs. Different LPs can provide liquidity across different price ranges. The liquidity L can be added up for each position within one discrete tick interval. A user can trade against L (reserves) in the current tick as they would in the CPMM. Intuitively, all the prices above (below) the current price in the pool are in the first (second) token in the pool. As new tokens are added to the pool, L is held constant, and the price is pushed away from the side where the tokens are being added. Trading in the pool can move the price into a new tick range where the L in the pool can change. To control for this, swaps are calculated iteratively,

[2] This pricing function is also commonly known as $xy = k$. However, this is not positive homogenous and using the geometric mean of reserves solves this issue (**othmanNewInvarientsAutomated21**). Using the geometric mean is the standard used in Uniswap v3 and in the smart contract implementations in Uniswap v2 to mint the liquidity pool tokens for proportional wealth distribution.

stepping through each tick range until the total swap amount is depleted. Adams et al. (2021) provide a detailed explanation of the Uniswap v3 pricing function and implementation.

In AMMs, the fees are often taken as a haircut of the assets entering or exiting the pool. The fee in the AMM emulates a spread in a LOB market. In Uniswap, the fee is taken from the asset that enters the pool. Uniswap v2 has a 0.3% fee for all pools. Uniswap v3 pools can have 4 different fee levels: 1%, 0.3%, 0.05% or 0.01%. Each pool is unique and the same trading pair may different fee pools with their own liquidity. The fees in a Uniswap v2 and v3 pool do not change overtime, however LPs can change the pool that they supply liquidity in order to change their fee return.

AMMs are state-based markets. The state that a user interacts with the market depends on where the transaction is included on the blockchain. This feature of AMMs means the ordering of transactions is important for traders in the market. There is value associated with being able to order the transactions in a block. This is often known as maximal (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 profit. The proposer can earn more from a block than just the gas fees if they include other transactions, such as arbitrage between a CEX and DEX or sandwich attacks as in Daian et al. (2019).

We consider Uniswap's largest market on the Ethereum blockchain. Ethereum has had two consensus models: proof of work and proof of stake. When Ethereum was based on a proof of work consensus model, extracting the value from the block was left up to the miner who won the block. This miner could build a block with their own transactions around other user transactions found in the mempool. Building an optimal block is costly and building the most optimal block is infeasible for most miners. However, with the shift towards proof of stake, proposer builder separation (PBS) was introduced. PBS separates the block building process into 4 roles: the searcher, the builder, the relay, and the proposer. PBS ensures the block with the highest economic value is produced by shifting the costly task of building the optimal block away from the proposer and to a builder. The role of a searcher is to sequence transactions into bundles and submit them to a builder. The searcher needs incentivize the builder to be included in the block. This is typically done in the form of transaction fees. Builders create a completed block from the bundles sent to them by searchers (or their own transactions). Their own transactions can be sandwich attacks on other users or more commonly arbitrage between CEXs and DEXs as discussed in Heimbach, Pahari, and Schertenleib (2024). Builders send these blocks to the relays with a bid to send to the proposer. The relays validate the block for correct cryptographic signatures and announce to proposers the block headers with the associated bid. If a proposer is listening to the relay, they can select the block they want to propose by signing the block header. Importantly, the proposer does not see the contents of the block, just the block header and the bid for that block. If the proposer signs a block, the relay propagates this block to the rest of the network as a complete block for validation[3].

3 Data

We collect data on the two largest exchanges of each respective market design: Uniswap, the AMM, and Binance, the LOB. As of April 2023, 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 and to be traded. In contrast, Binance has roughly 1200 asset pairs, including over 350 unique assets.

Our analysis covers the period from June 2020 to March 2023. This period captures the launch and subsequent growth of Uniswap v2. Introduced in May 2020, the launch of Uniswap v2 serves as a significant milestone in the adoption of AMMs. We collect data for Uniswap v2 and Uniswap v3 pools directly from an Ethereum node. Binance trade data is collected from the Binance data vision webpage. Binance quote data is collected from Tardis.Dev. We use the MVIS® CryptoCompare Digital Assets 100 Index (MVDA) as a market index to calculate market returns for the variance decomposition.[4] MVDA is a market-cap weighted index that tracks the performance of the top 100 digital assets.

Many of the Uniswap pools that trade are inactive and/or illiquid. We focus our study on trading pairs with over 250 trades in the month, trade actively for 3 or more months and have over $500k TVL across all Uniswap pools. We exclude stablecoin to stablecoin pairs to prevent conflicting price discovery results because of their connection to a pegged asset.[5] Where possible, we consider the wrapped version of tokens which give them the ERC-20 standard and allow them to be traded on Uniswap[6].

Table 1 presents the summary statistics for trade and liquidity metrics for the LOB (Binance) and the AMM (Uniswap) for pair month observations. We measure dollar volume, number of trades, the mean (median) trade size, and the realized volatility in each market.

[3] John et al. (2024) provide an excellent overview of how the Ethereum block building and validating process.

[4] See `https://bit.ly/3PCOuKo` for MVDA fact sheet.

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

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

Following Johnson, Putniņš, and Félez-Viñas (2023), we evaluate liquidity using four metrics for both the AMM and LOB: the half quoted spread (equivalent to the AMM fee), the effective spread, market depth (along with its relative variance).[7]

Table 1 shows that Binance has larger trading volumes and number of trades compared to Uniswap pools. However, average and median trade sizes are larger in AMM pools than on Binance. The average half-quoted spread on Binance is 0.21%, whereas the AMM fee is lower only in Uniswap v3 pools, where fees (spread) are set at 0.05% and 0.01%. Despite these lower fee structures, effective spreads tend to be larger on Uniswap, likely due to the larger trade sizes in AMM pools. These larger trade sizes also contribute to higher volatility observed in AMM prices. While the AMM shows greater average depth, depth variability is lower in AMMs compared to LOBs, showing a more stable liquidity supply in AMM pools.

[Insert Table 1 Here]

Our analysis is conducted in two stages. First, we compare trading pairs that only trade on an AMM with those trading simultaneously on an AMM and a limit order book (LOB). This allows us to test whether AMMs can serve as effective venues for price discovery when they are the sole market. Second, we focus solely on trading pairs listed on both an AMM and the LOB to assess whether AMMs can lead the price discovery process.

For the first sample, we get a list of tokens that trade on a centralized exchange from CC-Data and identify those that trade only on Uniswap. This identification yields 243 trading pairs and 1150 pair-month observations that only trade on an AMM. To ensure comparability between AMM-only and AMM LOB-market pairs, we employ a matched sample approach. Observations are matched without replacement by market, year, month, and nearest neighbor based on trading volume, with a tolerance of up to a 20% difference. Observations failing to meet this match criterion are discarded. Importantly, our results are robust even when unmatched trading pairs are included in the analysis. The final sample comprises 92 matched pairs and 522 pair-month observations. The second sample examines tokens listed concurrently on both Uniswap and Binance. Our final dataset for this stage includes 58 asset pairs with 1577 pair month observations.

[7] The relative variance of depth is calculated by taking the standard deviation of hourly depth and normalizing it by the mean for each pair-month.

4 Can AMMs provide price discovery?

Price discovery is the process by which information is reflected in asset prices. In LOB markets, most of the price discovery occurs through quotes from liquidity providers (Brogaard, Hendershott, and Riordan, 2019; Klein et al., 2023). AMMs, however, rely on trades from liquidity demanders to adjust prices and incorporate new information. When AMMs trade alongside a LOB market, the bulk of the price discovery can be performed by the LOB with arbitrageurs updating the price in the AMM. However, when the AMM is the only market to trade an asset, can it provide price discovery?

To assess whether AMMs contribute to price discovery, we first quantify the amount of information in an assets price using a variance decomposition. Following Brogaard et al. (2022) we measure various components of information: market-wide, public, and private- as well as noise in a price series. By decomposing the variance, we can identify the amount of information in an assets price, which we can then use to compare the AMM and LOB markets[8].

The variance decomposition derives the amount of information in a price series from innovations in price. An asset's price is made up of two parts: m_t the efficient price and s_t the pricing error.

$$p_t = m_t + s_t \tag{4}$$

Pricing errors have short-run effects on price but do not have any permeant effect on price in the long run. m_t follows a random walk with drift μ and innovations w_t

$$m_t = m_{t-1} + \mu + w_t \tag{5}$$

The innovations w_t reflect new information entering the price and are unpredictable ($E_{t-1}[w_t] = 1$). The drift μ can be thought of as the discount rate over the next period. An assets return for log prices p is

$$r_t = p_t - p_{t-1} = \mu + w_t + \Delta s_t \tag{6}$$

[8]To control for any impact that may be caused by market design, we consider the AMMs price where the implicit benchmark is the LOB price.

The innovations in a stock's price w_t can be split into three sources of information

$$w_t = \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} \tag{7}$$

and thus an assets return is

$$r_t = \mu + \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} + \Delta s_t \tag{8}$$

where $\varepsilon_{r_m,t}$ is the unexpected innovation in the market return and $\theta_{r_m}\varepsilon_{r_m,t}$ is the market-wide information incorporated into an assets price, $\varepsilon_{x,t}$ is an unexpected innovation in signed dollar volume and $\theta_x\varepsilon_{x,t}$ is the firm-specific information revealed through trading on private information, and $\theta_r\varepsilon_{r,t}$ is the remaining part of firm-specific information that is not captured by trading on private information ($\varepsilon_{r,t}$ is the innovation in the stock price). Changes in the pricing error, Δs_t, can be correlated with the innovations in the efficient price, w_t. This model assumes that both the permanent (information) and transient (noise) components are driven by the same shocks (Beveridge and Nelson, 1981). This assumption explicitly allows for correlation between information and noise, consistent with theory.

We estimate these components for pair month observations using a structural VAR model based on hourly returns with 12 hours of lags to account for serial correlation and any other lagged effects:

$$\begin{aligned}
r_{m,t} &= \sum_{l=1}^{12} a_{1,l} r_{m,t-l} + \sum_{l=1}^{12} a_{2,l} x_{t-l} + \sum_{l=1}^{12} a_{3,l} r_{t-l} + \epsilon_{r_m,t} \\
x_t &= \sum_{l=1}^{12} b_{1,l} r_{m,t-l} + \sum_{l=1}^{12} b_{2,l} x_{t-l} + \sum_{l=1}^{12} b_{3,l} r_{t-l} + \epsilon_{x,t} \\
r_t &= \sum_{l=1}^{12} c_{1,l} r_{m,t-l} + \sum_{l=1}^{12} c_{2,l} x_{t-l} + \sum_{l=1}^{12} c_{3,l} r_{t-l} + \epsilon_{r,t}
\end{aligned} \tag{9}$$

where $r_{m,t}$ is the market return, x_t is the signed dollar volume of trading in the given asset (positive values for net buying and negative values for net selling), and r_t is the asset return.

By explicitly modeling the contemporaneous relationships between variables, the structural VAR innovations $\{\epsilon_{r_mt}, \epsilon_{x_t}, \epsilon_{r_t}\}$ are designed to be contemporaneously uncorrelated. The VAR model identifies market-wide, private, and public information components by capturing their long-term effects on asset prices through cumulative impulse responses $\{\theta_{r_m,t}, \theta_{x,t}, \theta_{r,t}\}$. Permanent returns linked to market-return shocks estimate market-wide information, shocks to signed dollar volume reveal private information, and shocks to stock returnscontrolling for market and trading variableshighlight public information. Noise emerges as the transitory return component after removing information-driven influences. The cumulative impulse responses then quantify the contributions of each information component to price variance within the structural VAR framework.

Taking the variance of the innovations in the efficient price we get $\sigma_w^2 = \theta_{r_m}^2 \sigma_{\epsilon_{r_m}}^2 + \theta_x^2 \sigma_{\epsilon_x}^2 + \theta_r^2 \sigma_{\epsilon_r}^2$. The contribution to the variation in the efficient price from each of the information components is $\theta_{r_m}^2 \sigma_{\epsilon_{r_m}}^2$ (market-wide information), $\theta_x^2 \sigma_{\epsilon_x}^2$ (private firm-specific information), and $\theta_r^2 \sigma_{\epsilon_r}^2$ (public firm-specific information). The estimated components of variance can be normalized to give shares of the variance in a price series.

$$
\begin{aligned}
MarketInfoShare &= \theta_{r_m}^2 \sigma_{\varepsilon_{r_m}}^2 / (\sigma_w^2 + \sigma_s^2) \\
PrivateInfoShare &= \theta_x^2 \sigma_{\varepsilon_x}^2 / (\sigma_w^2 + \sigma_s^2) \\
PrivateInfoShare &= \theta_r^2 \sigma_{\varepsilon_r}^2 / (\sigma_w^2 + \sigma_s^2) \\
NoiseShare &= \sigma_s^2 / (\sigma_w^2 + \sigma_s^2)
\end{aligned}
\tag{10}
$$

$MarketInfoShare$, $PrivateInfoShare$, and $PublicInfoShare$, are the corresponding shares of variance from those various sources of stock-price movements. Meanwhile, $NoiseShare$ reflects the relative importance of pricing errors due to an over (under) reaction to information, illiquidity, price pressures, or other microstructure frictions. We get the inputs for the VAR using the procedure in Appendix A.

Table 2 provides summary statistics on the variance decomposition shares, particularly highlighting the noise component. These estimates allow us to quantify the net level of unexplained noise within asset prices. Focusing on this noise component, we assess whether AMMs alone can support effective price discovery. Both samples of trading pairs reveal substantial noise and private information shares, each exceeding 40%. This result aligns with Nguyen et al. (2024), who find that variance in cryptocurrency prices is largely driven by noise with a roughly 47% noise share.

[Insert Table 2 Here]

When an AMM is the only market available to trade an asset, the amount of information in its prices may be limited because of the market structure of AMMs. AMMs operate on blockchains which require traders to pay an explicit fee (usually as gas) to get inclusion in the block. In combination with AMMs needing trades to update prices, this may impact the amount of information in prices.

AMM market structure may also lead to more noise within prices. MEV and sandwich attacks, as described by Daian et al. (2019), may increase the amount of noise in the variance decomposition. Traders often protect themselves from sandwich attacks using tools such as slippage tolerances (Chemaya et al., 2023). However, the default values set for these protections could introduce further noise into the analysis. There is a structural relationship between trade prices and the mid-quote prices before and after a trade, as trade prices are the geometric mean between these mid-quote prices. This relationship impacts liquidity providers (LPs), as noted by Milionis et al. (2022), through the concept of Liquidity Value at Risk (LVR), representing the undiversifiable risk of providing liquidity in an AMM. Structurally, this results in post-trade mid-quote prices that deviate from trade prices, suggesting noisier prices in AMMs compared to LOB markets. We control for this difference in noise by considering the AMM prices only.

The impact of liquidity on the levels of information in AMMs prices is ambiguous. On the one hand, liquidity reduces price impact and noise in the price series. It also acts as an incentive for informed traders to participate, as a more liquid market allows them to profit more from their information. This encourages greater information acquisition, leading to increased overall information production and more informative prices (Admati and Pfleiderer, 1988; Kyle, 1989). On the other hand, the presence of informed traders can negatively impact liquidity due to adverse selection. This can cause liquidity being withdrawn from the AMM, worsening informational efficiency. Adverse selection is a well-documented source of illiquidity in markets (Kyle, 1985; Glosten and Milgrom, 1985).

To test if AMMs can provide price discovery, we compare variance shares of pairs that only trade on the AMM with matched pairs that trade on the AMM and LOB. We regress the different variance shares on a dummy variable for if the AMM is the only market to trade the asset. This regression examines if the amount of information in the AMMs price is lower when they are the only market to trade the asset. We estimate the following regression:

$$VarShare_{i,t} = \alpha_{i,t} + \beta_1 AMMOnly_{i,t} + \beta_2 Liquidity_{i,t} + \beta Controls_{i,t} + \epsilon_{i,t} \tag{11}$$

Where $VarShare$ is a measure of variance shares such as the $NoiseShare$, $MarketInfoShare$, $PrivateInfoShare$, or the $PublicInfoShare$. The independent variables of focus will be the AMMOnly dummy variable. This dummy variable will show whether the AMM has more (less) information when it is the only market to trade an asset. The inherit benchmark is the LOB information content. We include controls for market liquidity due to the interconnection between adverse selection costs and illiquidity (Kyle, 1985; Glosten and Milgrom, 1985). Specifically, we consider three measures of liquidity, the effective spread, the 1.5% depth and the variance of the 1.5% depth. Each measure captures a different aspect of liquidity: width, depth, and resiliency, respectively. We also control for the realized volatility, whether the market uses concentrated liquidity and explicit (gas) costs. All continuous variables are in are in natural log form.

Table 3 presents regression coefficients from Equation 11. The AMMOnly dummy variable in regression 1 shows that the $NoiseShare$ is significantly lower for pairs traded only on AMMs compared with those trading across both AMMs and LOB. While the reduction in noise share is marginal and not economically significant, it highlights a key finding: AMMs can provide price discovery when they are the only market to trade an asset. There is no less information in prices compared to assets that also trade on a LOB.

[Insert Table 3 Here]

The observed difference in $NoiseShare$ appears primarily driven by variations in private information, as noted by regression 3. Token listings on centralized exchanges are non random and could lead to biases in our results. In contrast, DEXs operate with a permissionless listing process, allowing anyone to list new asset pairs. This distinction likely affects the type of information reflected in prices—whether private or public—while having a lesser impact on overall noise shares. Importantly, any potential bias from this process would likely skew results against our findings, reinforcing the robustness of AMMs' price discovery.

$PrivateInfoShare$ is negatively related to market depth and effective spread. This suggests that LPs in AMMs step away from the market when adverse selection is high, reducing the liquidity in the market. LPs strategically withdraw liquidity when they perceive high levels of private information, protecting themselves from unfavorable trades against informed participants.

Our analysis also shows that explicit transaction costs, such as gas fees, do not significantly affect the information or noise shares estimated in the variance decomposition. However, concentrated liquidity pools as used in Uniswap v3 are positively related to the $NoiseShare$, largely because of reduced levels of both private and public information.

5 Can AMMs lead price discovery?

Information must enter AMM prices, regardless of whether it originates from an arbitrage opportunity with a centralized exchange or from an informed trader trading in the AMM first. This prompts a key question: can AMMs lead the price discovery process?

AMMs face informational disadvantage because of their market structure. In AMMs, prices cannot be updated without a trade, meaning that price adjustments rely solely on the actions of liquidity takers, who may possess varying levels of information. As a result, the price set by these traders can leave AMMs exposed to adverse selection, as the AMM price only becomes informed post-trade. This dynamic underscores the potential inefficiencies in AMMs, as LPs remain uninformed about the true market price until after the trade occurs, highlighting the unique challenges that AMMs face in the price discovery process.

Informed traders face a strategic decision when choosing their trading venue. Trading on an AMM entails variable explicit costs, such as gas fees, which can make trading expensive. Informed traders must ensure favorable execution relative to other market participants, often by competing for priority inclusion within a block. To maximize their informational advantage, informed traders may bid for priority inclusion with a block builder, capturing the AMM's state at the start of the block. Capponi, Jia, and Yu (2023) provide evidence to show that informed traders actively compete for block inclusion, frequently bidding higher transaction fees to secure their position. However, this introduces a tradeoff between the value of acting on information and the costs associated with timely inclusion, as high gas fees may erode potential profits.

Block builders are in a central position for capturing information. Traders reveal information to the builder when paying for priority inclusion. However, compared to a LOB, information is only revealed to one actor and not the whole market. The builder has some incentive not to exploit the private information they receive from informed traders. If the informed trader is exploited, they can stop using providing the builder with their transactions. Reducing any future revenue from transaction fees the builder may earn from the informed trader.

Effective operation by informed traders on an AMM requires not only variable explicit costs but also sufficient liquidity. The balance between AMM liquidity and the cost of securing block inclusion is an important factor for an informed trader. Barbon and Ranaldo (2022) show that while AMMs can offer favorable trading conditions for large orders, smaller orders face higher relative costs due to gas fees. Informed traders also encounter competition from other market participants vying for block inclusion, which can drive up explicit costs and deter trading activity within the AMM.

In LOB markets, market makers mitigate adverse selection risk by widening bid-ask spreads Kyle (1985), Glosten and Milgrom (1985), and Easley et al. (1996). LPs in AMMs cannot directly adjust spreads; instead, they may withdraw their liquidity to limit exposure to adverse selection. This action disincentivizes informed trading but also reduces overall pool liquidity. Aoyagi and Ito (2021) theorizes that the number of informed traders correlates with AMM liquidity, indicating that a more liquid AMM may attract informed traders and offer greater value for their information, potentially driving price discovery. Collin-Dufresne and Fos (2015) highlight that informed traders selectively time their trades based on liquidity.

Volatility introduces complexity to price discovery in AMMs. Prices in AMMs do not change without trades, creating opportunities for informed traders to exploit stale prices, especially during volatile periods when discrepancies may be pronounced. However, volatility also amplifies arbitrage opportunities between centralized and decentralized exchanges. In this context, arbitrageurs—often builders or searchers—gain informational advantages over LPs in AMMs. Their profits arise from exploiting AMM design inefficiencies rather than directly contributing to price discovery.

To test whether AMMs can lead the price discovery process, we measure each markets contribution of new information in prices by calculating the price discovery shares for Uniswap and Binance through ILS, extending the method of Putniņš (2013) to be used for n markets.

Other widely used empirical measures of price discovery include the information share (IS) proposed by Hasbrouck (1995) and the component share (CS) from Gonzalo and Granger (1995). Both measures decompose price changes into permanent and temporary components. The IS metric evaluates whether a market efficiently incorporates new information while minimizing the impact of liquidity shocks (i.e., noise), whereas the CS metric assesses the sensitivity of each market to lagged transitory shocks from the other. Both measures effectively capture the relative avoidance of noise. Table 1 highlights the difference in noise (realized volatility) between Uniswap and Binance. To account for this, we use the ILS measure, which focuses on incorporating information into prices, independent of the noise differences between markets. The IS is widely used in literature and we also report the results following the IS throughout the paper and in the internet appendix.

We estimate a reduced form vector error correction model (VECM) model for each pair month based on end of block mid-quote prices (p_t) for each market that trades the asset. We estimate the VECM with 300 lags, equating to roughly one hour based on a 12-second block time (details on the estimation process are provided in Appendix B).[9]

$$\Delta p_t = aZ_{t-1} + \sum_{i=1}^{300} b_i \Delta p_{t-i} + \epsilon_t \tag{12}$$

where Δp_t is the $n \times 1$ mid-quote return vector, α is the $n \times (n-1)$ matrix of error correction coefficients, Z_{t-1} is the $n \times 1$ co-integrating vector, b_i is the $n \times n$ coefficient matrix for lag i and ϵ_t is the $n \times 1$ vector of residuals.

We calculate IS_1 to IS_n, and CS_1 to CS_n, from the VECM estimates following Hasbrouck (1995) and Gonzalo and Granger (1995) which is detailed in Appendix B. Next, we calculate market i's propensity to reflect new information (how much market i's price responds to an innovation in the efficient price) through the ratio $\beta_i = \frac{IS_i}{CS_i}$, Normalising the information leadership propensities as per Putniņš (2013) gives ILS:

$$ILS_n = \frac{\beta_n^2}{\sum_{i=1}^{n} \beta_i^2} \tag{13}$$

AMMs rely on trades to update prices, which has led many to consider them a slow market that merely mirrors price movements on centralized exchanges through arbitrage when the AMM quotes a stale price. This assumption holds at an aggregate level, across all Uniswap pools, the average ILS is 8.7%. However, when examining individual pools with varying fee structures, the low-fee pools contribute meaningfully to price discovery. For instance, the Uniswap v3 pool with a 0.05% fee has an average ILS of 24.1%. Similarly, the 0.01% fee pool exhibits an even higher ILS at 61.1%, although this pool predominantly trades FUNToken against Ethereum and other major stablecoins, which is likely to bias the results. In contrast, other AMM pools have very low price discovery shares, confirming the belief that prices on the AMM follow the centralized exchanges.

Figure 1 plots the monthly average ILS for different Uniswap pools [10], highlighting the contribution of the Uniswap v3 0.05% and 0.01% pools compared to Uniswap v2, Uniswap v3 0.3%, and Uniswap v3 1% pools. Notably, prior to the release of Uniswap v3, the Uniswap v2 pools exhibited an ILS around 10%, which significantly declined after Uniswap v3 was introduced. This figure provides partial support for the idea that low fee or low cost AMM

[9] Under Ethereum's previous proof-of-work consensus, block timestamps varied with the likelihood of block completion. However, since the transition to proof-of-stake, blocks are more consistently spaced at approximately 12-second intervals, only deviating when a slot is missed.

[10] Figure IA1 presents the same figure plotting the information share. The results are consistent with Figure 1

pools having a meaningful contribution to the price discovery process.

[Insert Figure 1 Here]

Figure 1 illustrates that AMMs, particularly the low-fee pools, can lead price discovery. To statistically investigate the factors driving price leadership we regress liquidity measures, trading costs, and volatility on the price discovery shares (ILS and IS) of the AMM markets. We estimate the following regression model:

$$PDS_{i,t} = \alpha_{i,t} + Liquidity_{i,t} + Volatility_{i,t} + Gas_t + Controls_{i,t} + \epsilon_{i,t} \tag{14}$$

Where PDS is the AMM price discovery share (ILS or IS). We consider three measures of liquidity, the effective spread, the 1.5% depth and the variance of the 1.5% depth. Each measure of liquidity captures a different aspect of liquidity: width, depth, and resiliency, respectively. We consider both the effect of liquidity in the AMM and LOB market and also the relative effect by taking the ratio between the AMM and LOB. We also consider the explicit cost of inclusion on-chain by measuring the value of gas on Ethereum. Volatility is measured as the realized volatility by the average of squared returns in the LOB market. In this regression, we control for trade volume, pair fixed effects and time fixed effects. All continuous variables are in natural log form.

Table 4 presents the coefficient estimates from OLS regressions based on Equation 14. To test whether the AMM leads price discovery when it is more liquid. The quoted spread (fee) in the AMM shows a significant negative relationship with both the ILS and IS, consistent with the results from Figure 1. These findings suggest that the fee in the AMM plays a significant role in whether the AMM contributes to price discovery. However, the effective spread does not exhibit a significant impact on AMM price discovery shares, likely due to the correlation between effective spread and trade size in the AMM. The AMM price discovery share is also significantly and positively related to the volume on the AMM. Overall, when using spreads to assess AMM liquidity, our findings suggest the AMM leads price discovery when it is more liquid than the LOB market.

[Insert Table 4 Here]

We also assess AMM liquidity by considering market depth. A positive relationship between depth and the AMM's price discovery share is expected, as greater depth should imply that informed traders are more likely to profit from their information through the

AMM. However, the results show a negative relationship between depth and the AMM's price discovery share. This finding contradicts the notion that informed traders are more likely to trade in the AMM when it is liquid. One explanation is that LPs in the AMM withdraw liquidity when adverse selection costs from informed traders are high. However, this seems unlikely, as the AMM must adjust prices through trading regardless of whether the information is new or arises from arbitrage in another market. The significance and magnitude of the relationship between AMM price discovery shares and depth drops when controlling for pair and month fixed effects.

The variance of depth shows a positive relationship with the AMM's price discovery share, though this becomes insignificant when controlling for pair and month fixed effects. There is no clear relationship between realized volatility and AMM price leadership. Price deviations do not appear to affect significantly whether the AMM leads in price discovery.

When including liquidity variables from the LOB market, we observe that AMM price leadership is positively related to the quoted spread in the LOB. After controlling for pair and month fixed effects, AMM price leadership also shows a positive relationship with the effective spread. These findings suggest that the AMM leads price discovery when it is more liquid than the LOB, as higher LOB costs drive informed traders toward the AMM.

The significance of the relation between realized volatility and the AMM price discovery shares when combined with the LOB variables and fixed effects, suggest potential multi-collinearity issues. In the internet appendix[11], we offer alternative specifications that exclude LOB variables such as spread and volatility, given their known explanatory overlap. Notably, removing these variables does not significantly affect the results presented in Table 4.

High explicit costs negatively impact the AMM price discovery shares. Table 4 highlights the negative relation between the price of gas and the price discovery share in the AMM pools. These findings are consistent with the findings of Capponi, Jia, and Yu (2023) which shows that informed traders will bid for priority inclusion in the blockchain. Trading costs in the AMM, both explicit like gas fees and implicit like trading fees, have a significant impact on the AMMs price discovery.

Next, we consider whether the AMMs price discovery share is impacted by aspects of the centralized exchanges in relative terms, such as the AMM being the main liquid market. To test this, we regress on relative measures of spread, depth, and volatility following Equation 14. The relative measures are the log difference between the AMM and LOB measures

[11] In Table IA1 we provide a different specification for regressions focusing on the ILS. In Table IA2 we provide a different specification for regressions focusing on the IS.

used to examine the determinants of the price discovery shares in Table 4.

Table 5 reports coefficient estimates from OLS regressions. Consistent with our findings in Table 4 we find a significant negative relation between the difference in the quoted spread and the AMM price discovery share. We also find a significant positive relation between the volume ratio and the AMM price discovery share. We do not find a significant relation between the difference in the effective spread and the AMM price discovery shares.

[Insert Table 5 Here]

Our findings for the ratio of quoted spread are consistent with this hypothesis. However, the findings in autoreftab:relative-PD-determinant show that when controlling for pair and date fixed effects, the difference between the depth in the AMM and the LOB is negatively related to the price discovery share in the AMM. This finding suggests that a deeper LOB or less liquid AMM is positively related to the AMMs price discovery share. We do not find any significant relation between the variance of depth and the AMM price discovery share.

Aoyagi and Ito (2021) theorizes that informed trading in the AMM should reduce adverse selection in the LOB, reducing spreads in the LOB market. Contrary to this theory, our results suggest when information first enters the market through the AMM, spreads in the LOB are higher. It is possible, but unlikely, that market makers do not learn from the AMM price. However, when liquidity in the LOB is low (i.e. high spreads) the AMM is an attractive market for informed traders as they can profit more from their information. Informed traders appear to be sensitive to the cost structure in each market, limiting their engagement with the AMM when these costs outweigh potential profit from their information. This dynamic may explain why we do not observe a significant reduction in LOB spreads, despite informed trader presence in the AMM.

6 Conclusion

This paper investigates whether AMMs can provide price discovery. Through a variance decomposition, we find that, for assets only traded on AMMs, there is no significant change in the level of information within prices compared with assets traded on both AMMs and LOBs. This finding highlights that AMMs can provide price discovery. Our results show that LPs in AMMs respond to heightened risks of adverse selection by withdrawing their liquidity.

We also find that AMM prices often lag the price in a LOB market. However, in low-fee, high-liquidity pools where trading costs are low, AMMs can lead price discovery. This emphasizes the role of trading costs in influencing AMM price leadership.

AMMs present a viable alternative for efficient and cost-effective trading, particularly in foreign exchange (Foley, O'Neill, and Putniņš, 2023; Malinova and Park, 2023). With potential cost savings and improved gains from trade, AMMs could be a suitable market structure for trading tokenized assets, offering significant clearing and settlement improvements over traditional markets without sacrificing market efficiency and still facilitating price discovery a key function of markets.

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Appendix A Estimation of variance decomposition

To estimate the level of information in a price series, we follow the variance decomposition method of Brogaard et al. (2022). Two key inputs are needed to construct the components of variance which we can get by estimating a reduced form structural VAR model: the variance of the innovations in each variable, $\sigma^2_{\epsilon_{r_m}}$, $\sigma^2_{\epsilon_x}$, $\sigma^2_{\epsilon_r}$ and the long-run cumulative responses to these shocks θ_{r_m}, θ_x, θ_r.

$$
\begin{aligned}
r_{m,t} &= a_0^* + \sum_{l=1}^{12} a_{1,l}^* r_{m,t-l} + \sum_{l=1}^{12} a_{2,l}^* x_{t-l} + \sum_{l=1}^{12} a_{3,l}^* r_{t-l} + e_{r_m,t} \\
x_t &= b_0^* + \sum_{l=1}^{12} b_{1,l}^* r_{m,t-l} + \sum_{l=1}^{12} b_{2,l}^* x_{t-l} + \sum_{l=1}^{12} b_{3,l}^* r_{t-l} + e_{x,t} \\
r_t &= c_0^* + \sum_{l=1}^{12} c_{1,l}^* r_{m,t-l} + \sum_{l=1}^{12} c_{2,l}^* x_{t-l} + \sum_{l=1}^{12} c_{3,l}^* r_{t-l} + e_{r,t}
\end{aligned}
\tag{A1}
$$

The reduced form residuals can be written as linear models of the structural-model residuals:

$$
\begin{aligned}
e_{r_m,t} &= \epsilon_{r_m,t} \\
e_{x,t} &= \epsilon_{x,t} + b_{1,0}\epsilon_{r_m,t} = b_{1,0}e_{r_m,t} + \epsilon_{x,t} \\
e_{r,t} &= \epsilon_{r,t} + (c_{1,0} + c_{2,0}b_{1,0})\epsilon_{r_m,t} + c_{2,0}\epsilon_{x,t} = c_{1,0}e_{r_m,t} + c_{2,0}e_{x,t} + \epsilon_{r,t}
\end{aligned}
\tag{A2}
$$

Although the structural-model residuals are uncorrelated contemporaneously by design, Equation A2 shows that the reduced-form residuals exhibit contemporaneous correlation. This correlation allows for inference about the structural-model residuals. Specifically, we estimate $b_{1,0}$ by regressing the reduced-form innovation $e_{x,t}$ on $e_{r,t}$ following the second equation in Equation A2. Similarly, we estimate $c_{1,0}$ and $c_{2,0}$ by regressing the reduced-form innovation $e_{r,t}$ on $e_{r_m,t}$ and $e_{x,t}$ as indicated in the third equation in Equation A2.. Using the estimated parameters $b_{1,0}$, $c_{1,0}$ and $c_{2,0}$, along with the estimated variances of the reduced-form residuals $\sigma^2_{e_{r_m}}$, $\sigma^2_{e_x}$, and $\sigma^2_{e_r}$ we derive estimates for the variances of the structural model shocks by rearranging the variance expression of Equation A2.

$$
\begin{aligned}
\sigma_{\epsilon_{r_m}} &= \sigma_{e_{r_m}} \\
\sigma_{\epsilon_x} &= \sigma_{e_x} - b_{1,0}^2\sigma^2_{e_{r_m}} \\
\sigma_{\epsilon_r} &= \sigma_{e_r} - (c_{1,0}^2 + 2c_{1,0}c_{2,0}b_{1,0})\sigma^2_{e_{r_m}} - c_{2,0}^2\sigma^2_{e_x}
\end{aligned}
\tag{A3}
$$

To estimate the long-run cumulative impulse response functions of the structural model, we compute the equivalent reduced-form shocks and feed them through the reduced-form model. Specifically:

1. A structural shock to market returns $[\epsilon_{r_m,t}, \epsilon_{x,t}\epsilon_{r,t}]' = [1, 0, 0]'$ has a reduced-form equivalent $[e_{r_m,t}, e_{x,t}e_{r,t}]' = [1, b_{1,0}, (c_{1,0} + c_{2,0}b_{1,0})]'$

2. A structural shock to market returns $[\epsilon_{r_m,t}, \epsilon_{x,t}\epsilon_{r,t}]' = [0, 1, 0]'$ has a reduced-form equivalent $[e_{r_m,t}, e_{x,t}e_{r,t}]' = [0, 1, c_{2,0}]'$

3. A structural shock to market returns $[\epsilon_{r_m,t}, \epsilon_{x,t}\epsilon_{r,t}]' = [0, 0, 1]'$ has a reduced-form equivalent $[e_{r_m,t}, e_{x,t}e_{r,t}]' = [0, 0, 1]'$

The cumulative return response to each of these shocks, evaluated at $t = 36$ (the point where the responses stabilize), provides estimates for θ_{r_m}, θ_x, and θ_r respectively.

The structural VAR innovations $\epsilon_{r_m,t}, \epsilon_{x,t}, \epsilon_{r,t}$ are the shocks that contain information and noise. The information in each shock is the estimated long-run effect on the price, which is the permanent component in the Beveridge and Nelson (1981) decomposition. Therefore, the market-wide information at time t is $\theta_{r_m}\epsilon_{r_m,t}$ where $\epsilon_{r_m,t}$ is the innovation in the structural VAR and θ_{r_m} is the long-run effect of a unit shock, inferred from the cumulative impulse response function of returns to a unit shock. Similarly, the private firm-specific information revealed through trading and the public firm-specific information revealed through other sources are estimated as $\theta_x\epsilon_{x,t}$ and $\theta_r\epsilon_{r,t}$, where $\epsilon_{x,t}$ and $\epsilon_{r,t}$ are the innovations in the structural VAR and θ_x and θ_r are the long-run cumulative impulse responses of returns to a unit shock to a unit shock.

The sum of the estimated information components gives the innovation in the efficient price, $w_t = \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t}$. The change in the pricing error (noise return), is the realized return that is not attributable to information or discount rate (drift): $s_t = r_t - \mu - w_t = r_t - a0 - \theta_{r_m}\varepsilon_{r_m,t} - \theta_x\varepsilon_{x,t} - \theta_r\varepsilon_{r,t}$, and the noise variance, σ_s^2, is estimated as the variance of the time series of Δs_t

Taking the variance of the innovations in the efficient price we get $\sigma_w^2 = \theta_{r_m}^2\sigma_{\epsilon_{r_m}}^2 + \theta_x^2\sigma_{\epsilon_x}^2 + \theta_r^2\sigma_{\epsilon_r}^2$. Recall, the errors in the structural model are contemporaneously uncorrelated by construction and therefore the covariance terms are all zero. The contribution to the variation in the efficient price from each of the information components is $\theta_{r_m}^2\sigma_{\epsilon_{r_m}}^2$ (market-wide information), $\theta_x^2\sigma_{\epsilon_x}^2$ (private firm-specific information), and $\theta_r^2\sigma_{\epsilon_r}^2$ (public firm-specific information). The estimated components of variance are therefore

$$\begin{aligned} MarketInfo &= \theta_{r_m}^2 \sigma_{\varepsilon_{rm}}^2 \\ PrivateInfo &= \theta_x^2 \sigma_{\varepsilon_x}^2 \\ PrivateInfo &= \theta_r^2 \sigma_{\varepsilon_r}^2 \\ Noise &= \sigma_s^2 \end{aligned} \tag{A4}$$

Normalizing these variance components to sum to 100% gives variance shares:

$$\begin{aligned} MarketInfoShare &= \theta_{r_m}^2 \sigma_{\varepsilon_{rm}}^2 / (\sigma_w^2 + \sigma_s^2) \\ PrivateInfoShare &= \theta_x^2 \sigma_{\varepsilon_x}^2 / (\sigma_w^2 + \sigma_s^2) \\ PrivateInfoShare &= \theta_r^2 \sigma_{\varepsilon_r}^2 / (\sigma_w^2 + \sigma_s^2) \\ NoiseShare &= \sigma_s^2 / (\sigma_w^2 + \sigma_s^2) \end{aligned} \tag{A5}$$

$MarketInfo$, $PrivateInfo$, $PublicInfo$, and $Noise$ are the variance contributions of market-wide information, trading on private firm-specific information, firm-specific information other than that revealed through trading, and noise, respectively. $MarktInfoShare$, $PrivateInfoShare$, and $PublicInfoShare$, are the corresponding shares of variance from those various sources of stock-price movements. Meanwhile, $NoiseShare$ reflects the relative importance of pricing errors due to over- or underreaction to information, illiquidity, price pressures, or other microstructure frictions.

Appendix B Estimation of price discovery shares

For each pair-month, we estimate a reduced form VECM of the log price series ($p_{1,t}$ to $p_{n,t}$) with 300 lags (prices are sampled based on the Ethereum block time where trading is continuous in the AMM and the LOB).

$$\Delta p_t = aZ_{t-1} + \sum_{i=1}^{300} b_i \Delta p_{t-i} + \epsilon_t \tag{A6}$$

where Δp_t is the $n \times 1$ midquote return vector, α is the $n \times (n-1)$ matrix of error correction coefficients, Z_{t-1} is the $n \times 1$ co-integrating vector, b_i is the $n \times n$ coefficient matrix for lag i and ϵ_t is the $n \times 1$ vector of residuals.

From the reduced form VECM estimates in Equation A6 we derive the corresponding infinite lag VMA representation in structural form assuming recursive contemporaneous causality running from the first through to the last price series.

$$\begin{aligned}
\Delta p_{1,t} &= \sum_{l=0}^{\infty} A_{1,l}\varepsilon_{1,t-1} + \sum_{l=0}^{\infty} A_{2,l}\varepsilon_{2,t-1} + \cdots + \sum_{l=0}^{\infty} A_{n,l}\varepsilon_{n,t-1} \\
\Delta p_{2,t} &= \sum_{l=0}^{\infty} B_{1,l}\varepsilon_{1,t-1} + \sum_{l=0}^{\infty} B_{2,l}\varepsilon_{2,t-1} + \cdots + \sum_{l=0}^{\infty} B_{n,l}\varepsilon_{n,t-1} \\
&\vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad \vdots \\
\Delta p_{n,t} &= \sum_{l=0}^{\infty} N_{1,l}\varepsilon_{1,t-1} + \sum_{l=0}^{\infty} N_{2,l}\varepsilon_{2,t-1} + \cdots + \sum_{l=0}^{\infty} N_{n,l}\varepsilon_{n,t-1}
\end{aligned} \tag{A7}$$

We obtain the structural VMA coefficients by computing the orthogonalized impulse response functions and the (contemporaneously uncorrelated) structural VMA errors ($\varepsilon_{1,t}$ to $\varepsilon_{n,t}$) by mapping their relation to the reduced form errors. The permanent price impacts of shocks to the n price series are obtained from the structural VMA. For example, a unit shock to the first price ($\varepsilon_{1,t} = 1$) has a permanent effect on all of the prices equal to $\theta_{\varepsilon 1} = \sum_{l=0}^{\infty} A_{1,l}$. The permanent price impact is the same for all prices $\theta_{\epsilon 1} = \sum_{l=0}^{\infty} A_{1,l} = \sum_{l=0}^{\infty} B_{1,l} = \sum_{l=0}^{\infty} N_{1,l}$ because permanent impacts are innovations in the efficient value and the efficient value is common to all prices as they refer to the same underlying asset (Hasbrouck, 1995).

Following Hasbrouck (1995) the temporary-permanent decomposition (which is based on Stock and Watson (1988) common trend representation), innovations in the permanent component (the efficient price, m_t) are given by

$$\Delta m_t = \theta_{\varepsilon 1}\varepsilon_{1,t} + \theta_{\varepsilon 2}\varepsilon_{2,t} + \cdots + \theta_{\varepsilon n}\varepsilon_{n,t}$$

The variance of the innovations in the efficient price is therefore:

$$\begin{aligned} Var(\Delta m_t) &= Var(\theta_{\varepsilon 1}\varepsilon_{1,t} + \theta_{\varepsilon 2}\varepsilon_{2,t} + \cdots + \theta_{\varepsilon n}\varepsilon_{n,t}) \\ &= \theta_{\varepsilon 1}^2 Var(\varepsilon_{1,t}) + \theta_{\varepsilon 2}^2 Var(\varepsilon_{2,t}) + \cdots + \theta_{\varepsilon n}^2 Var(\varepsilon_{n,t}) \end{aligned}$$

because the structural VMA errors are uncorrelated by construction (contemporaneous correlation in the reduced form errors is absorbed in the recursive contemporaneous effects that are part of the structural VMA). Hasbrouck (1995) information shares (IS) are obtained as each price's contribution to the variance of the efficient price innovations

$$IS_n = \frac{\theta_{\varepsilon n}^2 Var(\varepsilon_{n,t})}{Var(\Delta m_t)} \tag{A8}$$

The Gonzalo and Granger (1995) component shares (CS) are obtained by normalizing the permanent price impacts of each price series in the reduced form model. Obtaining the permanent price impacts of the reduced form model is similar to the procedure for the structural model, except that simple impulse response functions from the reduced form VECM are used instead of orthogonalized impulse response functions. We ensure all permanent price impacts are non-negative so that the CS take the range $[0, 1]$.

$$CS_n = \frac{\theta_{\epsilon n}}{\sum_{i=1}^{n} \theta_{\epsilon i}} \tag{A9}$$

Finally, we calculate the information leadership share (ILS) by extending the approach in Yan and Zivot (2010) and Putniņš (2013) to the case of multiple markets. In the two-price case, market's propensity to reflect new information (how much market i's price responds to an innovation in the efficient price) can be obtained from the ratio $\beta_i = \frac{IS_i}{CS_i}$, which when normalized gives the information leadership share

$$ILS_n = \frac{\beta_n^2}{\sum_{i=1}^{n} \beta_i^2} \tag{A10}$$

The IS estimated in Hasbrouck (1995) are not unique and depend on the ordering of the prices in the estimation procedure. This is due to the recursive contemporaneous causality assumed to run from the first through to the last price series (this assumption is implicit in procedures that use Cholesky factorization of the covariance matrix of reduced form errors, and explicit in the structural VMA that we present above). We apply the standard approach used in the literature and estimate IS (and subsequently ILS) for each price under all possible orderings of the prices. This gives a range of IS values for each price, with the minimum and maximum values providing the lower and upper bounds on IS. We take the median IS and ILS from the range of IS and ILS values to get a single estimate for each price.

Table 1. Summary statistics of AMM and LOB trading pairs

This table presents the summary statistics for the LOB (Panel A) and AMM (Panel B) trading pairs based on pair month observations for the sample period between June 2020 and March 2023. Volume is the value of trade volume in millions of dollars. Trades are the number of thousands of trades for the month. Mean Trade is the average trade size in dollars for the pair in the month. Median Trade is the median trade size in dollars for the pair in the month. Realized Volatility is the average of squared hourly mid-quote returns. The Half Quoted Spread for the AMM is equal to the liquidity pool fee. The Half Quoted Spread for Binance is the time weighted average half quoted spread for the month. Effective Spread is the volume weighted effective spread in AMM winsorized at 99% before taking the weighted average to control for large outliers. $\text{Depth}_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month. Depth $\text{Variance}_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month.

Panel A. Limit Order Book Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Volume ($)	4,532	20,109	3	24	4,018
Trades	3,966.2	19,541.8	16.1	85.8	4,803.5
Mean Trade ($)	480	486	113	294	1,223
Median Trade ($)	147	161	30	90	370
Realized Volatility (%)	1.46	2.02	0.24	0.85	3.41
Half Quoted Spread (%)	0.21	0.17	0.04	0.18	0.40
Effective Spread (%)	0.25	0.30	0.03	0.18	0.51
$\text{Depth}_{[1.5\%]}$ ($)	1.81	6.13	0.01	0.07	3.30
Depth $\text{Variance}_{[1.5\%]}$ (%)	45.34	24.52	23.77	40.04	71.33

Panel B. Automated Market Maker Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Volume ($)	298	1,596	1	8	455
Trades	9.5	31.5	0.4	1.7	15.0
Mean Trade ($)	15,395	35,404	1,348	5,101	29,865
Median Trade ($)	7,167	19,007	393	2,266	12,649
Realized Volatility (%)	17.43	211.33	0.22	1.53	11.43
Half Quoted Spread (%)	0.33	0.20	0.30	0.30	0.30
Effective Spread (%)	4.57	17.67	0.44	1.50	4.30
$\text{Depth}_{[1.5\%]}$ ($)	2.47	14.13	0.00	0.02	1.38
Depth $\text{Variance}_{[1.5\%]}$ (%)	36.98	54.22	6.74	18.54	82.68

Table 2. Summary statistics for shares of variance

This table presents the summary statistics for the LOB (Panel A) and AMM (Panel B) trading pairs based on pair month observations for the sample period between June 2020 and March 2023. $NoiseShare$, $MarketInfoShare$, $PrivateInfoShare$, and $PublicInfoShare$, are the shares of variance explained by noise, market information, private information and public information respectively.

Panel A. AMM and LOB Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
$MarketInfoShare$ (%)	7.44	14.86	0.04	2.24	17.58
$PrivateInfoShare$ (%)	42.35	25.03	4.99	45.22	73.88
$PublicInfoShare$ (%)	5.45	9.37	0.21	2.14	11.72
$NoiseShare$ (%)	44.76	25.11	17.59	39.67	88.37
Panel B. AMM Only Summary Statistics					
$MarketInfoShare$ (%)	5.64	11.67	0.05	1.23	14.77
$PrivateInfoShare$ (%)	45.02	21.87	11.47	48.85	71.57
$PublicInfoShare$ (%)	4.80	5.73	0.21	2.99	12.47
$NoiseShare$ (%)	44.53	19.82	20.07	43.34	72.32

Table 3. Regressions to assess the determinants variance shares

This table reports coefficient estimates from OLS regressions using pair-month observations to examine the determinants of the AMM variance shares. The dependent variables $NoiseShare$, $MarketInfoShare$, $PrivateInfoShare$, and $PublicInfoShare$, are the shares of variance explained by noise, market information, private information and public information respectively (Regressions 1-4). $EffectiveSpread$ is the volume weighted effective spread in the AMM winsorized at 99% before taking the weighted average to control for large outliers. $Depth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $DepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $Volume$ is the value of trade volume in dollars on the AMM. $RealizedVolatility$ is the average of squared hourly mid-quote returns on Binance. Gas is the average price of gas on the Ethereum blockchain in dollars in a month. ConcLiquidity is a dummy variable for that is equal to one if the market uses concentrated liquidity from Uniswap v3. All explanatory variables are in natural log form. The sample comprises x observations from x trading pairs during the period June 2020 to March 2023. Standard errors are clustered by pair month. t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	$NoiseShare$	$MarketInfoShare$	$PrivateInfoShare$	$PublicInfoShare$
AMM Only	−0.036**	−0.004	0.039**	0.002
	(−2.26)	(−0.42)	(2.09)	(0.31)
$EffectiveSpread$	0.092***	0.002	−0.103***	0.009
	(5.51)	(0.27)	(−6.74)	(0.95)
$Depth_{[1.5\%]}$	0.004	0.014*	−0.020**	0.002
	(0.76)	(1.84)	(−2.22)	(0.56)
$DepthVariance_{[1.5\%]}$	−0.042***	0.017	−0.003	0.027***
	(−3.76)	(1.50)	(−0.19)	(4.39)
$Volume$	−0.035***	0.014**	0.026**	−0.006
	(−4.59)	(2.14)	(2.50)	(−1.53)
$RealizedVolatility$	0.052***	−0.024***	−0.017	−0.012*
	(4.61)	(−3.52)	(−1.35)	(−1.95)
Gas	0.007	−0.006	−0.007	0.006*
	(0.72)	(−0.79)	(−0.60)	(1.73)
ConcLiquidity	0.121***	0.027	−0.123***	−0.025***
	(4.76)	(1.53)	(−4.07)	(−2.64)
Intercept	1.712***	−0.514***	−0.369*	0.171**
	(10.96)	(−3.38)	(−1.71)	(2.40)
Observations	522	522	522	522
Adjusted R^2	39.3%	20.3%	20.8%	6.4%

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

Table 4. Regressions to assess the determinants of AMM price discovery

This table reports coefficient estimates from OLS regressions using pair-month observations to examine the determinants of the AMM price discovery shares. The dependant variable in regression 1 and 2 is the Yan-Zivot-Putnins information leadership share (ILS). The dependant variable in regression 3 and 4 is the Hasbrouck information share (IS). $QuotedSpread$ is the fee in the AMM. $EffectiveSpread$ is the volume weighted effective spread in the AMM winsorized at 99% before taking the weighted average to control for large outliers. $Depth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $DepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $Volume$ is the value of trade volume in dollars on the AMM. $LOBQuotedSpread$ is the average half quoted spread on Binance. $LOBEffectiveSpread$ is the volume weighted effective spread on Binance. $LOBDepth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on Binance. $LOBDepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on Binance. $LOBVolume$ is the value of trade volume in dollars on Binance. $RealizedVolatility$ is the average of squared hourly mid-quote returns on Binance. Gas is the average price of gas on the Ethereum blockchain in dollars in a month. All explanatory variables are in natural log form. The sample comprises 1577 observations from 58 trading pairs during the period June 2020 to March 2023. Standard errors are clustered by pair month. 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	IS	IS	IS	IS
$QuotedSpread$	−0.085***	−0.079***	−0.070***	−0.068***	−0.085***	−0.079***	−0.070***	−0.068***
	(−9.54)	(−9.45)	(−9.04)	(−8.93)	(−9.54)	(−9.45)	(−9.04)	(−8.93)
$EffectiveSpread$	−0.006	−0.003	0.000	0.001	−0.006	−0.003	0.000	0.001
	(−1.52)	(−0.75)	(0.03)	(0.34)	(−1.52)	(−0.75)	(0.03)	(0.34)
$Depth_{[1.5\%]}$	−0.005***	−0.004***	−0.003*	−0.003*	−0.005***	−0.004***	−0.003*	−0.003*
	(−3.49)	(−2.96)	(−1.84)	(−1.71)	(−3.49)	(−2.96)	(−1.84)	(−1.71)
$DepthVariance_{[1.5\%]}$	−0.017***	−0.012***	−0.001	−0.001	−0.017***	−0.012***	−0.001	−0.001
	(−4.82)	(−3.72)	(−0.43)	(−0.18)	(−4.82)	(−3.72)	(−0.43)	(−0.18)
$Volume$	0.015***	0.025***	0.020***	0.022***	0.015***	0.025***	0.020***	0.022***
	(5.35)	(8.67)	(6.86)	(7.36)	(5.35)	(8.67)	(6.86)	(7.36)
$LOBQuotedSpread$		0.016***		0.004		0.016***		0.004
		(5.18)		(1.43)		(5.18)		(1.43)
$LOBEffectiveSpread$		0.005		0.022***		0.005		0.022***
		(0.76)		(3.03)		(0.76)		(3.03)
$LOBDepth_{[1.5\%]}$		−0.026***		−0.021***		−0.026***		−0.021***
		(−3.90)		(−2.79)		(−3.90)		(−2.79)
$LOBDepthVariance_{[1.5\%]}$		0.001		0.000		0.001		0.000
		(0.13)		(0.01)		(0.13)		(0.01)
$LOBVolume$		0.008*		−0.011		0.008*		−0.011
		(1.66)		(−1.63)		(1.66)		(−1.63)
$RealizedVolatility$	0.015***	−0.008*	−0.011**	−0.006	0.015***	−0.008*	−0.011**	−0.006
	(3.95)	(−1.65)	(−2.12)	(−0.92)	(3.95)	(−1.65)	(−2.12)	(−0.92)
Gas	−0.018***	−0.015***			−0.018***	−0.015***		
	(−5.32)	(−4.96)			(−5.32)	(−4.96)		
Intercept	−0.691***	−0.698***	−0.694***	−0.098	−0.691***	−0.698***	−0.694***	−0.098
	(−9.52)	(−9.56)	(−6.95)	(−0.67)	(−9.52)	(−9.56)	(−6.95)	(−0.67)
Pair Effects	N	N	Y	Y	N	N	Y	Y
Month Effects	N	N	Y	Y	N	N	Y	Y
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577
Adjusted R^2	28.2%	34.4%	47.1%	48.6%	28.2%	34.4%	47.1%	48.6%

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

Table 5. Regressions to assess the relative determinants of AMM price discovery

This table reports coefficient estimates from OLS regressions using pair-month observations to examine the determinants of the AMM price discovery shares. The dependant variable is the Yan-Zivot-Putnins information leadership share ILS. $QuotedSpreadRatio$ is a ratio between the fee in the AMM and the average half quoted spread for Binance. $EffectiveSpreadRatio$ is the ratio of the volume weighted effective spread between the AMM and Binance. $Depth_{[1.5\%]}Ratio$ is the ratio of the average value of orders in dollars between 0% and 1.5% of the mid-quote price for the AMM and Binance, respectively. $DepthVariance_{[1.5\%]}Ratio$ is the ratio of the standard deviation divided by the average of orders in dollars between 0% and 1.5% of the mid-quote price for the AMM and Binance, respectively. $VolumeRatio$ is the ratio of the value of trade volume in dollars between the AMM and Binance. $RealizedVolatilityRatio$ is the ratio of average of squared hourly returns between the AMM and Binance. $RealizedVolatility$ is the average of squared hourly mid-quote returns on Binance. Gas is the average price of gas on the Ethereum blockchain in dollars in a month. All explanatory variables are in natural log form. The sample comprises 1577 observations from 58 trading pairs during the period June 2020 to March 2023. Standard errors are clustered by pair month. t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	ILS	ILS	IS	IS
$QuotedSpreadRatio$	−0.046***	−0.040***	−0.041***	−0.038***
	(−7.34)	(−6.94)	(−7.91)	(−7.96)
$EffectiveSpreadRatio$	0.022***	0.011*	0.014**	0.006
	(3.39)	(1.87)	(2.54)	(1.11)
$Depth_{[1.5\%]}Ratio$	−0.003	−0.006**	−0.001	−0.005***
	(−1.46)	(−2.50)	(−0.90)	(−2.72)
$DepthVarience_{[1.5\%]}Ratio$	−0.001	0.002	−0.004	−0.001
	(−0.15)	(0.66)	(−1.17)	(−0.36)
$VolumeRatio$	0.016***	0.026***	0.017***	0.029***
	(6.04)	(7.27)	(7.62)	(9.48)
$RealizedVolatilityRatio$	−0.029***	−0.007	−0.028***	−0.009**
	(−5.93)	(−1.57)	(−6.82)	(−2.46)
$RealizedVolatility$	−0.022***	−0.019***	−0.011**	−0.007
	(−3.80)	(−3.04)	(−2.30)	(−1.18)
Gas	−0.010**		−0.012***	
	(−2.45)		(−3.24)	
Intercept	−0.241***	−0.129	−0.100**	0.049
	(−4.22)	(−1.42)	(−2.07)	(0.62)
Pair Effects	N	Y	N	Y
Month Effects	N	Y	N	Y
Observations	1,577	1,577	1,577	1,577
Adjusted R^2	18.2%	39.8%	24.3%	45.3%

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

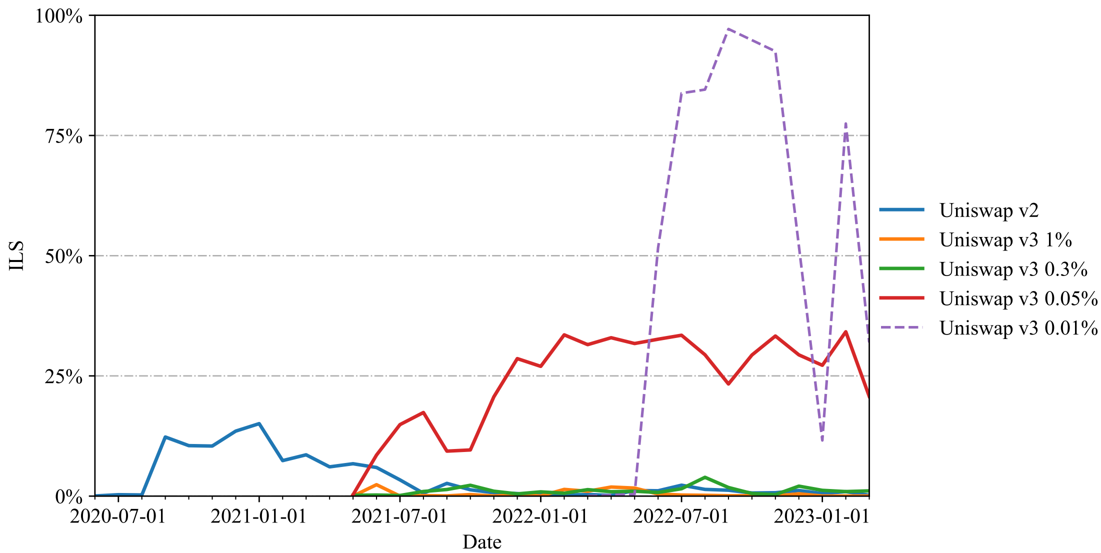

Figure 1. AMM Price discovery shares.
This figure plots the Yan-Zivot-Putnins information leadership share (ILS) for Uniswap pools from 58 trading pairs during the period June 2020 to March 2023. The plotted ILS is the mean price discovery share for each different Uniswap market (Uniswap v2, Uniswap v3 1%, Uniswap v3 0.3%, Uniswap v3 0.05%, and Uniswap v3 0.01%).

Can Automated Market Makers provide price discovery?

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Internet Appendix

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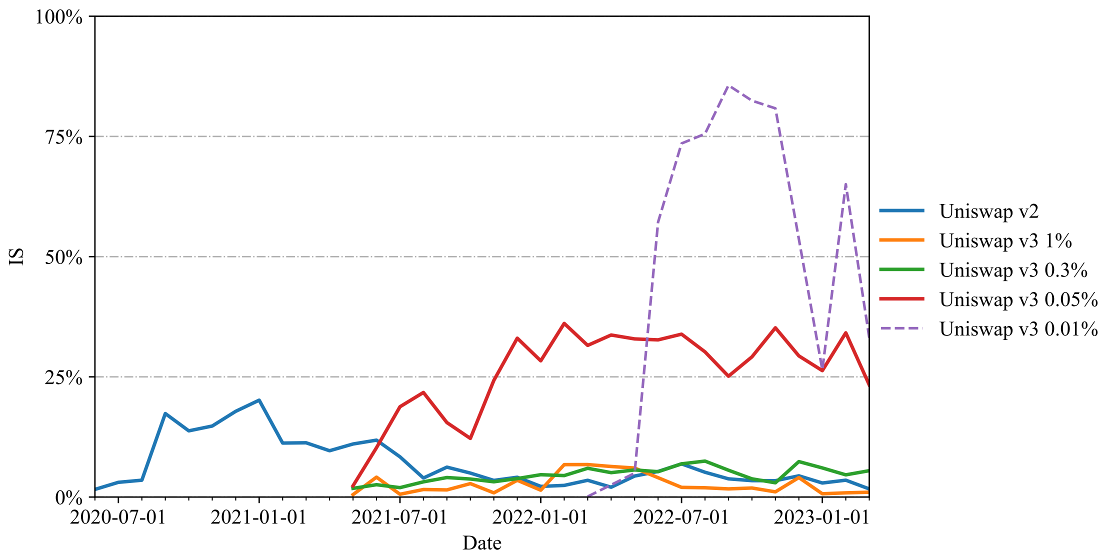

Figure IA1. AMM Price discovery shares (IS).
This figure plots the Hasbrouck information share (IS) for Uniswap pools from 58 trading pairs during the period June 2020 to March 2023. The plotted ILS is the mean price discovery share for each different Uniswap market (Uniswap v2, Uniswap v3 1%, Uniswap v3 0.3%, Uniswap v3 0.05%, and Uniswap v3 0.01%).

Table IA1. Alternate specifications of regressions to assess the determinants of AMM price discovery (ILS)

This table reports coefficient estimates from OLS regressions using pair-month observations to examine the determinants of the AMM price discovery shares. The dependant variable in these regressions is the Yan-Zivot-Putnins information leadership share (ILS). $QuotedSpread$ is the fee in the AMM. $EffectiveSpread$ is the volume weighted effective spread in the AMM winsorized at 99% before taking the weighted average to control for large outliers. $Depth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $DepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $Volume$ is the value of trade volume in dollars on the AMM. $LOBQuotedSpread$ is the average half quoted spread on Binance. $LOBEffectiveSpread$ is the volume weighted effective spread on Binance. $LOBDepth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on Binance. $LOBDepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on Binance. $LOBVolume$ is the value of trade volume in dollars on Binance. $RealizedVolatility$ is the average of squared hourly mid-quote returns on Binance. Gas is the average price of gas on the Ethereum blockchain in dollars in a month. All explanatory variables are in natural log form. The sample comprises 1577 observations from 58 trading pairs during the period June 2020 to March 2023. Standard errors are clustered by pair month. 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)	(9)	(10)	(11)	(12)
Dependent variable:	ILS	ILS	ILS	ILS	ILS	ILS	ILS	ILS	ILS	ILS	ILS	ILS
$QuotedSpread$	−0.089***	−0.088***	−0.088***	−0.091***	−0.091***	−0.089***	−0.075***	−0.075***	−0.076***	−0.076***	−0.077***	−0.076***
	(−8.31)	(−8.26)	(−8.29)	(−8.28)	(−8.28)	(−8.18)	(−7.77)	(−7.77)	(−7.81)	(−7.84)	(−7.85)	(−7.83)
$EffectiveSpread$	0.004	0.003	0.003	0.003	0.003	0.002	0.009*	0.009*	0.008*	0.008*	0.008*	0.008*
	(0.79)	(0.60)	(0.59)	(0.63)	(0.63)	(0.51)	(1.86)	(1.84)	(1.81)	(1.73)	(1.76)	(1.73)
$Depth_{[1.5\%]}$	−0.005***	−0.006***	−0.006***	−0.004**	−0.004**	−0.006***	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003
	(−2.86)	(−3.32)	(−3.25)	(−2.43)	(−2.45)	(−3.05)	(−1.43)	(−1.46)	(−1.46)	(−1.26)	(−1.31)	(−1.29)
$DepthVariance_{[1.5\%]}$	−0.009**	−0.010**	−0.010**	−0.009**	−0.009**	−0.010**	0.003	0.003	0.003	0.003	0.003	0.003
	(−2.42)	(−2.52)	(−2.52)	(−2.38)	(−2.36)	(−2.49)	(0.88)	(0.87)	(0.93)	(0.88)	(0.93)	(0.87)
$Volume$	0.023***	0.023***	0.023***	0.022***	0.022***	0.023***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(6.66)	(6.65)	(6.59)	(6.25)	(6.25)	(6.29)	(5.26)	(5.27)	(5.24)	(5.05)	(5.12)	(5.06)
$LOBQuotedSpread$	0.019***			0.017***	0.015***		0.004			0.002	0.004	
	(5.05)			(4.55)	(4.42)		(1.07)			(0.69)	(1.18)	
$LOBEffectiveSpread$	−0.005	0.001		−0.012*		−0.004	0.021**	0.022**		0.017**		0.017**
	(−0.68)	(0.08)		(−1.83)		(−0.59)	(2.44)	(2.55)		(2.03)		(2.13)
$LOBDepth_{[1.5\%]}$	−0.019**	−0.018**	−0.018**	−0.011	−0.007	−0.014*	−0.017*	−0.017**	−0.020**	−0.013	−0.016*	−0.014*
	(−2.29)	(−2.18)	(−2.20)	(−1.58)	(−1.04)	(−1.86)	(−1.87)	(−1.98)	(−2.23)	(−1.60)	(−1.93)	(−1.71)
$LOBDepthVariance_{[1.5\%]}$	−0.005	0.004	0.005	−0.004	−0.008	0.004	−0.002	−0.001	0.000	−0.004	−0.003	−0.004
	(−0.50)	(0.46)	(0.47)	(−0.44)	(−0.78)	(0.44)	(−0.18)	(−0.14)	(−0.05)	(−0.41)	(−0.29)	(−0.37)
$LOBVolume$	0.004	0.001	0.001	−0.003	−0.004	−0.003	−0.010	−0.011	−0.015*	−0.018***	−0.020***	−0.018***
	(0.63)	(0.21)	(0.19)	(−0.77)	(−0.85)	(−0.63)	(−1.33)	(−1.38)	(−1.90)	(−3.01)	(−3.10)	(−2.99)
$RealizedVolatility$	−0.013**	−0.008	−0.007				−0.016**	−0.015*	−0.009			
	(−2.14)	(−1.17)	(−1.38)				(−2.07)	(−1.95)	(−1.15)			
Gas	−0.013***	−0.010***	−0.010***	−0.014***	−0.015***	−0.011***						
	(−3.62)	(−2.76)	(−2.78)	(−4.02)	(−4.29)	(−3.07)						
Intercept	−0.805***	−0.763***	−0.761***	−0.709***	−0.703***	−0.708***	−0.240	−0.231	−0.216	−0.025	−0.078	−0.028
	(−8.81)	(−8.37)	(−8.54)	(−9.44)	(−9.38)	(−9.27)	(−1.38)	(−1.33)	(−1.22)	(−0.18)	(−0.62)	(−0.21)
Pair Effects	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Month Effects	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577
Adjusted R^2	26.9%	26.1%	26.2%	26.8%	26.7%	26.1%	43.1%	43.1%	42.9%	43.0%	42.9%	43.0%

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

Table IA2. Alternate specifications of regressions to assess the determinants of AMM price discovery (IS)

This table reports coefficient estimates from OLS regressions using pair-month observations to examine the determinants of the AMM price discovery shares. The dependant variable in these regressions is the Hasbrouck information share (IS). $QuotedSpread$ is the fee in the AMM. $EffectiveSpread$ is the volume weighted effective spread in the AMM winsorized at 99% before taking the weighted average to control for large outliers. $Depth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $DepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on the AMM. $Volume$ is the value of trade volume in dollars on the AMM. $LOBQuotedSpread$ is the average half quoted spread on Binance. $LOBEffectiveSpread$ is the volume weighted effective spread on Binance. $LOBDepth_{[1.5\%]}$ is the average value of orders in thousands of dollars between 0% and 1.5% of the mid-quote price for the pair-month on Binance. $LOBDepthVariance_{[1.5\%]}$ is the standard deviation divided by the mean of the depth between 0% and 1.5% of the mid-quote price for the pair-month on Binance. $LOBVolume$ is the value of trade volume in dollars on Binance. $RealizedVolatility$ is the average of squared hourly mid-quote returns on Binance. Gas is the average price of gas on the Ethereum blockchain in dollars in a month. All explanatory variables are in natural log form. The sample comprises 1577 observations from 58 trading pairs during the period June 2020 to March 2023. Standard errors are clustered by pair month. 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)	(9)	(10)	(11)	(12)
Dependent variable:	IS	IS	IS	IS	IS	IS	IS	IS	IS	IS	IS	IS
$QuotedSpread$	−0.079***	−0.078***	−0.079***	−0.080***	−0.080***	−0.079***	−0.068***	−0.068***	−0.068***	−0.068***	−0.069***	−0.068***
	(−9.45)	(−9.39)	(−9.49)	(−9.40)	(−9.42)	(−9.28)	(−8.93)	(−8.92)	(−8.96)	(−8.95)	(−8.95)	(−8.93)
$EffectiveSpread$	−0.003	−0.004	−0.004	−0.003	−0.003	−0.004	0.001	0.001	0.001	0.001	0.001	0.001
	(−0.75)	(−0.94)	(−1.00)	(−0.87)	(−0.87)	(−0.99)	(0.34)	(0.31)	(0.28)	(0.28)	(0.32)	(0.27)
$Depth_{[1.5\%]}$	−0.004***	−0.005***	−0.005***	−0.004***	−0.004***	−0.005***	−0.003*	−0.003*	−0.003*	−0.003*	−0.003*	−0.003*
	(−2.96)	(−3.47)	(−3.27)	(−2.67)	(−2.65)	(−3.36)	(−1.71)	(−1.75)	(−1.75)	(−1.66)	(−1.72)	(−1.71)
$DepthVariance_{[1.5\%]}$	−0.012***	−0.012***	−0.012***	−0.012***	−0.012***	−0.012***	−0.001	−0.001	0.000	−0.001	0.000	−0.001
	(−3.72)	(−3.82)	(−3.82)	(−3.68)	(−3.68)	(−3.80)	(−0.18)	(−0.19)	(−0.12)	(−0.18)	(−0.11)	(−0.19)
$Volume$	0.025***	0.025***	0.025***	0.024***	0.024***	0.025***	0.022***	0.022***	0.022***	0.021***	0.022***	0.021***
	(8.67)	(8.65)	(8.48)	(8.36)	(8.34)	(8.37)	(7.36)	(7.36)	(7.31)	(7.36)	(7.45)	(7.38)
$LOBQuotedSpread$	0.016***			0.015***	0.015***		0.004			0.004	0.006*	
	(5.18)			(4.74)	(5.19)		(1.43)			(1.27)	(1.96)	
$LOBEffectiveSpread$	0.005	0.010		0.001		0.008	0.022***	0.023***		0.020***		0.021***
	(0.76)	(1.54)		(0.12)		(1.49)	(3.03)	(3.17)		(2.86)		(3.04)
$LOBDepth_{[1.5\%]}$	−0.026***	−0.025***	−0.026***	−0.021***	−0.021***	−0.023***	−0.021***	−0.022***	−0.024***	−0.019***	−0.022***	−0.020***
	(−3.90)	(−3.73)	(−3.94)	(−3.62)	(−4.06)	(−3.88)	(−2.79)	(−2.94)	(−3.24)	(−2.77)	(−3.24)	(−2.96)
$LOBDepthVariance_{[1.5\%]}$	0.001	0.009	0.012	0.001	0.002	0.009	0.000	0.001	0.001	−0.001	0.001	0.000
	(0.13)	(1.12)	(1.45)	(0.17)	(0.18)	(1.11)	(0.01)	(0.07)	(0.18)	(−0.09)	(0.08)	(−0.02)
$LOBVolume$	0.008*	0.006	0.004	0.003	0.003	0.004	−0.011	−0.011*	−0.016**	−0.014***	−0.015***	−0.014**
	(1.66)	(1.20)	(0.84)	(0.93)	(0.93)	(1.07)	(−1.63)	(−1.70)	(−2.33)	(−2.59)	(−2.75)	(−2.56)
$RealizedVolatility$	−0.008*	−0.004	0.000				−0.006	−0.005	0.002			
	(−1.65)	(−0.67)	(0.08)				(−0.92)	(−0.76)	(0.24)			
Gas	−0.015***	−0.013***	−0.012***	−0.016***	−0.016***	−0.013***						
	(−4.96)	(−4.07)	(−4.01)	(−5.30)	(−5.38)	(−4.29)						
Intercept	−0.698***	−0.662***	−0.638***	−0.637***	−0.638***	−0.637***	−0.098	−0.089	−0.072	−0.016	−0.082	−0.021
	(−9.56)	(−9.07)	(−8.93)	(,−10.61)	(,−10.70)	(,−10.44)	(−0.67)	(−0.61)	(−0.48)	(−0.15)	(−0.78)	(−0.19)
Pair Effects	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Month Effects	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Observations	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577
Adjusted R^2	34.4%	33.7%	33.7%	34.4%	34.4%	33.7%	48.6%	48.6%	48.3%	48.6%	48.4%	48.6%

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